DOLB

MASTER'S THESIS :

Failure Modeling and Analysis of Offshore Process Components

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منشورات البرنامج الوطني لتطوير المجلات العلمية

Failure Modeling and Analysis of Offshore Process Components

by

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Abstract

This thesis investigates the risk of offshore oil and gas processing equipment operating in a harsh environment. It comprises of two major studies which form the core of journal papers submitted for publication. The first study presented a new risk assessment methodology with applications to fire scenarios in compressor and heat exchanger units. A sensitivity analysis was conducted to identify the critical components, their interdependence, and importance in causing failure. In the second study, a risk assessment approach is proposed that demonstrates how process system failure risk could be assessed in the absence of complete data. The approach also highlighted the importance of interdependence of the failure causation factors. The Bayesian Network (BN) is used in the study to capture interdependence of and uncertainty the variables. Noisy-OR and Leaky Noisy-OR logics are used to improve uncertainty-handling capacity and overcome the data requirement. Application of the proposed approach is demonstrated on a subsea pipeline failure scenario. As a first step, a Bowtie (BT) was developed which captures all the possible failure causes of a leak and shows the potential consequences of a leak in the subsea pipeline. The BT was then mapped to a BN for OR, Noisy-OR and Leaky Noisy-OR logics. Failure probabilities of Subsea Pipeline and its Safety Barriers were calculated with Bow-tie and Bayesian Network for different Logics. Finally, importance analysis was performed for 21 basic events using OR, Noisy- OR and Leaky Noisy OR Logics to determine safety critical elements.

In Summary, this thesis provides scientifically sound and applied approaches to conduct risk assessment of process components with limited data. Applications of these approaches demonstrated on different case studies. Use of the proposed approaches would help better understanding of failure and hence improving safety of process system.

Acknowledgements

First and foremost, I would like to express my profound gratitude to my supervisor, Dr. Faisal Khan for his support, motivation, encouragement, supervision and suggestions throughout the research work. Their extensive guidance motivated me to complete my research work successfully. Without his encouragement and advice, this thesis might not have been completed successfully. Besides my advisor, I would also like to thank Memorial University for its support and Libyan Government for partially funding this research.

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Chapter 1

Introduction

1.1 Overview of offshore facilities accidents

As processing facilities handle enormous quantities of dangerous chemicals, risk analysis is an essential component in their operational procedures. Process areas tend to be filled with high-pressure compressors, separators and complex piping systems, may lead to accidents and equipment malfunctions, which in turn can cause catastrophic events (Khan et al., 2002; Torres-Toledano and Sucar, 1998). A number of offshore events have occurred since the early 1980s, such as the Piper Alpha event in the North Sea on July 6, 1988. The Piper Alpha accident was the result of a malfunctioning gas compression module that led to a massive gas condensate leak of ignition fuel, causing explosions and igniting a platform fire (Pate-Cornell, 1993). Though relatively minor initially, the pool fire then caused an explosion and fireball, collapsing the platform. Over 167 were killed; 62 survived, but suffered severe burns (Pate-Cornell, 1993).

A little over a decade later (March 21, 2001), a similar accident occurred in the Campos Basin off the coast of Brazil. There were two large explosions. The first one happened as the result of high pressure on the storage tank located at the aft starboard, where the pressure had risen to 10 bars. The resulting rupture caused the fluid inside the tank to leak out. The spilled gas caused the second explosion when it contacted an ignition source. The two blasts ended up sinking the entire platform, with one worker officially being declared dead and nine more missing and presumed dead (Baksh et al., 2016).

Another catastrophic event happened on July 27, 2005, in the Mumbai High Field, but unlike the deadly incidents mentioned above, the Mumbai event was due mainly to inclement weather. Hurricane-force winds compromised the equipment on one of the platforms, which then caused a gas leak and ignition. The fire that resulted quickly destroyed the first platform and jumped to neighbouring platforms. By August 1, the platforms had disappeared beneath the waves. In all, 22 workers were killed (Mitra, 2008; Walker, 2005).

Another major incident was the BP refinery explosion in Texas City on March 23, 2005. It caused the death of 15 workers and seriously injured at least 170 more (CNN, 2005). BP's official report (2005) placed the blame squarely on the lack of process safety measures at the refinery, along with inadequate risk reduction(Khan and Amyotte 2007). A few years later, on March 25, 2012, a gas and condensate leak on a North Sea platform sparked an evacuation, followed by a raging fire. No-one died or was injured in the incident, but it took five days to put the fire out (Henderson and Hainsworth, 2014). On July 23, 2013, a gas leak accident occurred in the Gulf of Mexico that destroyed a rig (Romero et al., 2016). On February 11, 2015, the Cidade de São Mateu on the Floating Production Storage and Offloading (FPSO), based off the coast of Brazil, was destroyed by an explosion and subsequent fire. The FPSO's pump room exploded from a leak of condensed material and the resulting shock between the engine room and pumps. Nine workers died in that event (Baksh et al., 2016; ANP, 2015). In yet another incident (April 1, 2015), a fire was sparked on the Abkatun Alpha platform in the Gulf of Mexico by a gas-leak-ignited explosion. Four workers died and 16 were injured (Baksh et al., 2016).

The most notorious and well-known of recent oil rig disasters is the accident that occurred on the Deepwater Horizon platform on April 20, 2010. This event in the Gulf of Mexico not only led to the death of 11 workers and the sinking of the platform, but also caused the near demise of the seafood industry in the Gulf. The leak poured out hundreds of millions of barrels of oil, while the toxins used to clean it up also contributed to the destruction of the Gulf's ecosystem. At its worst, the oil slick from the uncapped well trailed for 80 miles along the coast of Florida and 140 miles off the coasts of Alabama, Louisiana, and Mississippi. Although 15 million gallons of oil and water mixture have since been recovered, the negative impact of the explosion, sinking and spill continue to be endured by all wildlife in the affected areas of the Gulf as well as in the states bordering the Gulf (Levy and Gopalakrishnan, 2010; Ciavarelli, 2016).

Considering the above scenarios, enlarging the scope of risk analysis is crucial. This can be accomplished by analyzing accident scenarios and real-time safety plans in order to predict, gauge and revise the future potential for catastrophic events. The end goal is to take the appropriate actions to prevent events from occurring and to mitigate them should they occur.

1.2 Safety analysis in offshore facilities

As seen from the above descriptions, offshore platforms include the inherent risks of explosions, fires, spills, and sinking. Hydrocarbon leaks are the main cause of many of these incidents, which can lead to serious damage not only to the health and welfare of the rig workers, but also to the rigs themselves and to overall operations. At the same time, the environmental pollution that inevitably follows these types of events is also a major issue, along with compromises in power supply and economic impacts. The workers' lack of safety measures and safety training is the main reason behind most of the accidents.

Considering the wide effect these events have on people and ecosystems near and far, it is necessary to devise, adopt and apply safety measures that are rooted in solid and relevant information and data. This information can then be analyzed in relation to a few or several factors that ignited the fire or explosion.

In the years that have followed the catastrophe, the Deepwater Horizon event has provided researchers with a wealth of information. International companies and organizations have, in the wake of the well-publicized disaster, become significantly more aware of their safety options. Within a year of the accident, the European Commission developed a working paper that advised those involved in the oil and gas industry to come together as colleagues rather than remain isolated as competitors in order to "meet the challenges and threats to oil and gas production platforms through the exchange of information about past disasters to prevent their recurrence in the future" (Christou and Konstantinidou, 2012). Since the paper's release, several EU members have begun compiling databases (the UK-ORION Database and Norway-Petroleum Safety Authority) on accidents that occur on the continental shelf as well as developing information sources, exchanges and joint coordination sessions (Christou and Konstantinidou, 2012). The intention is for safety analyses of the issues to result in solid measures to protect not just workers and the industry, but the environment as well (Khakzad et al., 2011). The widespread issues in the oil and gas industry over the past half-century make it essential for the industry to achieve a workable balance between profits and safety (Christou and Konstantinidou, 2012; Khakzad et al., 2011; Spouge, 1999).

1.3 Risk Assessment Methods

The purpose of risk analysis focuses is to quantify the likelihood of the occurrence of certain accident scenarios. Several techniques are available, including fault tree (FT), event tree (ET), bow-tie (BT), safety barrier diagram, and Bayesian network (BN). Over the years, standard risk assessment approaches have helped to identify major risks and maintain safety in facilities. However, these techniques have limitations to their application of risk analysis when faced with complicated and interlinked systems. For instance, conventional FT is a typical approach used in quantitative risk analysis, but it is unable to analyze large systems, especially if the system has dependent primary events, common cause failures, or redundant failures. Furthermore, events that occur in a conventional FT are assumed to be independent, even though this is not always a valid assumption (Bobbio et al., 2001; Torres-Toledano and Sucar, 1998; Simon et al., 2007).

Similarly, most of the limitations recognized in conventional techniques like FT and ET are inherent in these approaches' static nature, making them unable to keep up with the ever-changing dynamic operation environment of process systems. This ever-changing environment can result from several factors, including alterations to the process environment or operational situation (e.g., changes in temperature, humidity, pressure, etc.) or to an analyst's estimation of the event.

1.4 Objectives of the Research

There are two major objectives of the study. These include the following: i) use a Bayesian based approach to identify the critical components responsible for a potential offshore accident. This is to help in decision making in terms of where to invest resources and how much resources should be utilised to address the risk of an offshore accident,

ii) Map a FT and ET to a Bayesian Network and illustrate the use of a BN in the absence data. The latter is achieved through the use of Noisy-OR and Leaky Noisy-OR logics.

1.5 Organization of the Thesis

This thesis is written in manuscript format. Outline of each chapter is explained below:

Chapter 1 is a brief introduction of the offshore facilities accidents, safety analysis in offshore facilities and risk assessment methods. The research objectives are mentioned in this chapter.

Chapter 2 is the literature review part of this thesis. Risk assessment and conventional risk assessment methods are discussed in this chapter.

Chapter 3 discusses process failure analysis considering causation dependency. This chapter briefly presents two case studies which are compressor and heat exchanger tubes failure. A sensitivity analysis is conducted to determine the most critical equipment to fail.

Chapter 4 presents the technique of mapping a Bow-tie to a BN. This study further shows how limitations of the bow-tie can be effectively addressed by adopting the mapping technique. The approach is good for capturing interdependency among events as well as uncertainty. Also, this research highlights how limited data can be incorporated in a BN by using Noisy-OR and Leaky Noisy-OR logics.

Chapter 2

Literature Review

2.1 Risk Assessment

Risk assessment consists of a number of different approaches for assessment potential accident scenarios within the process industries. The most common of these approaches is quantitative risk assessment (QRA), probabilistic safety analysis (PSA), and maximum credible accident analysis (Khan, 2001; Khan and Abbasi, 1998). Despite involving different procedures and stages, all of the risk assessment methods include: 1) likelihood and 2) accident scenario identification of mechanisms. Based on reliability and efficiency in analyzing and identifying accident scenarios, the most popular models are fault tree (FT), event tree (ET), and bow-tie (BT).

Conventional risk assessment methods have played a key role in maintaining safety in process facilities and in warning users about risks in the system. However, the tried-and-trued approaches mentioned above are static in that they mainly utilize generic failure data (Meel and Seider, 2006). Given this shortfall, a probabilistic method grounded in Bayes' rule i.e., a Bayesian network (BN) is gaining in popularity with safety experts.

2.2 Conventional Risk Assessment Methods

2.2.1 Fault Tree (FT)

A Fault Tree (FT) is defined as a graphic methodology that applies deductive reasoning to gauge the failure probability rates of a system. In an FT, the top event refers to an unwanted incident that can subsequently cause hazardous conditions. The intermediate and basic events are assigned in a downward direction from the top event. Any failure of a basic event can cause a failure in the intermediate event and initiate an unwanted event.

FT is a combination of a series of events and logic gates (Khakzad et al., 2011). Two types of Boolean logic gates – OR and AND gates – are used, and analysis can be either quantitative or qualitative (Nivolianitou et al., 2004). In the AND gate, there is an interaction of process components in a parallel structure. Hence, process failure can only result from the simultaneous failure of all components in parallel. On the other hand, process components interact in a series structure in the OR gate. Hence, the failure of any basic event causes the failure of the process (Adedigba et al., 2016a). As a visualization example, Figure 2.1 shows two typical OR (left) and AND (right) gates and their equations.

Equation (2.1) describes the event failure probability in a parallel structure (i.e., AND gate), while Equation (2.2) describes the top event failure probability in a series structure (i.e., OR gate):

$$P = \prod_{i=1}^{n} P_i \tag{2.1}$$

$$P = \prod_{i=1}^{n} (1 - P_i) \tag{2.2}$$

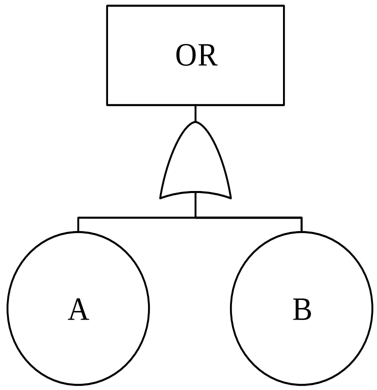

Figure 2-1: Illustration of the OR (left) and AND gate (right) in fault trees

Figure 2.2 illustrates a standard FT comprised of various components such as the top event (TE), intermediate events (IE), and basic events (BE).

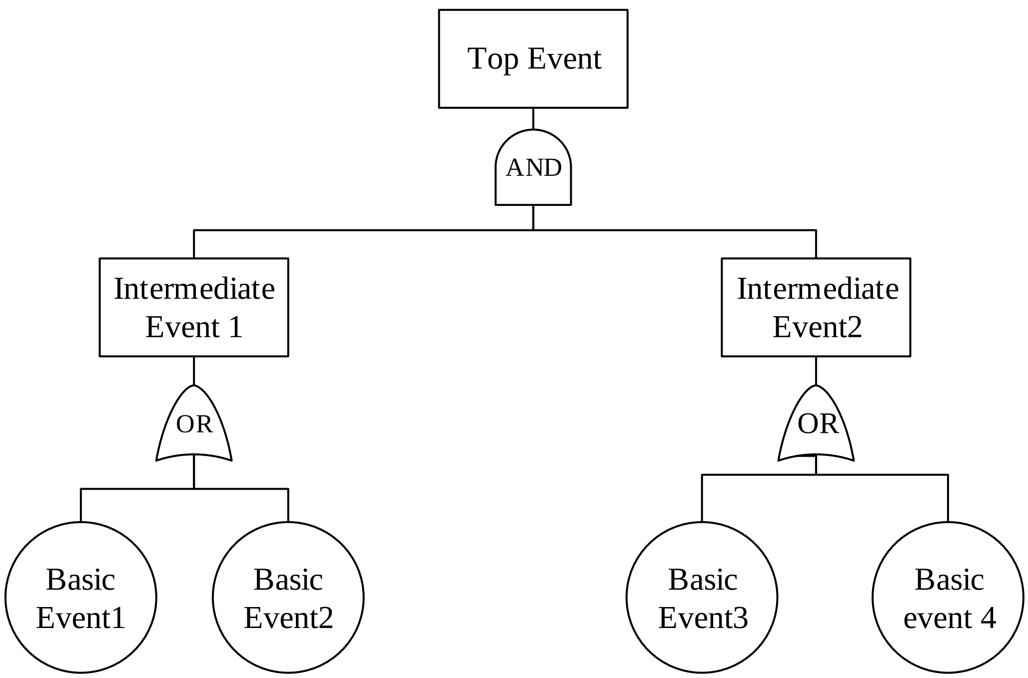

Figure 2-2: Generic Fault Tree model

2.2.2 Event Tree (ET)

Event Tree (ET) is a graphical representation of the logical model that determines the potential outcomes after the initiation of an undesired event (Marhavilas et al., 2011). ETA can be applied to both qualitative and quantified risk analysis and shows the consequences of the sequential failure of safety barriers. Although ETA can be considered an intuitive approach, it does not represent either the state of the system or its environment, both of which can have an impact on the evolution of events (Bearfield and Marsh, 2005). Figure 2 illustrates an ETA comprised of various components such as accident consequences (C) and safety barriers (SB).

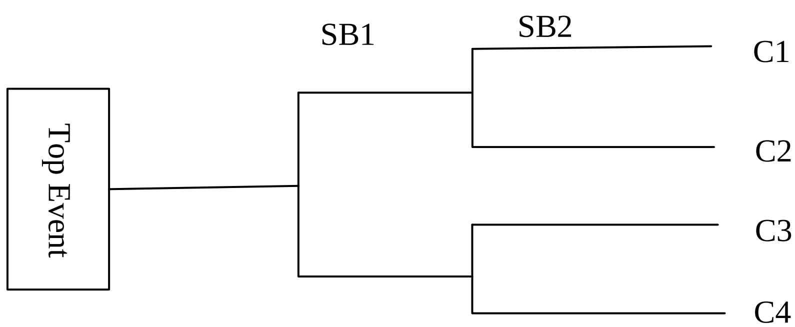

Figure 2-3: Generic Event Tree model

It is useful to know which possible combinations of primary events in a fault tree could result in a top event and which safety function failures can escalate the top event to a specific event tree consequence. For instance, in Figure 2.3, the occurrence probability of consequence C4 can be calculated as:

$$P\ (C4) = \ P\ (TE)\times P\ (SB1)\times(\ 1 - P\ (SB2)) \qquad (2.3)$$

Where *P (TE)* indicates the top event probability and *P (SB1)* and *P (SB2)* indicate, respectively, the failure probabilities of SB1 and SB2.

2.2.3 Bow-Tie (BT)

Bow-Tie (BT) is a tool in quantitative risk analysis that provides a pictorial representation of the process of risk assessment. It is a combination of FT and ET and is becoming increasingly popular in the oil and gas industry (Saud et al., 2014). An FT of an undesired event is shown on the left side of the BT diagram, and an ET of the possible consequences due to initiation of the top event of the FT is shown on the right side. BT helps in the evaluation of the possible failure causes and several possible consequences of a hazard. Figure 2.4 illustrates a standard BT comprised of various components, including basic events *(BE)*, intermediate events *(IE)*, and top event *(TE)*. The figure also shows safety barriers (SB) and accident consequences (C).

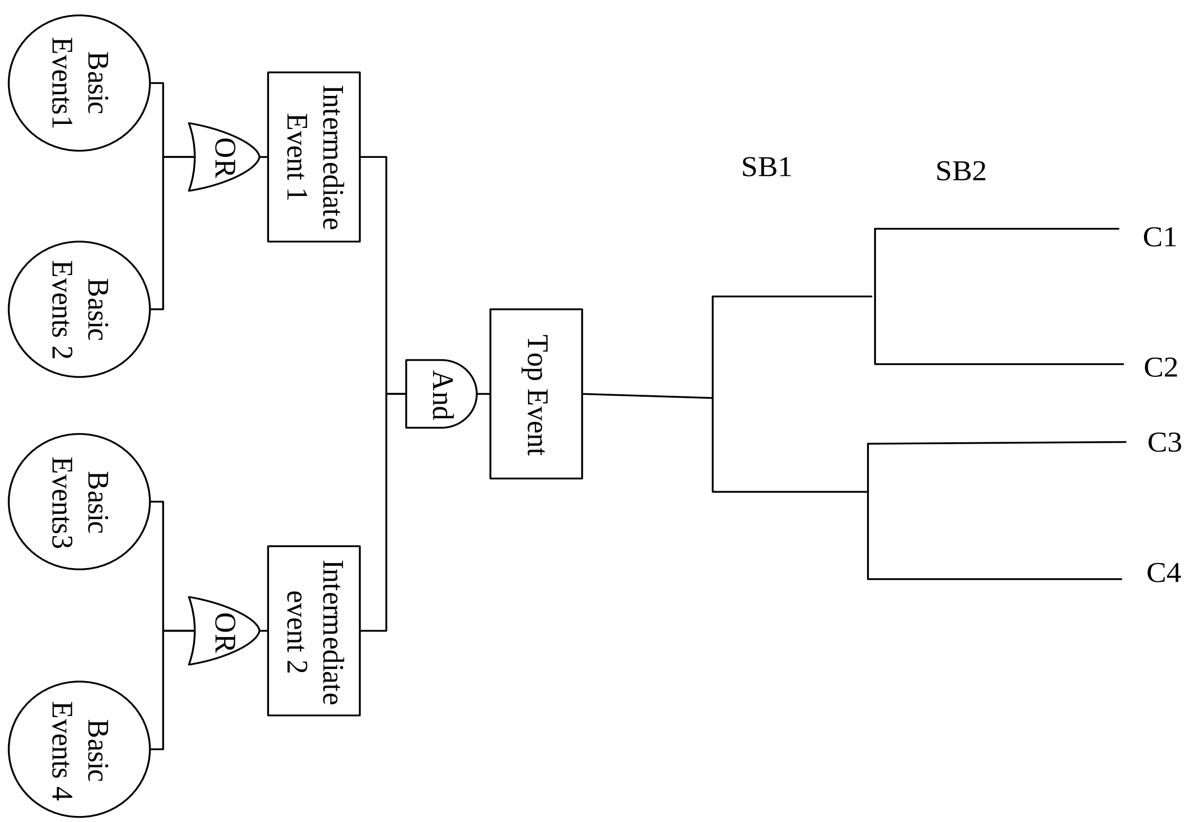

Figure 2-4: Generic Bow-Tie model

It is useful to know which possible combinations of primary events in a fault tree could result in a top event and which safety function failures can escalate the top event to a specific event tree consequence. For instance, in Figure 2.4, the occurrence probability of consequence C4 can be calculated as shown in equation (2.3).

2.3 Bayesian Methods

2.3.1 Bayesian Networks

The use of Bayesian networks (BNs) is increasing in the construction of risk management, system reliability models, and safety analysis profiles that depend on probabilistic and weak data. Like fault tree and reliability block diagramming, BN is a graphical probabilistic method that includes both quantitative and qualitative elements. More specifically, BNs are considered directed acyclic graphs where nodes indicate variables, arcs indicate direct causal relationships among linked nodes, and conditional probability tables connected to the nodes indicate how robustly the interconnected nodes impact each other (Torres-Toledano and Sucar, 1998).

The node from which an arc is created is called a parent node, while the node at which the arc is directed is called a child node. Conditional probability tables (CPTs) denote the degree of dependency among different events (Khakzad et al., 2013b). A BN is another tool that can be used in safety and risk analysis. Its main advantages include the ability to represent event dependencies, capture uncertainty, and update probabilities (Khakzad et al., 2011). It also allows for the incorporation of process knowledge of experts in case of data unavailability.

According to the chain rule and conditional independence, the joint probability distribution, $\mathrm{P(U)}$ of a set of random events, $\mathrm{U} = \{\mathrm{A1}, \ldots\ldots, \mathrm{An}\}$ is incorporated into the network as

$$P(U) = \prod_{i=1}^{n} P(A_i \mid P_{a(A_i)}) \qquad (2.4)$$

Where $\mathrm{Pa}(\mathrm{A_i})$ is the parent set of $\mathrm{A_i}$ (Pearl,1998; Jense and Nielsen,2007).

A BN utilizes the Bayes' theorem to update the prior occurrence probability of events based on information. This information is known as evidence (E). Posterior (P/E) refers to the belief of an event based on evidence. The posterior probability can be calculated by using the Equation (2.5).

$$\mathrm{P}\,(\mathrm{U}/\mathrm{E}) = \frac{\mathrm{P(U,E)}}{\mathrm{P(E)}} = \frac{\mathrm{P(U,E)}}{\sum_{\mathrm{U}} \mathrm{P(U,E)}} \qquad (2.5)$$

2.3.2 Bayes' Theorem

Bayes' theory is often aligned with methods such as BT (Badreddine and Ben Amor, 2010; Khakzad et al., 2011) and ET (Meet and Seider, 2006; Kalantarnia et al., 2009; Rathnayaka et al., 2011) as well as dynamic risk assessment and safety analysis. These types of hybrid approaches utilize the Bayes' theory to revise initial beliefs or prior probabilities of events by using information taken from a specific event. Thus:

$$\mathrm{P}\,(\mathrm{X/\ data}) = \frac{P\,(x)P\,(data/x)}{P(\,data)} \qquad (2.6)$$

where *P(x)* indicates the prior failure probability of event *x*, *P(datalx)* refers to the likelihood function of *x, P(data)* refers to the probability of data observed (i.e., evidence), and *P(xldata)* indicates the posterior probability of *x.* Ferson (2005) noted that calculating *P(data)* as an estimation can be highly complex. However, if both the prior and likelihood function were *conjugate* (Ferson, 2005; Meel and Seider, 2006), then the prior and posterior distribution would be the same and the calculation would be relatively straight-forward. So, for instance, if the prior probability involves a *Beta* distribution (or *Gamma)* while the likelihood function shows a *Bernoulli* (or *Poisson)* one, the posterior's distribution is *Beta (Gamma).* In instances involving non-conjugate distributions, however, the posterior distribution can be derived *via* numerical methods, which somewhat restricts the application of the approach.

Chapter 3

Failure Analysis of the Offshore Process Component Considering Causation Dependence

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Preface

A version of this manuscript is submitted in the Process Safety and Environmental Protection (PSEP), Febraury 2017. The co-authors of this research work, Dr. Ming Yang and Mohammed Taleb-berrouane guided the principal author Samir M. Deyab to develop the research methodology on the entitled topic and helped him to conceptualize the techniques and theories available for this topic. Corresponding author Dr. Khan was the principal supervisor of this work and provided knowledgebase support to the author and co-authors.

Abstract

Offshore oil and gas processing equipment operating in harsh environment poses high risk. This risk is further increased by the susceptibility of the equipment to natural disasters such as hurricanes and snowstorms due to harsh environment. When equipment functionality is compromised, it can become a hazard to personnel as well as to other equipment. The key safety practice on the offshore facility to isolate the equipment and minimize consequences associated with the processing equipment failures. When and how to isolate vulnerable equipment is a challenge due to limited understanding of the equipment's susceptibility and dependency to failure causes and consequences. This paper presents a methodology to analyze potential failure scenarios considering causation dependency and also to determine which parameter(s) have the most impact on the failure. The results of the analysis are used to identify most sensitive equipment and the failure causes. This analysis will help to develop effective risk management strategies focusing on critical equipment. The methodology comprises of multiple phases which include data collection, probabilistic analysis and sensitivity analysis.

Keywords: Sensitivity analysis; Offshore safety analysis; Bayesian network; Causal dependency; Probabilistic modelling.

3.1. Introduction

Accidents in the offshore oil and gas industry are mainly caused by human factors, climatic conditions, mechanical facilities and technical lapses (Gordon, 1998). Numerous offshore accidents have taken place over the past few decades, such as the Piper Alpha incident that occurred in the North Sea on July 6, 1988. This accident was caused by a compromised gas compression module, which resulted in a massive leakage of gas condensate. The leak on ignitions caused explosions and a pool fire on the platform (Pate-Cornell, 1993). The pool fire led to the subsequent explosion and fireball that resulted in the collapse of the platform. In this accident, over 167 people were killed and 62 survived, with severe injuries, mostly burns (Pate-Cornell, 1993). A similar accident took place on March 21, 2001, in the Campos Basin, off the coast of Brazil. On the P-36 platform, two large explosions occurred. The first one occurred mainly as a result of excessive application of pressure to the aft starboard drains storage tank, where pressure had risen to 10 bars. When the tank could no longer hold the pressure, a rupture occurred and the fluid inside the tank began to leak. The leakage was followed by a second and more intense blast that was caused by contact between the spilled gas and an ignition source. The two blasts ultimately caused the destruction and sinking of the giant platform. As a result of the accident, one worker died immediately and nine others were missing and presumed dead (Baksh et al., 2001). More recently, an incident occurred on July 27, 2005, in the Mumbai High Field. Unlike the two accidents described earlier, this one was caused by inclement weather. During the storm, equipment on board one of the platforms was damaged due to hurricane-force winds, leading to a gas leak and ignition. The subsequent fire devoured that platform and moved onto others. Moreover, the risers' failure led to the leakage of massive amounts of gas, such that on August 1, 2005, the first platform sank, followed a few hours later by another one. In total, the week-long event killed at least 22 workers (Mitra, 2008; Walker, 2005). On March 25, 2012, a gas and condensate leakage on a platform in the North Sea led to the evacuation of workers due to a fear of fire and explosion. Despite precautionary measures taken, the fire burned for five days before being extinguished (Henderson and Hainsworth., 2014). On July 23, 2013, an incident took place in the Gulf of Mexico that resulted in the burning of a rig, likely caused by a gas leak (natural gas condensate) (Romero et al., 2016). Then, on February 11, 2015, yet another accident took place in Brazil, this time on the Cidade de São Mateu on the Floating Production Storage and Offloading (FPSO). In this event, the FPSO's pump room exploded due to a leakage of condensed material and the shock between the engine room and pumps. Nine workers were reported dead (Baksh et al., 2016; ANP, 2015). On April 1, 2015, a gas leak-caused explosion ignited a fire on the Abkatun Alpha platform in the Gulf of Mexico, resulting in 4 deaths and 16 injuries (Baksh et al., 2016).

Perhaps the most well known recent disaster in recent history is that which occurred on April 20, 2010, on the Deep-water Horizon platform in the Gulf of Mexico. The disaster caused not only the deaths of 11 workers and the near destruction of the platform, but it also led to the decimation of the seafood industry in and around the Gulf due to the unprecedented levels of toxins caused by both the leak itself and the chemicals used to clean it up. The Deep-water Horizon's oil slick spanned 80 miles off the coast of Florida and 140 miles off Mississippi, Louisiana, and Alabama states. Fifteen million gallons of oil and water mixture were recovered, but the impact of the spill is still being felt in the affected states (Levy and Gopalakrishnan., 2010; Ciavarelli, 2016).

It is evident from past accidents in the offshore process facility that equipment failure risk is strongly dependent on the harsh environment operating condition. In offshore facility, equipment failure quickly becomes a hazard to personnel as well as to other equipment. There is limited understanding on when and how to isolate vulnerable equipment to minimize equipment failure risk. There is no work reported in public domain that help better understanding of the of the equipment's susceptibility and dependency to failure causes and consequences. This paper aims to fill this gap between analyzing potential failure scenarios and determine which parameters have the most impact on the failure. Sensitivity analysis is also performed to study the vulnerability of the causes and interaction of different failure scenarios. This work will help to develop effective operational risk management strategies focusing on key equipment to minimize overall facility risk.

This paper is organised is six sections. Section 1 provides background information on the importance of safety in offshore operation, particularly the one in harsh environment. Section 2 briefly captures offshore process operation, whereas section 3 details the research methodology. Application of the proposed methodology is discussed in sections 4 and 5. Section 6 presents the conclusions.

3.1.1 Safety Analysis and Risk Assessment in Offshore Facilities

Following the descriptions in the previous section, it is apparent that offshore platforms bring with them extensive risks in the form of fires, explosions, and spills. Many of these accidents are caused by hydrocarbon leaks and have major impacts on operations as well as on the workers. The environmental pollution caused by these incidents is an equally compelling issue, as is the loss of power supplies and subsequent economic impacts. Most of these problems are the direct result of the absence of safety measures and safety training among platform and rig workers. Given the broad impact of these events which occur on offshore platforms but affect people thousands of kilometres away, it is essential to adopt safety measures based on the relevant information and data. This information should then be analyzed with reference to the factors that led to the critical equipment failure, which then caused the accidents.

In terms of lessons learnt, the Deep-water Horizon spill is a watershed of information. Since the occurrence of the disaster in 2010, international companies and organizations have become considerably more safety-conscious. For instance, the European Commission (Christou, and Konstantinidou, 2012) has tabled a working paper calling for a concerted effort of all involved in the oil and gas industry to "meet the challenges and threats to oil and gas production platforms through the exchange of information about past disasters to prevent their recurrence in the future". The working paper has prompted several members of the EU to develop a database on accidents that take place on the continental shelf (e.g., the UK – ORION Database and Norway – Petroleum Safety Authority). There are also additional information sources, exchanges and joint coordination, such as the OGP – Well Control Incident Database, the main purpose of which is to analyze accidents (Christou and Konstantinidou, 2012). Safety analysis would lead to measures that will protect the environment (Khakzad et al., 2011). Given the death and destruction caused by accidents over the past 50 years, it is imperative that the marine industry strive for a workable balance between safety and the profits flowing from oil and gas production (Christou and Konstantinidou, 2012; Khakzad et al., 2011; Spouge, 1999).

3.1.2 Techniques for Safety Analysis of Offshore Processing

Several analysis techniques are used to analyze safety and estimate risks. These include quantitative analysis and qualitative approaches. Quantitative risk assessment (QRA) is, for the most part, a prerequisite in offshore installations in Norway, the United Kingdom, and most oil producing countries. The aim of QRA is to give the designer sufficient information to enable him/her to build a complete picture of the maritime system properties. At the same time, the quantified occurrence probability of each major failure condition and possible consequences should also be addressed. In contrast, qualitative safety evaluations set forth a series of steps that define or identify any potential risks. In this approach, information is relayed via chart, tables, fault trees, event trees and other tools. The goal here is to devise some measures to address potential safety, as highlighted by information obtained from the qualitative assessment (Rouvroye, and Van den Bliek, 2002). Table 1 is a list of some of the most used risk assessment tools. The qualitative ones include Analysis by experts (Domain expert knowledge) and Failure Mode and Effect Analysis whiles the quantitative ones are Fault Tree Analysis, Hybrid methods, Enhanced Markov Analysis and Bayesian Network.

Table 3-1: Quantitative and qualitative risk analysis tools

Scenario Analysis Method	Details
Analysis by experts (Domain expert knowledge)	Uses information from previous experiences centred on the same or similar applications. This approach is classified as a qualitative analysis (Rouvroye, and Van den Bliek, 2002).
Hazard and Operability Study (HAZOP)	Design review technique used for hazard, and design deficiencies' identification affecting the system operability. Uses guide words (i.e more, less, early, late) to describe the deviations. Performed by a multi-discipline team including a safety specialist to lead the study (Kletz, 1999).
Hazard Identification (HAZID)	Early hazards detection technique in the conceptual or detailed design stage. Similar to HAZOP, HAZID uses guide words (i.e more, less, early, late) to describe the deviations. It identifies the required safeguards and the areas where further understanding of safeguard effectiveness is needed (Halliburton, 2015).
Fault Tree Analysis (FTA)	Analyzes from the top down. This approach reveals the impacts of basic events on the top event (Talebberrouane and Lounis, 2016)
Hybrid methods	This approach can be a combination between, fault tree analysis and Markov process (Talebberrouane et al.,

	2016) or reliability block diagrams.
Enhanced Markov Analysis (EMA)	This approach groups together uncertainty analysis, sensitivity analysis and Markov analysis.
Reliability Block Diagram (RBD)	Graphical representation indicating the relationship between the components that comprise a system, including how the reliability and functionality of each component affects the success or failure of the entire system.
Bayesian Network (BN)	A directed acyclic graphs based on the conditional probability given by the Bayes rule. Popular technique for determining safety analysis, a comparison with the fault tree is given in (Khakzad et al., 2011).

Bayesian networks are widely used, as a probabilistic tool, in multiples domains with significant number of applications (Wilson et al., 2007). Comparing to other quantitative risk analysis methods, the BN provides multi-levels and multi-states dependencies to be taken in consideration. Additionally, BN structure is easily tractable to check the way that the dependencies are described, also if all the features are taken into consideration. In case of any feature is missing, it can be easily implemented in the network. Similarly, the implementation of new information such as the evidence on one or multiple parameters can be done on mathematical basis, which is the Bayes rule.

In BN modelling, dependency is presented in two ways; vertical dependency (i.e the intermediate nodes depend on the basic or the root cause nodes), and horizontal dependency where the basic nodes are depending on each other. This horizontal dependency is what differentiates the BN from the logical diagram methods such as fault tree (FT) and event tree (ET) where the structure is based on the basic event independency. These dependencies vertical and horizontal are all dictated in form of CPT based on the domain expert knowledge. For more details about the CPT, the reader is referred to the work of Wilson et al (2007).

3.1.3 Equipment Safety during Offshore Processing

In oil and gas production, the processing of liquids is first done at the drilling sites, which in this case are offshore platforms. The product is then transferred onshore. The offshore production facility comprises six main units, namely the platform, the rig, the processing plant, the means of transport, employee accommodations, and utilities. Several different processes take place on the platforms, such as the removal (i.e., separation) of oil/gas from the water and the compression of gas. These activities can be hazardous, as even a small leak or error could cause a fatal or costly accident. Some issues that could potentially affect offshore platforms are structural failure, helicopter incidents, and collisions with marine craft. However, even more dangerous is the potential for events involving fire and explosions. Given the damage that such incidents can cause on platforms, this study will highlight two main areas of the processing plant – gas compression and dehydration (Khan et al., 2002).

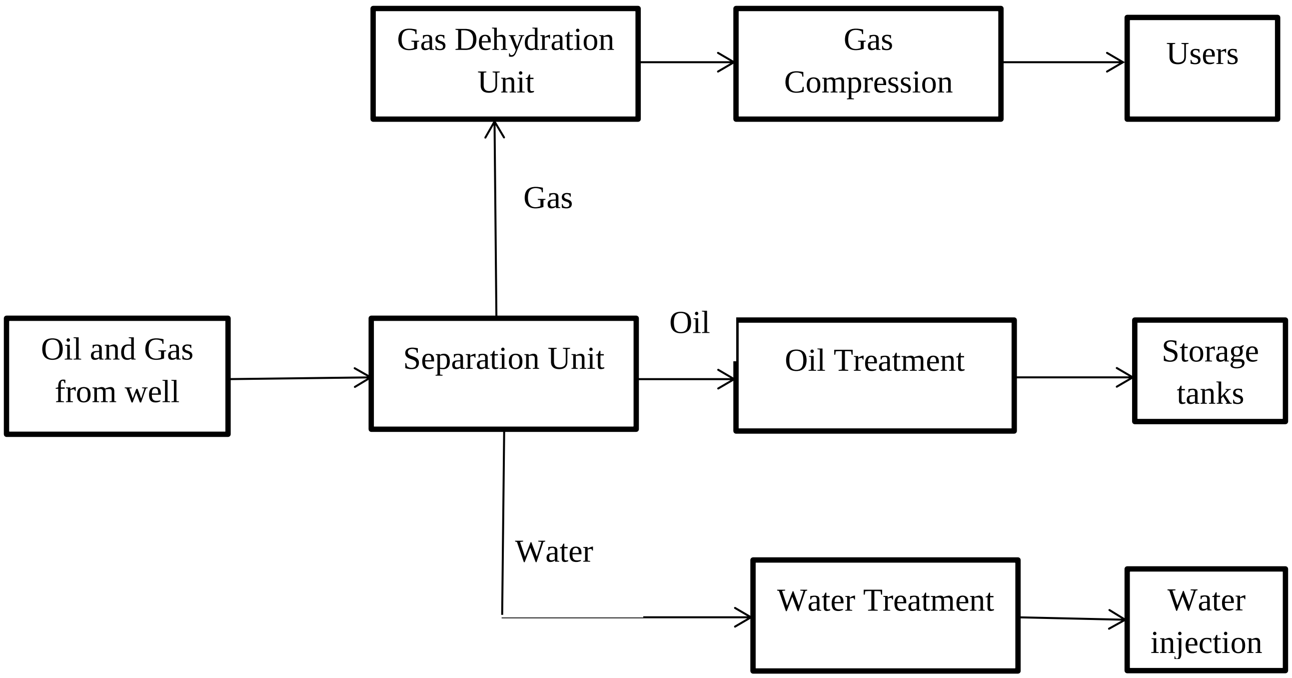

Figure 3-1: Schematic of the offshore oil and gas processing equipment.

3.2. Description of the Process

Table 3-2 gives a detailed description of the main units and their components as well as the potential problems in the system. The focus is on gas processing. Therefore oil and water treatment systems are not given much attention.

Table 3-2: Table showing description and problems of the offshore oil and gas processing equipment.

Unit	Description
Separation	This unit enables a separation of the volatile fluids in order to achieve the best possible recuperation of fluid while isolating the water for removal and settling the oil and gas (Havard, 2013).
Water	This unit is used for treating contaminated water which contains sand. This is

treatment	done by using a sand cyclone to isolate the debris. After this, a hydro cyclone is used to separate the oil from water (Havard, 2013).
Gas compression unit	This unit is used for re-pressurizing the gas after it emerges from the three-phase separators (Havard, 2013; Mokhatab et al., 2006). The gas compression unit is made up of centrifugal compressor, heat exchanger, gas turbine, and electric generator. Centrifugal compressor allows the passage of gas through the compressor's inlet nozzle and onto the impeller inlet (Mokhatab et al., 2006). Due to the constant stream of gases being released in this unit it is very vulnerable to fire (Mokhatab et al., 2006). Heat exchanger lowers the temperature, through a cool-down process (Havard, 2013). A corroded unit may lead to heat exchange tubes failure (Usman, and Khan, 2008). Gas turbine is the source of electrical energy for powering the compressor. It is prone to major failures which include the entire system breakdown due to malfunction of the blade, (Farrahi, et al., 2011). Corrosion, creep, and fatigue (Carter, 2005) are other notable problems. Electric generator converts electrical energy from mechanical energy and is prone to bearing failures, cooling system damage, rotor insulation failure (Alewine, and Chen, 2012).
Storage Tank	Storage is used for storing the oil and is susceptible to explosions, fires, lightning strikes, open flames, cracks and leaks. These are caused by operational defects, human error, and terrorism (Chang and Lin., 2006).
Gas dehydration	This unit consist of Absorption column, Re-boiler, Still (Stripper), Glycol circulation pump, and Heat exchanger. The whole unit functions as a gas drying

unit	unit. The absorption column may suffer from foaming. Re-boilers are subject to glycol degradation, salt contamination, and heat-related stress. Still (Stripper) faces condensation and flooding issues. Over-circulation, under-circulation, and pump wear affect the Glycol circulation pump significantly while the heat exchanger have problems with regards to heat retention in the lean glycol, salt deposits and corrosion (Mokhatab et al., 2006; Anyadiegwu et al., 2014; Zangana, 2012).
Pipeline	The pipeline moves the gas from the offshore platforms to the processing facility. The main problems include erosion, corrosion, mechanical and material problems, and equipment failure ((Havard,2013; Brito, and de Almeida, 2009; Timashev and Bushinskaya, 2016).

3.3. Research Methodology

A crucial part of industrial processes is the safety system, which functions to prevent certain conditions from further developing into a hazard. Therefore, when safety systems fail, there can be direct consequences ranging from equipment damage, work stoppages, unexpected expenses, environmental degradation, crew injury and death. Safety systems should be operational at all times, regardless of cost or inconvenience to the operator. To achieve non-stop optimal operation of these systems, a multi objective design is needed. The methodology comprises of multiple phases and shown in figure 3-2. Sections 3.1 to 3.3 describe the steps adopted for this methodology

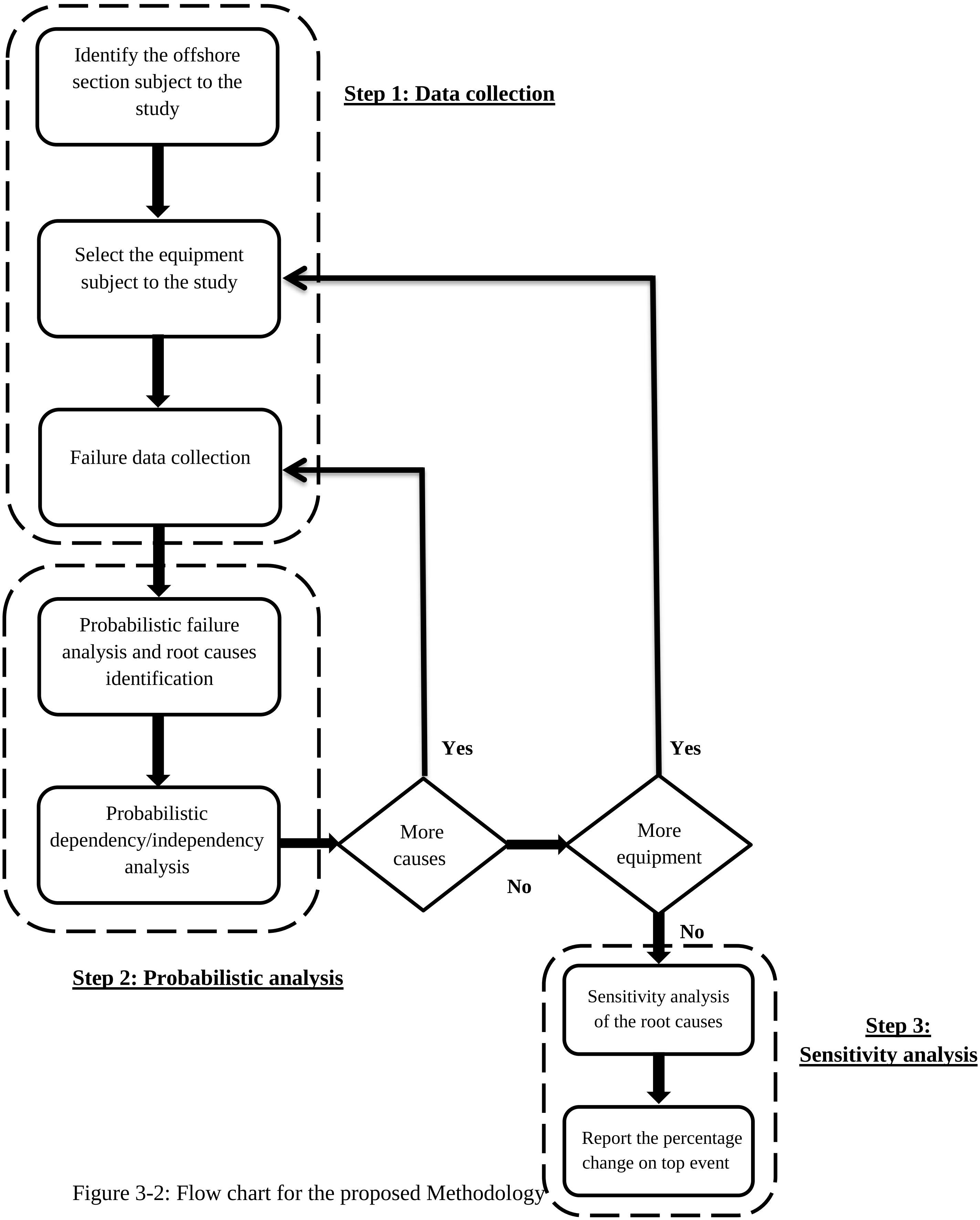

Figure 3-2: Flow chart for the proposed Methodology

3.1 Step 1: Data collection

Prior hazard identification, such as HAZOP study, should be performed to identify the section presenting relevant potential hazard. In this study, the compression section was taken as a subject of study due to the relevant risk associated with this section in all process industry, and especially the offshore facilities due to the specification of the offshore infrastructure. Eight important elements of the offshore processing equipment have been studied as well as the problems and failures that expose them. However, two elements have been presented for the purposes of illustrating the methodology in this paper. These include the compressor unit and the heat exchanger. The failure probability data of basic events were mostly collected from the Offshore Reliability Data Handbook (OREDA, 2002) and other resources.

3.2 Step 2: Probabilistic analysis

Bayesian Networks, (BNs) are probabilistic models which are derived from directed graphs. In these models, nodes represent random variables of the scenario or system under investigation. While links between the nodes show the dependence levels of the random variables. The graph structure of the BNs enables complex problems to be decomposed, as modelling can interpret causal relationships in the variables. Such an approach both facilitates the modelling process and has computational advantages. BNs can be applied at any stage of probabilistic analysis and may replace fault and event trees due to several advantages that have been presented in sub-section 1.2. Furthermore, because of their mind-mapping abilities, BNs can be utilized in the early stages of probabilistic analysis, where the primary aim is to find possible scenarios as well as the linkage of events that might lead to possible adverse consequences. Hence, BNs provide a versatile approach to assessing anticipated equipment failure, as they build model scenarios by asserting conditional probabilities of failure events. The probabilities of the most credible scenarios are analyzed using GeNie software (Faber et al., 2012). Probabilistic failure analysis was performed based on dependencies identification between the root causes, linking the scenarios' elements. It aims to provide accurate analysis where the elements are interconnected in a conditional way. Bayesian networks were chosen as modelling support for this study because of their ability to handle the uncertainty and the ability to represent the conditional interdependency between multiples nodes.

3.3 Step 3: Sensitivity analysis

The sensitivity analysis (SA) is the study of how the uncertainty in the output of a model, in this case the top event or the unwanted hazard, can be apportioned to different sources of uncertainty in the model input (Saltelli, 2002). In this study, the sensitivity analysis is performed in the case of dependency between the root causes and the case of independency. The approach adopted for conducting the sensitivity analysis is that, the percentages of each root cause representing a parameter have been increased from 0% to 100% by a step of 10%. Then based on the BN model, the percentage change on the probability of the top event is reported. All the generated data from the BN model are presented in charts below. To find out which of the basic events has more impact on the undesired event, a comparative study is performed based on the generated data. Equation (1) below is used for sensitivity analysis calculations:

$$\text{Percentage change} = \frac{\text{posterior probability} - \text{Prior probability}}{\text{Prior probability}} \times 100 \qquad (3.1)$$

3.4. Application of methodology to offshore processing system units

This section describes the various scenarios for each system unit investigated. The units include i) Compressor unit ii) Heat Exchanger iii) Turbine iv) Combustion v) Generator vi)

Storage tanks vii) Pipeline viii) Dehydration unit but only compressor and heat exchanger analysis are presented here. The compressor fire scenario has been divided into basic and intermediate events. The basic events contain major failure events such as break in seal, faulty installation of seal, lubrication decrease, crack in valve plates, weak springs, rotor cracks, rotor jammed, weak installation, casing friction with the rotor, pipeline joints, pipeline, break in blade, worn compressors, gear of the shaft breaks, rotor frictional with casing and the intermediate events comprise of release from seal, release from compressor valve, release from rotor, compressor or casing release, release from the compressor, release from downstream, release from upstream, frictional sparks, high operation temperature, ignition source and gas release. Formulation of the Bayesian networks is based on the conditional probabilities table (CPT), where the probability of intermediate event is based on the conditional states of the basic events. In example, the probabilities of over-speeding, lubrication failure, contamination, vibration during start-up and misalignment are the root causes influencing the bearing failure's occurrence. However, the presence of one or two of them cannot make ensure that the bearing will fail. On the other hand, the root causes are not contributing in the same level for the bearing failure. All this knowledge can be incorporate through deterministic probabilities in the CPT. For more details about the CPT, the reader is referred to the work of Nielsen and Jensen (2009) and the work of Jensen (1996).

For the heat exchanger tubes scenario, the basic events contain major failure events such as fretting due to vibration, microbes problems, presence of CO_2, H_2S,cavitation, high fluid velocity, presence of sand, weak material, high temperature, high pressure, foreign particles in fluid, improper filters, surface deposits, inappropriate filters cleaning, weak tube material, fluid hammer, external forces and the intermediate events comprise of corrosion, metal erosion, tubes cracking, buckling of tubes, tubes structure failure, fouling, tubes clogging and tube leakage.

Table 3-3: Elements of BN model for the compressor unit and their probabilities.

Basic Events	**Failure frequency per year**
Break in seal	1.2×10^{-3}
Lubrication decrease	1.8×10^{-3}
Faulty installation*	3.0×10^{-4}
Crack in valve plates*	3.0×10^{-3}
Weak springs*	2.5×10^{-3}
Draining valve left open	2.0×10^{-3}
Rotor cracks	2.1×10^{-2}
Rotor jammed*	1.0×10^{-2}
Weak installation	6.0×10^{-3}
Casing friction with Rotor *	1.0×10^{-3}
Downstream pipeline joints**	9.0×10^{-3}
Downstream pipeline**	6.5×10^{-4}
Upstream pipeline**	3.0×10^{-3}

Upstream pipeline joints**	4.5×10^{-3}
Break in blade	7.0×10^{-4}
Worn compressors	4.0×10^{-3}
Gear of the shaft breaks	2.5×10^{-2}
Rotor friction with casing	1.0×10^{-3}
Over-speeding*	5.0×10^{-4}
Lubrication failure*	1.0×10^{-4}
Contamination*	3.0×10^{-4}
Vibration during start-up*	2.5×10^{-3}
Misalignment*	2.0×10^{-4}

All the probabilities provided in Table 3-3 are taken from OREDA database (OREDA 2002), except the elements that carry one-star mark (*) are taken from domain expert knowledge, and the elements that carry two star marks (**) are taken from the reference (Khan et al., 2002).

Table 3-4: Elements of BN model for the Heat Exchanger tubes Failure and their probabilities.

Basic Events	**Failure frequency per year**
Vibration	0.4×10^{-3}
Baffle failure	0.1×10^{-3}
Material fatigue	0.2×10^{-3}
Microbes problems*	1.1×10^{-3}
Presence of Co2, H2S*	1.0×10^{-3}
Cavitation	2.1×10^{-4}

High fluid velocity	3.0×10^{-3}
Presence of sand*	2.3×10^{-4}
Weak material	1.0×10^{-3}
High temperature	8.8×10^{-4}
High pressure	4×10^{-4}
Foreign particles in fluid*	4.2×10^{-4}
Improper filters*	5×10^{-4}
Draining not performed	0.2×10^{-3}
Surface deposits	3.1×10^{-4}
Inappropriate filters cleaning	1×10^{-3}
Improper dimensions*	0.83×10^{-3}
Inadequate materials*	0.2×10^{-3}
Fluid hammer*	1.04×10^{-3}
External forces	8.3×10^{-3}

All the probabilities provided in Table 3-4 are taken from OREDA database (OREDA 2002), except the elements that carry one-star mark (*) are taken from domain expert knowledge. The data provided in Table 3-3 and Table 3-4 is presented as examples and it doesn't represent the definitive complete set.

3.5. Results and Discussion

As can be seen in the Bayesian Network of the compressor unit shown in Figure3-2, fire is assumed to be the top event scenario to occur in the unit, this model was constructed using

GeNie software. By employing the basic events data shown in Table 3-3, both the top event scenario failure probability and the intermediate event conditional probability table (packaged by Subject Matter Experts) were determined. For the top event scenario, the failure probability was calculated as $8.39\times10^{-4}\,\mathrm{occurrence/year}$ in the case of basic events (BE) or root causes independency. In Figure3-3, the root causes dependencies are represented in hatched arrows to differentiate them from the other dependencies. In the case of BE dependencies' consideration, the probability of fire is $7\times10^{-3}\,\mathrm{occurrence/year}$. As it is noticeable, considering the root causes dependencies has a big impact on the probability of hazard.

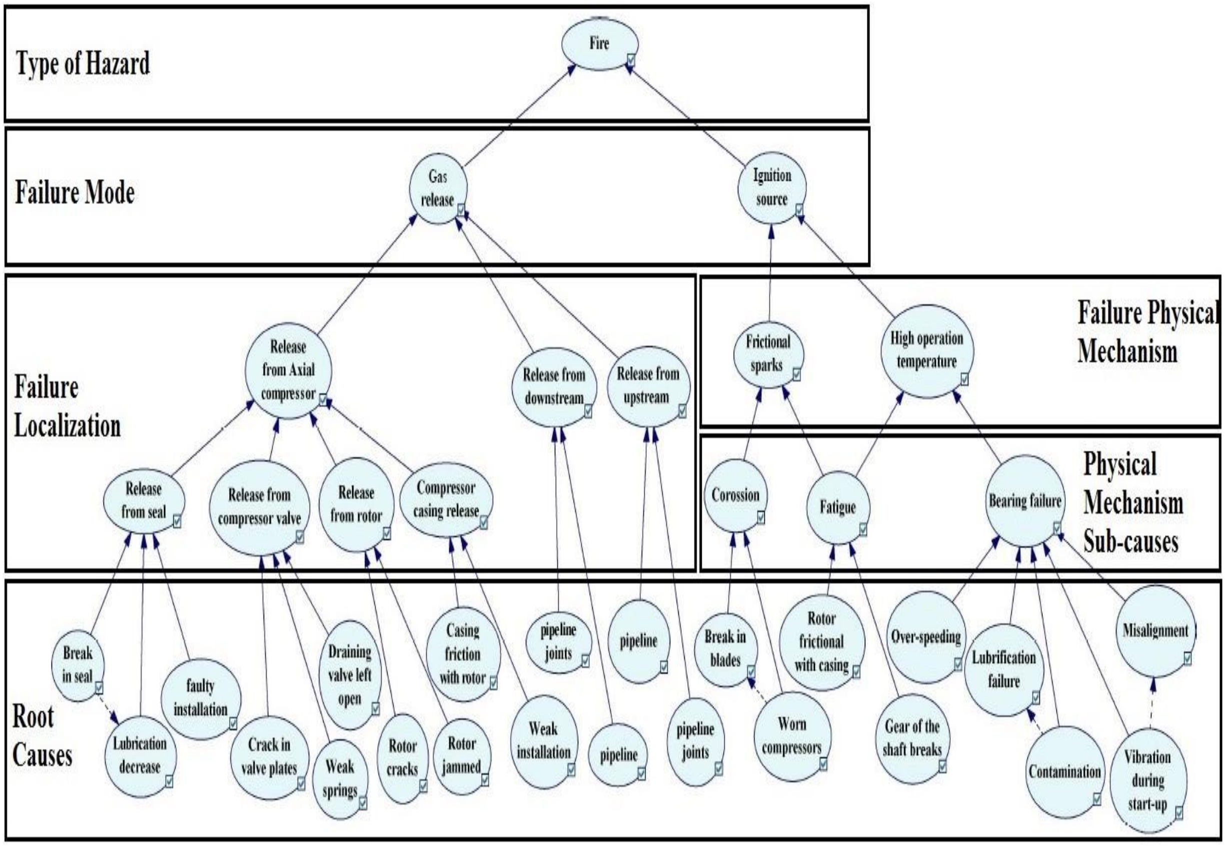

Figure 3-3: BN model for the compressor unit (BE dependencies in hatched arrows).

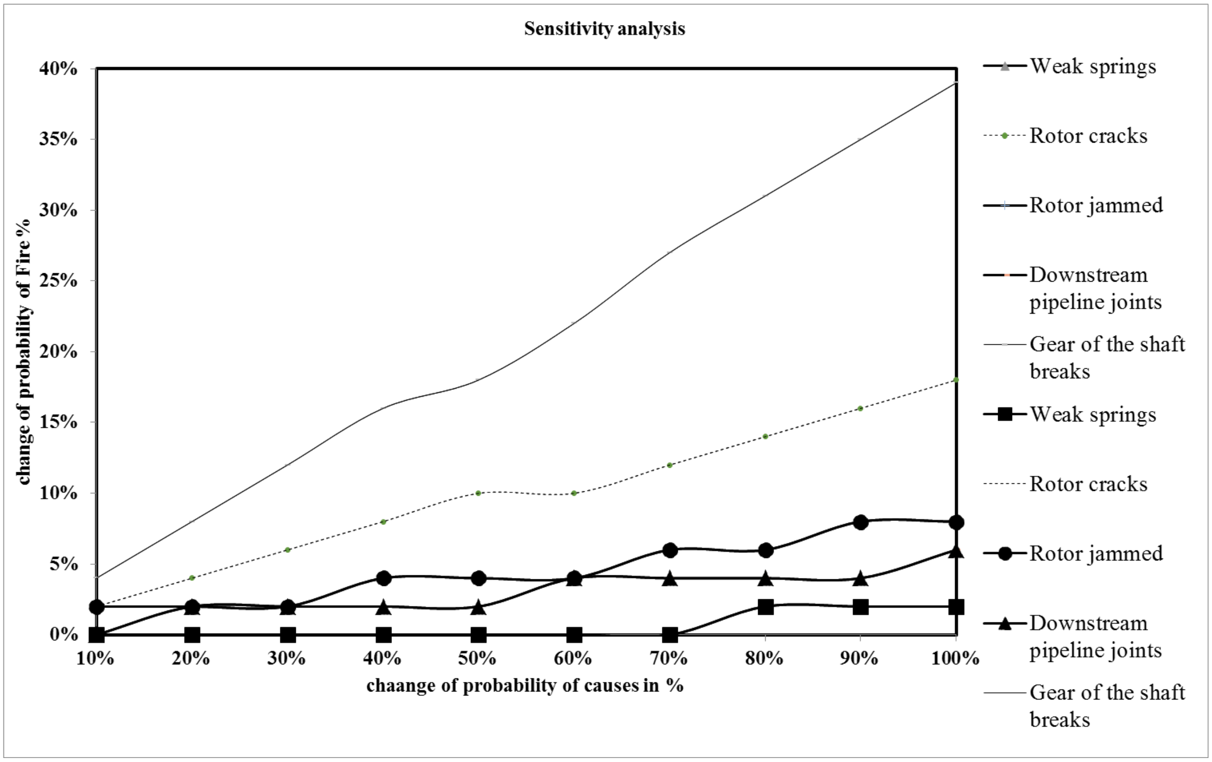

Figure 3-3(a): Sensitivity analysis of the compressor in case of independency.

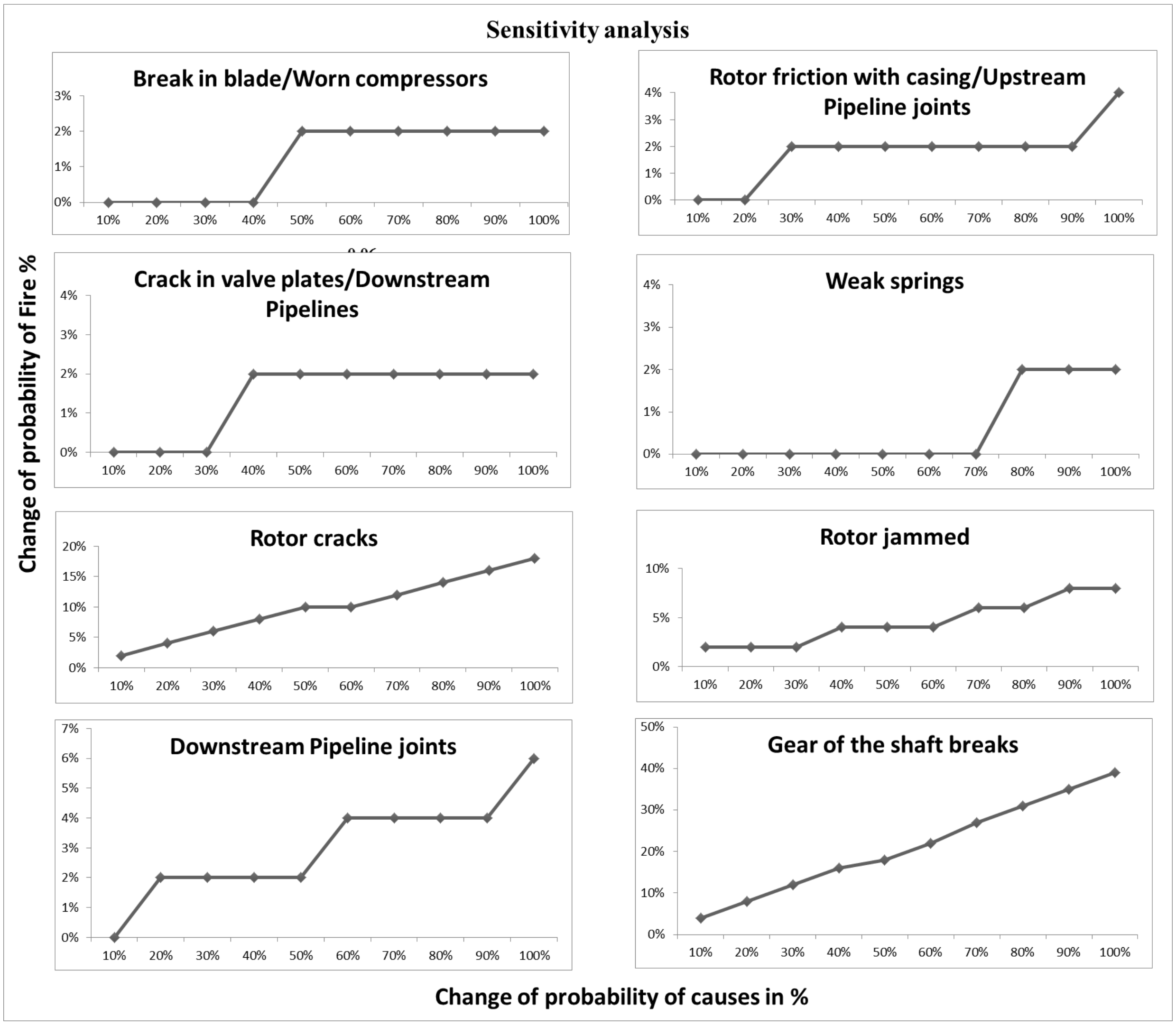

Figure 3-3 (b): Sensitivity analysis of the compressor in case of independency.

With independency, all basic events are considered in order to pinpoint the elements which are more sensitive than the others. Figure 3-3 (a, b) highlights elements which are sensitive in cases of independency. As we can see by the increasing slope on the graph for each element, 11 elements in total are sensitive, of which gear of the shaft breaks and rotor cracks emerge as the most sensitive.

When the element percentage rose from 10 to 100%, the probability of fire also rose. For gear of the shaft breaks, when the increase was 100%, the probability of fire rose to 39%. For rotor cracks, when the probability of failure rose 100%, the probability of fire rose to 18%.

Six out of the eleven elements are the same, such that every pair of elements share the same fire probability when the element percentage increases from 10% to 100%. Hence, they are illustrated separately in figure 3-3 (b).

In situations involving downstream pipelines and crack in valve plates, when the probability of crack in valve plates rise beyond 30%, the probability of fire increases by 2%.

Similarly, in instances involving rotor friction with casing and upstream pipeline joints, if the failure probabilities rise beyond 50%, the fire percentage probabilities also increases by 2%. For rotor friction with casing, when the probability rose beyond 20% until 80%, the probability of fire increases by 2% and 4% when the probability of rotor friction with casing is doubled. As can be seen, both of the elements are nearly the same.

In instances involving break in blade and worn compressors, if the failure probability increases beyond 30%, the fire probabilities percentages increases by 2%, showing them to be exactly the same.

The graph was created using the equations (3.1). The percentage of each element increased from 10% to 100% by a step of 10%, while equation (3.1) was used to determine whether there was a change in terms (i.e., rise or fall) in the percentage of fire probability.

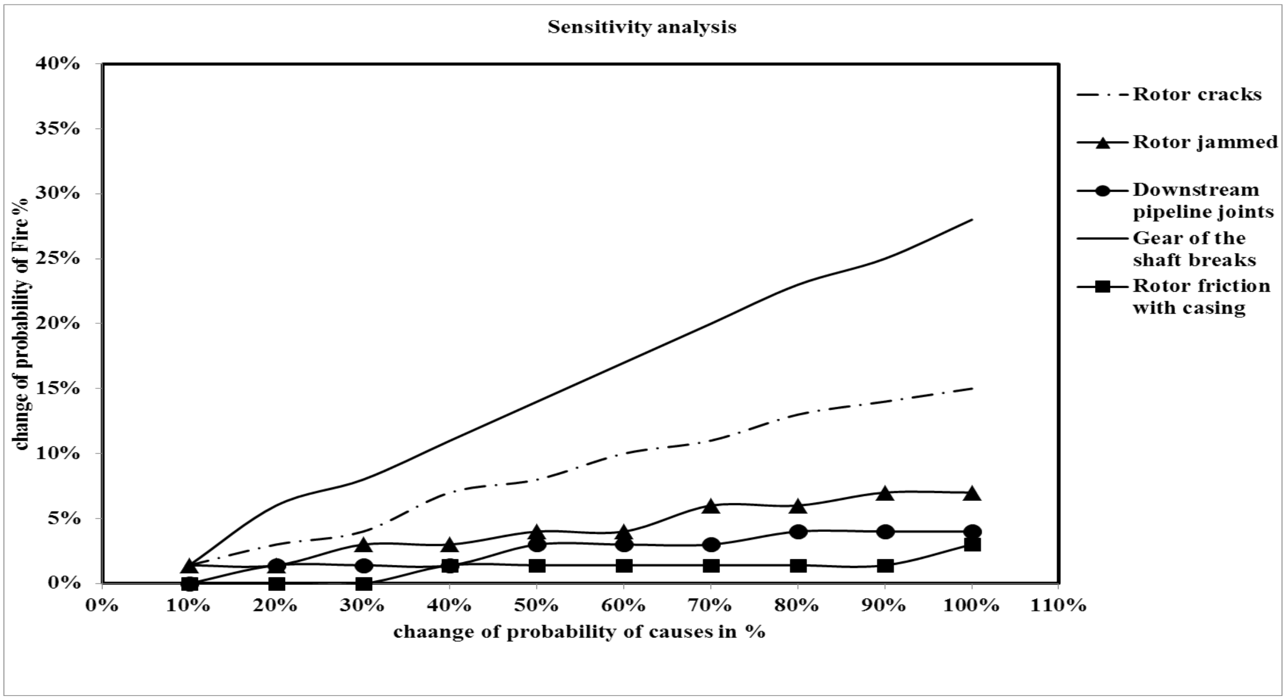

Figure 3-4(a): Sensitivity analysis of compressor in case of dependency.

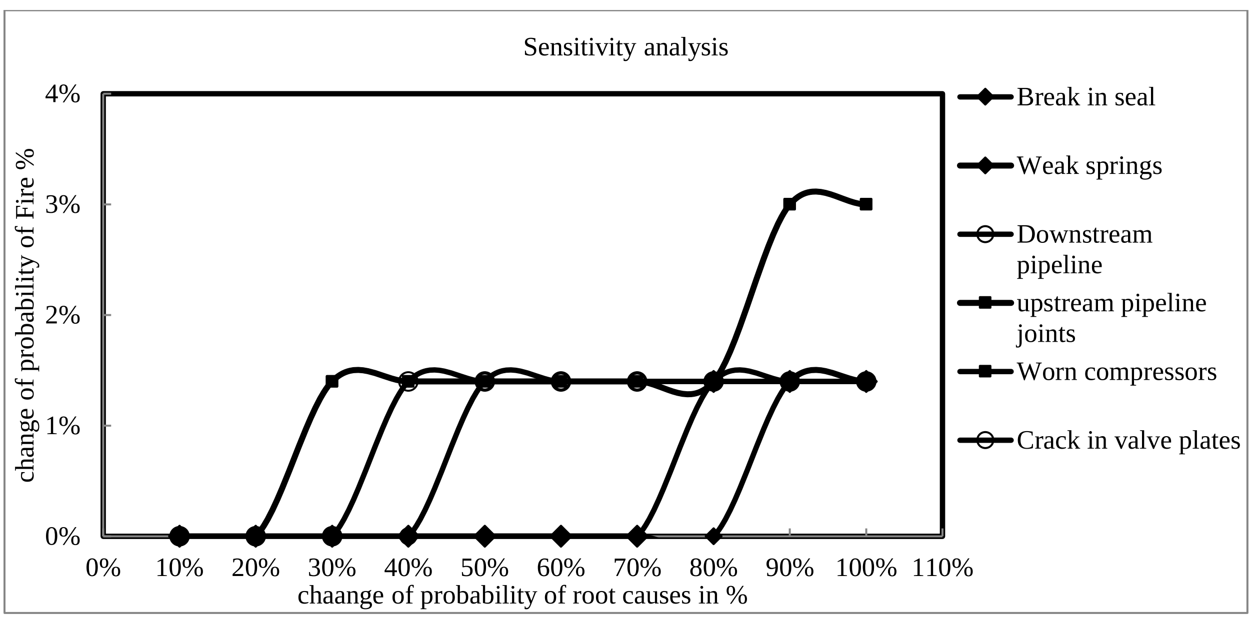

Figure 3-4(b): Sensitivity analysis of compressor in case of dependency.

For dependency cases, lubrication decrease and break in blade were not considered, as both of these occurrences are classified as intermediate events. Figure 3-4 (a) and (b) show elements those are sensitive to dependency. As can be seen, 11 elements show as being sensitive, but the most sensitive elements are gear of the shaft breaks and rotor cracks. This is determined by the rise in the steepness of each element's shape.

When each element's percentage rose between 10 and 100%, the probability of fire likewise rose. With gear of the shaft breaks, when the increase reached 100%, the fire probability rose by 28%. With impeller cracks, the fire probability stood at 15% when the probability of failure rose100%.

Six out of the total eleven elements are exactly the same, such that every pair of elements share the same fire probability when the element percentages increase from 10% to 100%. Therefore, they are illustrated separately in figure 3-4(b).

Moreover, situations involving weak springs and break in seal show that they both match and also share the same fire probability if the failure probability increases from 10% to 100%. However, there is a slight difference at the 80% marker, where the fire probability is 0% for weak springs but 1.40% for break in seal.

Furthermore, if the element percentage increases in a range from 10% to 100%, the fire probability is the same for downstream pipeline and crack in valve plates, with a few exceptions: At 40%, the fire probability for downstream pipeline is 0%, whereas for crack in valve plates it is 1.40%. When the probability of downstream pipeline and crack in valve plates rise beyond 10%, the probability of fire increased by 1.40%. Note that the same steps used to formulate Figure3-3 were also used to formulate Figure 3-4 (a, b).

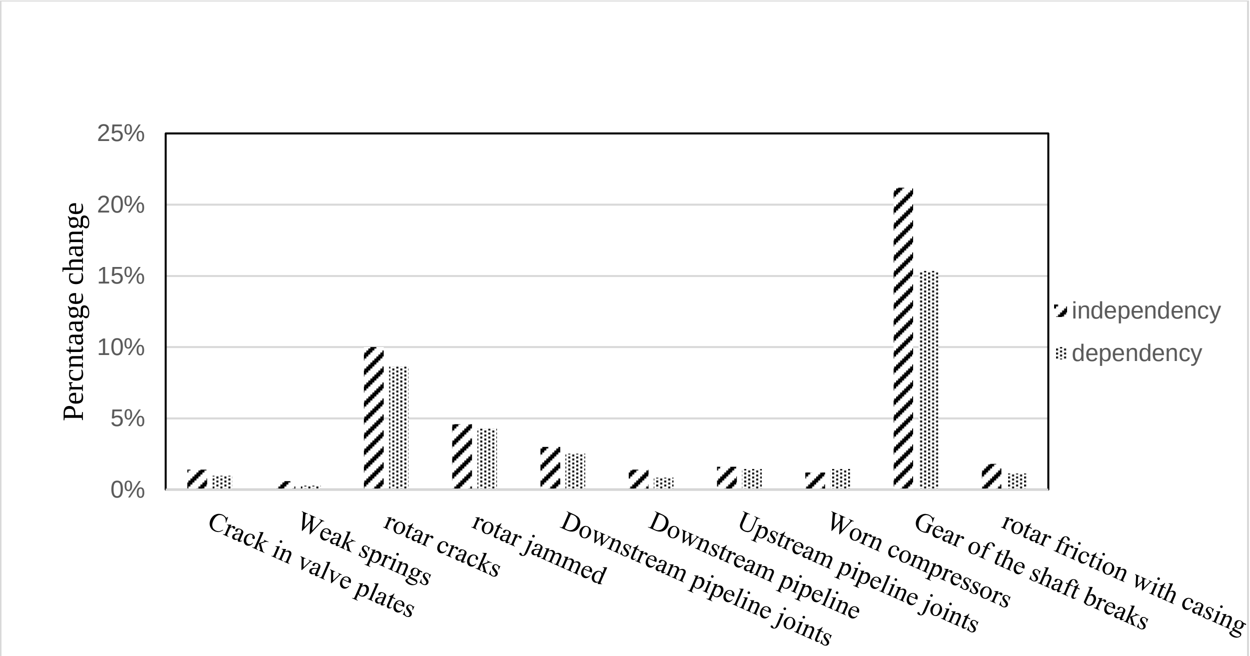

Figure 3-5: Comparison of percentage change for the dependency and independency relationship of the elements.

Figure 3-5 was derived from Figure 3-3 and 3-4(a, b). In Fig. 3-5, we can see the percentage changes for similar elements where there is either dependency or independency. So, for instance, we can see that gear of the shaft breaks show a higher percentage in case of independency (21.2%), while rotor cracks show a higher percentage in case of independency (10%). Figure 3-5 was obtained by first taking the average for each element according to dependency and independency, and then comparing them to see which elements have greater percentage changes.

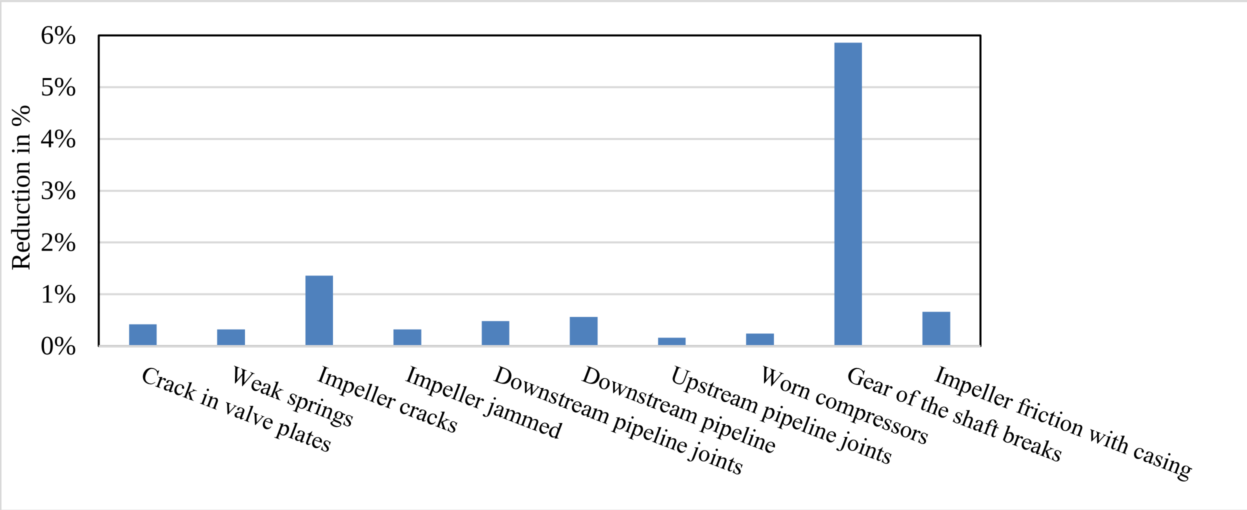

Figure 3-6: Reduction in percentage between dependency causation and independency causation.

Figure 3-6 was derived from Figure 3-5. It depicts comparisons of the dependency and independency calculated for each element in order to show a reduction percentage. Gear of the shaft breaks and impeller cracks show a reduction percentage of 5.86% and 1.36%, respectively. While, upstream pipeline joints and worn compressors display a reduction of 0.16% and 0.24%.

3.5.1. Heat exchanger tubes failure

Figure 3-7 is similar to Figure 3-3, except for the inclusion of 20 basic events and 11 intermediate events. Also, the failure of the heat exchanger tubes is the top event scenario, and data from Table 3-4 is used. Figure 3-7 illustrates basic events dependency, with the failure probability of the top event scenario being 1.09×10^{-3}. Also, in Figure 3-7, the dependencies among cavitation with high fluid velocity, high temperature with high pressure and surface deposits with inappropriate filters cleaning are shown. From this, the failure probability of the top event scenario can be calculated as 1.14×10^{-3}.

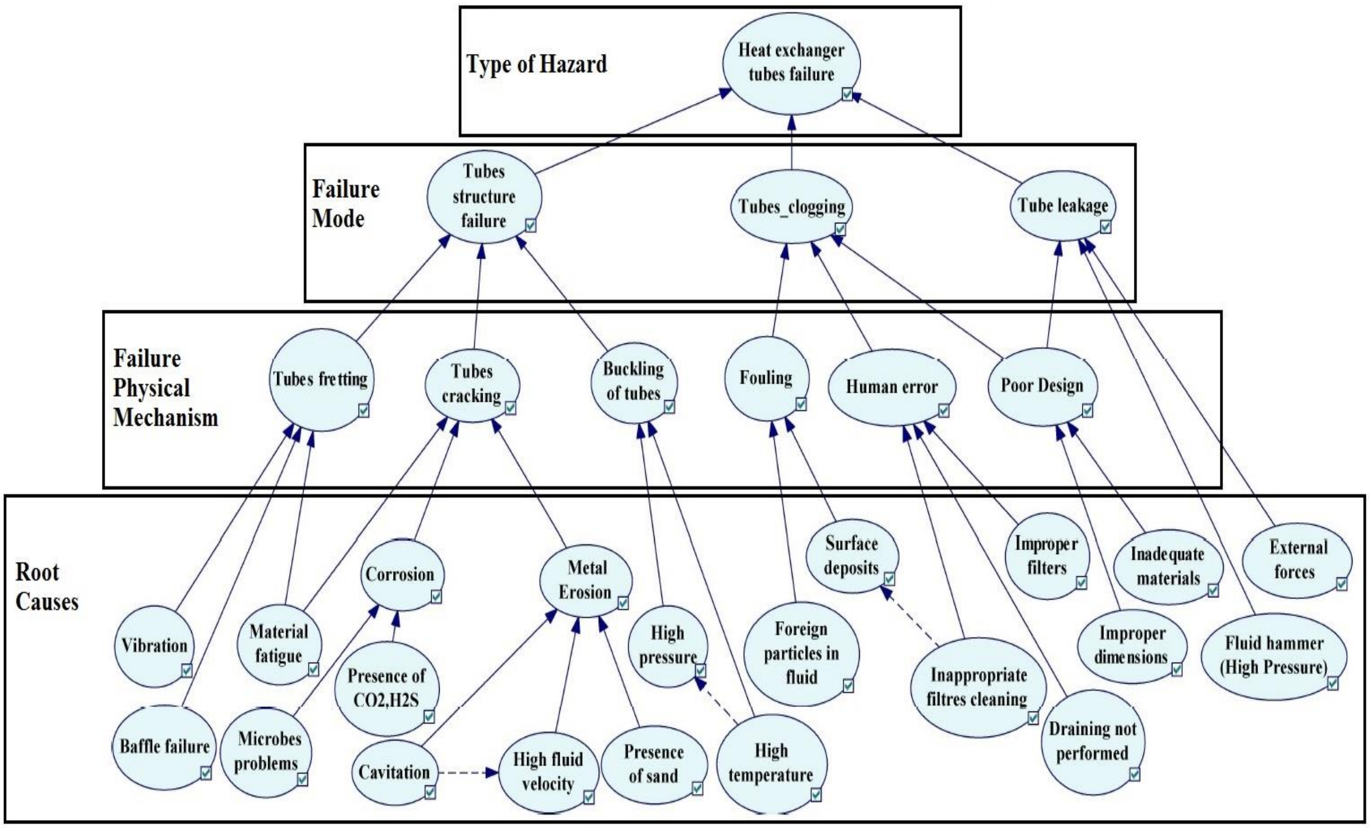

Figure 3-7: BN model for the Heat exchanger tubes failure (BE dependencies in hatched arrows).

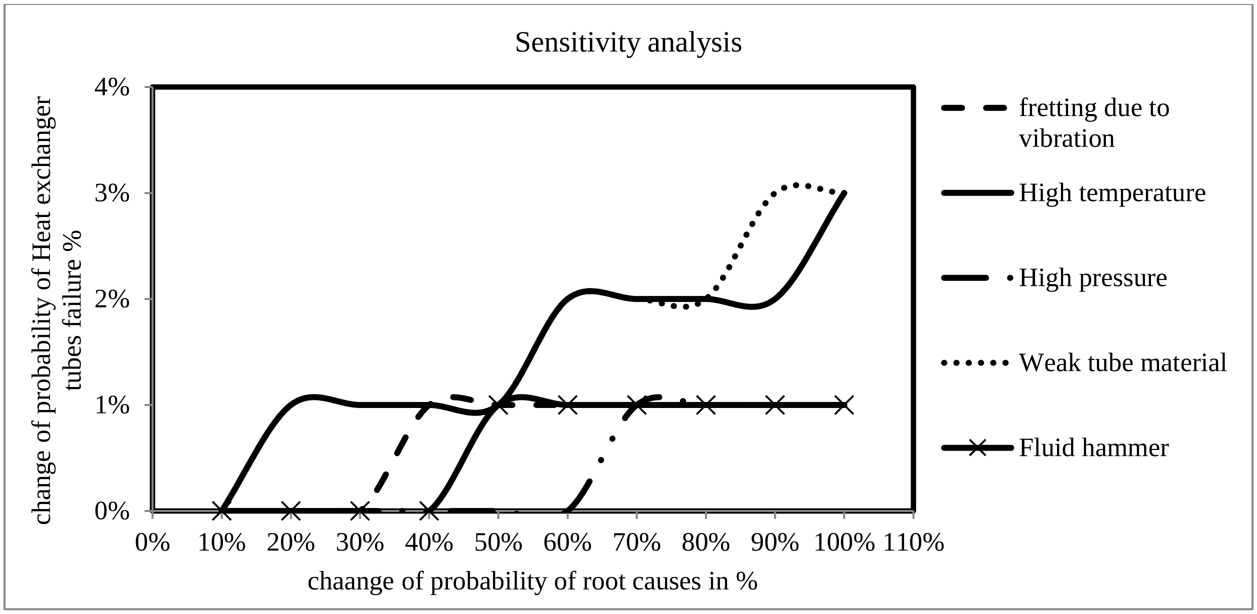

Figure 3-8: Sensitivity analysis of heat exchanger tubes failure in case of independency.

In case of independency, all basic events were considered in order to determine which of the elements are more sensitive. Figure 3-8 shows the more sensitive elements in relation to independency. Specifically, five elements are sensitive, with weak tube material and high temperature being the most sensitive. This may be caused by enhanced probability of heat exchanger tubes failure when there is an increase in the percentage of weak tube material and high temperature. Furthermore, although the probability of heat exchanger tubes failure remains the same from the fretting due to vibration, the high pressure and fluid hammer.

When the probability of failure rose from 10% to 100%, a subsequent rise occurred in the probability of heat exchanger tubes percentages. So, for instance, in the case of weak tube material, when the probability of failure rised beyond 60% and 90%, the probabilities of heat exchanger tube percentages rose 2% and 3% respectively. Similarly, when the probability of high temperature rise beyond 20%, 60% and 100%, the probabilities of heat exchanger tubes failure increase by 1%, 2% and 3% respectively. However, it remained only 1% when the probability of fluid hammer and fretting due to vibration were increased beyond 50%. When, the probability of having a high pressure rises beyond 70%, the probability of fire increases by 1%.

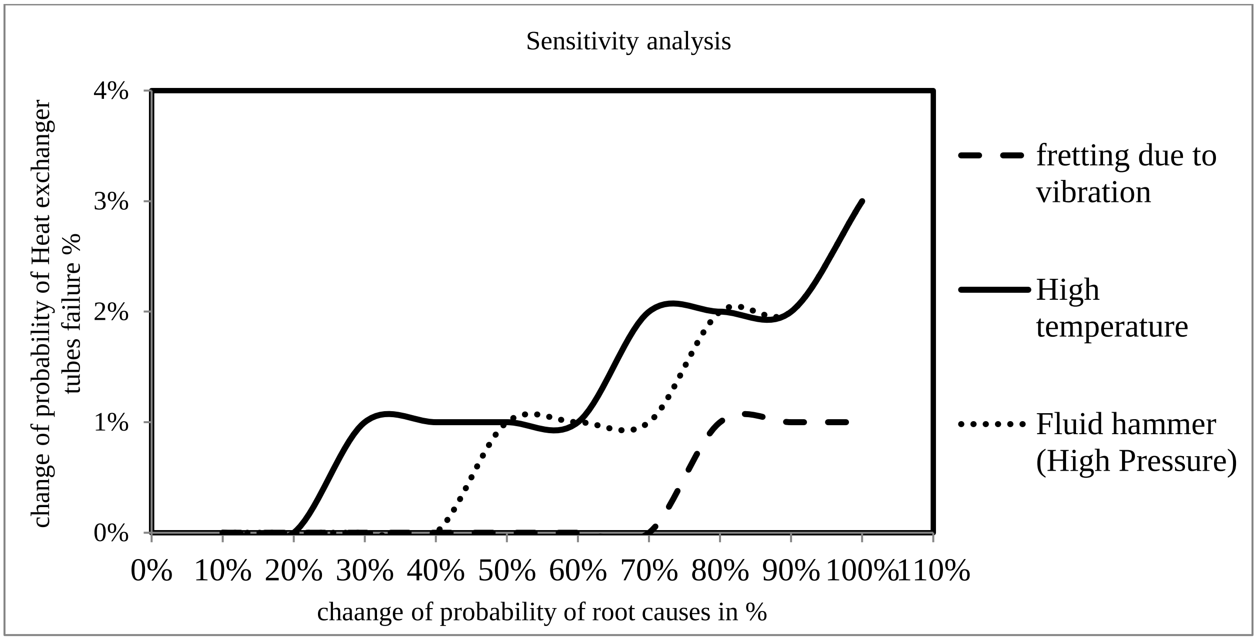

Figure 3-9: Sensitivity analysis of heat exchanger tubes failure in case of dependency.

In case of dependency, neither high pressure nor weak tube material were considered here, as they are classified as intermediate events. Figure 3-9 illustrates some of the more sensitive elements in case of dependency. Here we see that while three elements are sensitive, the most sensitive of these are high temperature and fluid hammer.

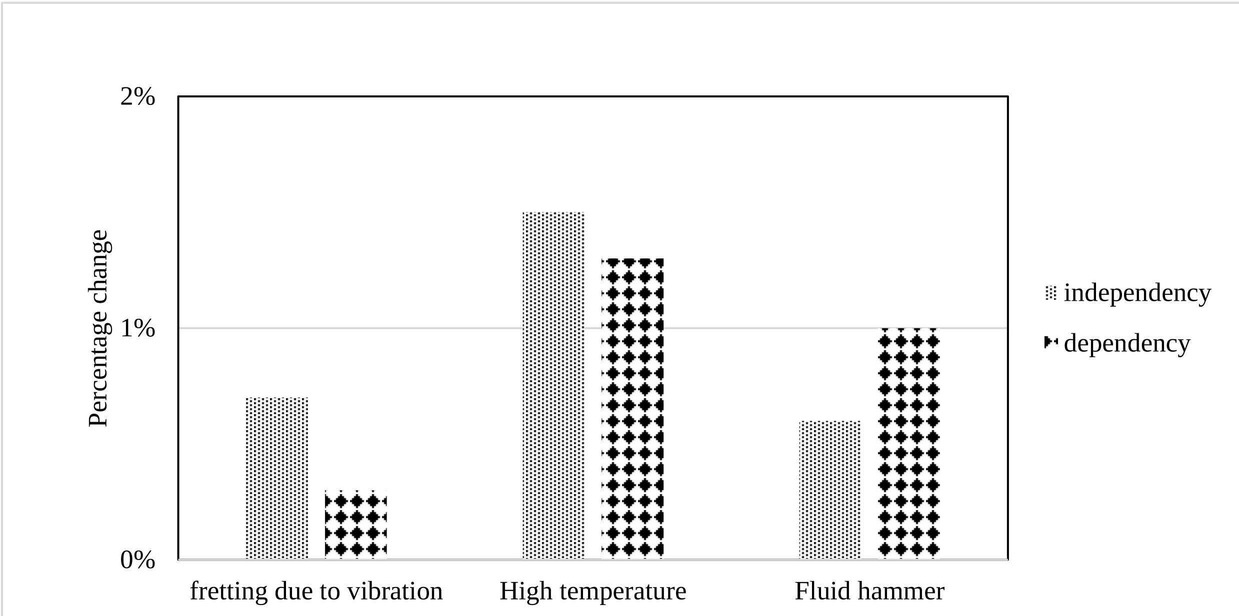

Figure 3-10: Comparison of percentage change for the dependency and independency relationship of the elements.

Figure 3-10 was obtained from Figure 3-8 and Figure 3-9. It compares percentage changes for elements in cases of independency and dependency. In case of independency, high temperature shows a greater percentage (1.5%), whereas in case of dependency, the fluid hammer shows a greater percentage (1%). Likewise, fretting due to vibration also shows a greater percentage in case of independency (0.7%). Figure 3-10 was obtained by averaging each element for independency and dependency and then comparing and contrasting to determine which of the elements show greater percentage changes.

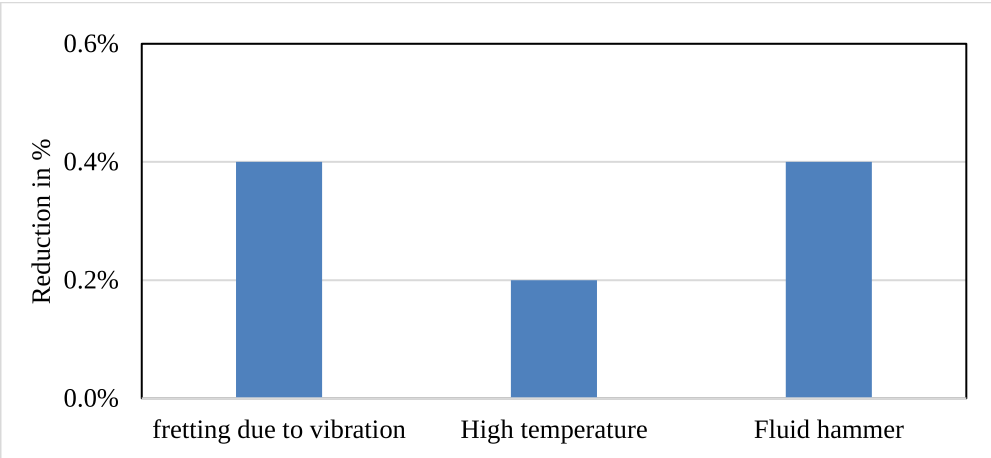

Figure 3-11: Reduction in percentage between dependency causation and independency causation.

Figure 3-11 was derived from Figure 3-10, which depicts the reduction percentage in each element. As we can see, fretting due to vibration and fluid hammer show a reduction percentage (0.4%), while high temperature shows a reduction percentage of around (0.2%).

The validation or the credibility of this study can be recognized due to the fact that this study is derived from a domain reference, which is OREDA database, coupled with domain expert knowledge for dependencies identification and quantification. Even the sensitivity analysis was not introduced in this manuscript for the first time; however, the methodology to implement it on a real offshore processing unit, and the ability to benefit from this application to perform other studies in wide range engineering fields, is the ancillary to accomplish these kind of studies.

For a compressor under a state of independency, it was determined that 11 elements were sensitive, as shown in Figures 3-3 (a and b). Of these 11 elements, the gear of the shaft breaks and rotor cracks were the most sensitive. For the compressor under state of dependency, 11 elements were sensitive, as illustrated in Figure 3-4 (a and b). Of these, the gear of the shaft breaks and rotor cracks were the most sensitive. The reduction percentage of each element under independency and dependency causation were also examined. It was determined that the gear of the shaft breaks and rotor cracks had the higher reduction percentage, as shown in Figure 3-6.

In investigating the failure of heat exchanger tubes under independency, it was noted that 5 elements were sensitive, as illustrated in Figure 3-8. Of these 5 elements, 2 were the most sensitive: weak tube material and high temperature. It was also discovered that the probability of heat exchanger tubes failure was the same for high pressure, fluid hammer, and fretting due to vibration. The failure of heat exchanger tubes under dependency was also investigated. It was discovered that 3 elements were sensitive (Figure 3-9), and of these 3 elements, 2 were the most sensitive: fluid hammer and high temperature. Next, similar elements were studied for independency and dependency in order to find out which of the elements experienced a greater percentage change. It was discovered that fretting due to vibration and high temperatures have a higher percentage under independency, whereas fluid hammer has a higher percentage under dependency (see Figure 3-10). Finally, the reduction percentages of all the elements in instances of dependency causation and independency causation were computed. As shown in Figure 3-11, it was found that fretting due to vibration and fluid hammer presented higher reduction percentages.

3.6. Conclusions

This paper has presented sensitive causal mechanism analysis that can be used to determine cause variation impact on the overall accident probability, including dependency analysis. In fact, this paper demonstrated that the use of detailed causal analysis rather than failure rate summary data such as that provided by OREDA database or OGP failure rate data resulted in an improvement in completeness and an increase in probability estimation for fire scenario on offshore compression unit from 5×10^{-3} to 7.32×10^{-3}, an increase by 46% and increase in probability estimation of heat exchanger tube failure from 4×10^{-3} to 7.32×10^{-3}, an increase by 75%. Particular attention is paid to the fact that other modelling tools can be used; however, BN have been selected due to their capability to enable causal dependencies to be expressed in a simple way, and allowed calculation of the impact of this on the calculated frequencies. It's worth noting that these conclusions are based on two examples from offshore processing unit; they can be applicable for a wide range of systems, as determined by a number of more limited trials. Furthermore, the data uncertainty is still depending on the subjective expert judgment and difficult to be standardized. Further research to solve these issues would be of interest.

Acknowledgments

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Chapter 4

Risk analysis of process components considering the dependence and uncertainty of the parameters

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Preface

A version of this manuscript is submitted in the journal of chemical engineering Research and Design, July 2017. The co-author of this research work, Mawuli Afenyo guided the principal author Samir M. Deyab to develop the research methodology on the entitled topic and helped him to conceptualize the techniques and theories available for this topic. Corresponding author Dr. Khan was the principal supervisor of this work and provided knowledgebase support to the author and co-authors.

Abstract

Safety analysis for process components is necessary to prevent unwanted events that may lead to accidents. Although the conventional Bow-Tie (BT) technique has been applied extensively in safety and risk analysis, it suffers from severe limitations, including a static structure and inability to handle uncertainty. A Bayesian Network (BN) approach is an alternative to capture uncertainty and also to capture the evolution of the scenario. It is similar to Bow-Tie in many respects. However, it outperforms BT in terms of its ability to represent interdependency among

events and uncertainty. This paper demonstrates the suitability of a BN as a safety analysis tool with an application to subsea pipelines. This paper also highlights how limited data can be incorporated in a BN by using Noisy-OR and Leaky Noisy-OR logics. These logics help to conduct a safety analysis when data is limited and a scenario is evolving.

Keywords: Bayesian Network analysis; Bow-Tie model; uncertainty modeling; Noisy-OR logic; Leaky Noisy-OR logic; dependency modeling.

4.1. Introduction

Ensuring sufficient safety can be challenging due to ongoing issues plaguing offshore facilities, such as inadequate ventilation, evacuation difficulties, high temperature/pressure, and limited space (Khan et al., 2002; Espen et al., 2012). Despite the presence of robust safety measures, accidents still occur in offshore process plants. The main instigators are process faults, human error, inappropriate design and manufacturing and component defects (Khan et al., 2002). In addition to affecting the environment, offshore accidents also affect people in terms of injuries and fatalities. For example, a slight breach in the transportation line of hydrocarbons can initiate a fire, resulting in a catastrophic event (Christou and Konstantinidou, 2012). Recent accidents like the Piper Alpha accident in the North Sea in 1988, the Petrobras P-36 in Brazil in 2001 (Baksh et al., 2016), and the Deepwater Horizon oil spill in the Gulf of Mexico in 2010 (Levy and Gopalakrishnan, 2010) resulted not only in injuries and loss of property, but also caused many deaths.

Risk analysis is carried out before designing any process operation. Offshore risk analysis is necessary for protecting facilities from danger and for mitigating problems should accidents occur (Shan et al., 2017). Risk is defined as the product of the probability of an unwanted event and the probability of consequences related to that event (Ceylan, 2013). The main purpose of risk analysis is to inform the decision-making system (DMS) when safety measures need to be strengthened to reduce the severity of an accident. It is worth mentioning that risk analysis cannot prevent accidents; it only helps mitigate adverse effects.

Under general circumstances, risk analysis is performed by utilizing available data and expert judgment in order to predict the effect of an accident on people, property and the environment (Harms-Ringdahl, 2004). In the existing literature, risk analysis techniques are divided into three methods: quantitative, qualitative and hybrid techniques (Khan et al., 2015). Typical quantitative risk analysis tools include Fault Tree Analysis (FTA) (Talebberrouane and Lounis, 2016), Event Tree analysis (ETA) (Cooke, 1997), Bow-Tie (BT) (Shan et al., 2017), and the Bayesian Network (BN) (Shan et al., 2017). FTA visualizes connections between basic events that might lead to an undesirable scenario that is the top event of the fault tree. ETA is used to calculate the likelihood of probable outcomes of different consequences due to the initiation of an undesirable event (Vesely et al., 1981). The BT model is considered one of the most accurate of graphical models for conveying details of a complete accident scenario, ranging from accident causes to accident consequences. BT includes a fault tree indicating possible events contributing to the critical event, as well as an event tree indicating the most important possible consequences of the event (Delvosalle et al., 2005; Delvosalle et al., 2006).

Both FTA and ETA are based on two main assumptions, both of which have challenges (Ferdous et al., 2011). The first assumption is that the probability of the basic events is crisp and known. This is nearly impossible in real-life scenarios due to incompleteness in data collection (Ferdous et al., 2009; Ferdous et al., 2011; Sadiq et al., 2008). Hence, it is often difficult to calculate precise numerical values (Yuhua and Datao, 2005). The second assumption is that basic events are considered independent, which is inaccurate (Ferdous et al., 2011; Ferson et al., 2004). As a result, uncertainty emerges (Ferdous et al., 2011). Since BT is a combination of FTA and ETA, it cannot overcome the inherent limitations of these tools. However, BT is an excellent tool to use in simple processes.

A Bayesian Network (BN) provides a more robust prediction than BT in complex systems (Pollino et al. 2007; Badreddine and Ben Amor, 2010). It can handle uncertainty and also show interdependency between basic events. Thus, it overcomes the generic nature of FTA (Khakzad et al., 2011) and allows the incorporation of different kinds of knowledge (e.g., expert judgment, feedback experience and observation) into a single model (Weber et al. 2012). Another major advantage of BN is that it easily combines existing frequency data with expert judgment within a probabilistic framework.

The success of a BN depends on the proper estimation of conditional probability tables (CPTs). If enough data are available, CPTs can easily be estimated or defined. However, this is often not the case, especially when dealing with accidents or unwanted situations, which often occur. Expert opinion is often used to develop this table. Table 4-1 provides a list of some pioneering recent works that have used expert opinion to develop CPTs as part of the detailed risk analysis.

Source	Focus
Li et al., 2016	Quantitative risk analysis on leakage failure of submarine oil and gas pipelines using Bayesian network
Celeux et al., 2006	Designing a Bayesian network for preventive maintenance using expert opinions in a rapid and reliable way
Wilson et al., 2007	Bayesian networks for multilevel system reliability
Weber et al., 2012	Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas

Adedigba et al., 2016a	Dynamic safety analysis of process systems using nonlinear and non-sequential accident model
Adedigba et al., 2016b	Process accident model considering dependency among contributory factors

Conventionally, BNs are constructed with OR logics, which require complete data. Incorporating Noisy-OR and Leaky Noisy-OR logics allows a BN to perform with limited data. The objective of this work is to examine the performance of Noisy-OR and Leaky Noisy-OR logics, with importance analysis being selected as the comparative criterion. It is a ranking technique mainly for vulnerable basic events (Oniśko et al., 2001, Heckerman and Breese 1996). First, a BT model is developed and its performance compared with conventional OR logic-based BN. Next, the BN is reconstructed with Noisy-OR and Leaky Noisy-OR logics. The probability of different consequences is calculated and compared with those of the BN with OR logic. Finally, importance analysis is performed for all three logics to check whether the reconstructed BN can satisfactorily perform or not. The rest of the paper is as follows. Section 2 discusses the methodology. Section 3 shows an application of the methodology. Finally, section 4 evaluates the contribution, advantages and limitations of the approach, and suggests directions for future work.

4.2. Methodology

The proposed methodology for dynamic risk assessment is presented in Figure 1. It is composed of five steps, as follows:

Step 1: The system of interest is selected and available data are collected.

Step 2: Potential hazardous accident scenarios are developed.

Step 3: The developed scenario is transformed to Bow-tie model for better understanding. BT has been chosen here, as it incorporates a higher degree of visual effects than other models with regard to the direct connections between accident causes and consequences. Bow-Tie is an effective tool for communicating and demonstrating risk controls and the management system. In the proposed methodology, BT is very appropriate, considering that there is a need to evaluate potential risk control options based on the potential consequences. It is also relatively easier to map information from a BT to a BN (Saud et al., 2014).

Step 4: In this step, causality analysis is done to determine interdependency among variables. Available data and expert opinion are incorporated with the BT developed in step 3 to construct the BN. It should be noted that the BN is constructed for three different types of logics – OR, Noisy-OR, and Leaky Noisy-OR. Details of these are presented in subsequent subsections.

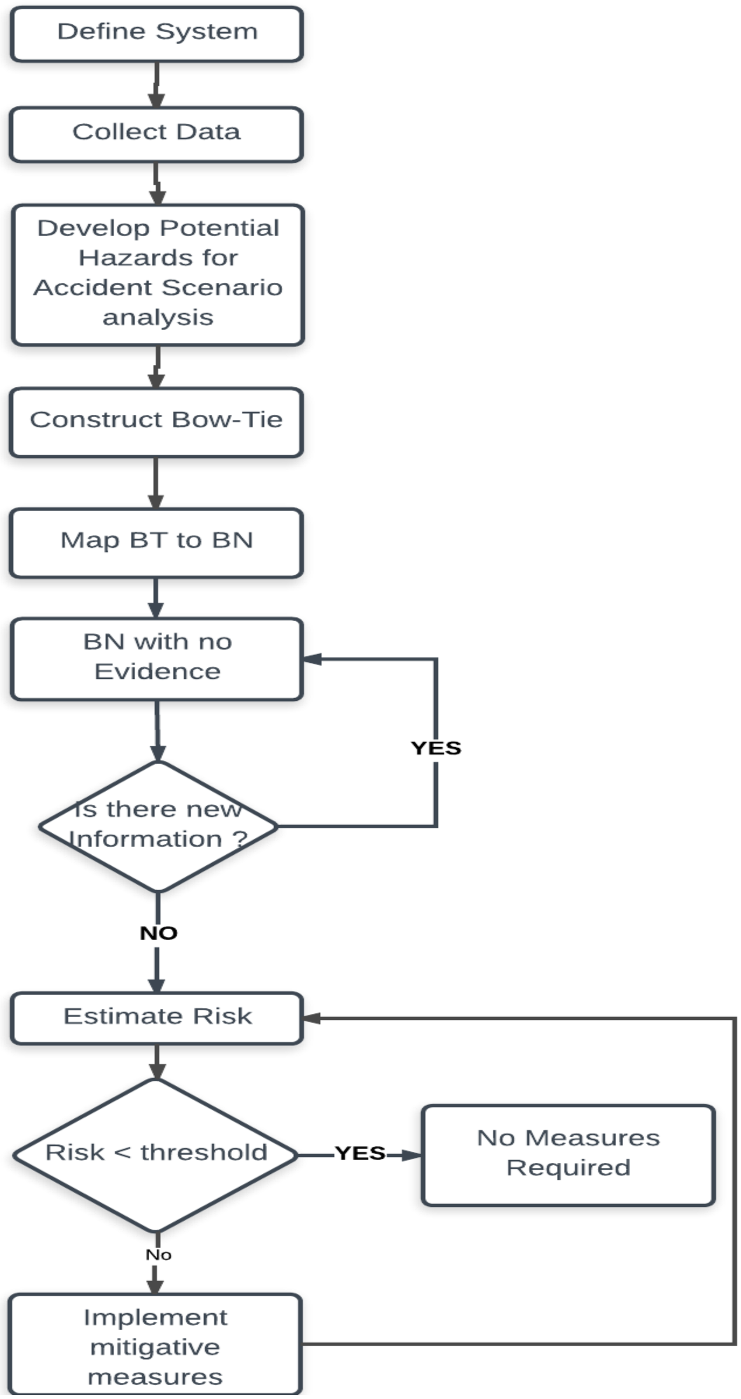

Figure 4-1: Flow chart of proposed risk analysis methodology

Step 5: One of the biggest advantages of a BN is that it gets updated at any state of any node, which makes it possible to renew the prior beliefs using the developed posterior probabilities. In this step, a BN is updated based on evidence when it becomes available, and the risk associated with different consequences is predicted. This helps the decision-makers using the model to take corrective measures.

4.2.1 Bayesian Network (BN)

A Bayesian Network (BN) is a directed acyclic graph (DAG) that is often applied to safety and risk analyses because of their probabilistic and uncertain knowledge (Pearl, 1988). It is mainly constructed by combining nodes, acyclic arcs, and prior and conditional probabilities. The nodes of a BN represent different basic events, while the arcs denote the causal relationships among the events. The direction of the arcs denotes the type of node. The node from which an arc is created is called a parent node, while the node at which the arc is directed is called a child node. Conditional probability tables (CPTs) denote the degree of dependency among different events (Khakzad et al., 2013b). A BN can be used in safety and risk analysis. Its main advantages include the ability to represent event dependencies, capture uncertainty and update probabilities (Khakzad et al., 2011). It also allows for the incorporation of process knowledge from experts in case of data unavailability.

According to the chain rule and conditional independence, the joint probability distribution, $\mathrm{P(U)}$ of a set of random events, $\mathrm{U} = \{\mathrm{A1}, \dots\dots, \mathrm{An}\}$ is incorporated into the network as:

$$P(U) = \prod_{i=1}^{n} P(A_i \mid P_{a(A_i)}) \qquad (4.1)$$

where $\mathrm{Pa(A_i)}$ is the parent set of $\mathrm{A_i}$ (Pearl,1998; Jense and Nielsen,2007).

A BN utilizes Bayes' theorem to update the prior occurrence probability of events based on information. This information is known as evidence (E). Posterior (P/E) refers to the belief of an event based on evidence. The posterior probability can be calculated using Equation (4.2):

$$\mathrm{P}\,(\mathrm{U}/\mathrm{E}) = \frac{\mathrm{P}(\mathrm{U},\mathrm{E})}{\mathrm{P}(\mathrm{E})} = \frac{\mathrm{P}(\mathrm{U},\mathrm{E})}{\sum_{\mathrm{U}} \mathrm{P}(\mathrm{U},\mathrm{E})} \qquad (4.2)$$

Canonical probabilistic models significantly reduce computational time and also make the construction of probabilistic models relatively easier. These types of models are now being frequently used in probabilistic systems (Oniśko et al., 2001; Diez and Druzdzel, 2007). In fact, different kinds of canonical models can readily co-exist in a variety of probabilistic networks. An effective way to make the elicitation of numerical probabilities less complex is to use canonical probabilistic models, as these can build probability distribution based on a small number of parameters (Diez and Druzdzel, 2007). Typical canonical interactions utilized in the BNs are Noisy-OR and Leaky Noisy-OR logics. Using canonical interactions in the BN provides an efficient means to model different kinds of non-linear interactions as well as statistical dependencies (Adedigba et al., 2016a).

4.2.1.1 OR Logic

OR logic is the most used logic in both BN and FT. Figure 4-2 is used for illustration purposes consider the two events- A and B in Figure 4-2.

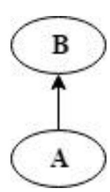

Figure 4-2: Simple BN of two nodes

A is the parent node and B is the child node. In FT, A is the basic event and B is the top event. The CPT of B with FT-OR and BN-OR logics is shown in Table 4-2.

Table 4-2: CPT of B for FT-OR Logic and BN-OR Logic

A		True	False
B	True	1	0
	False	0	1

4.2.1.2 Noisy-OR Logic

Noisy-OR logics follow a canonical model premised on the assumption that cause and effect are inherently binary and thus involve two states: True and False. The logics are utilized mainly if data are available, but they can also be used for describing interactions between n causes $X_1, X_2, \ldots, X_n$ and their common effect, Y. The concept behind Noisy-OR logics is that every cause, X_i, affects Y independently, and that the cause, X_i, has a probability, P_i, which should be sufficient to create the effect, Y, even if all the other causes prove to be False (Oniśko et al.,2001). Given the above assumptions, specifying the conditional probability distribution using only the n parameters, $P_1, P_2, \ldots, P_n$ is achievable. Hence, P_i indicates that the effect, Y, will be True if the cause X_i is True, but the other causes, $X_{j,j\neq i}$, are False (Oniśko et al., 2001). This can be mathematically expressed as:

$$P_i = \Pr(y \mid \overline{X}_1, \overline{X}_2, \ldots, X_i, \ldots, \overline{X}_{n-1}) \qquad (4\text{-}3)$$

It also follows that the probability of Y being given a subset of X_p of the X_i that are True and can be expressed in the equation:

$$\Pr(Y|X_p) = 1 - \prod_{i:xi \in X_p} (1 - P_i) \qquad (4\text{-}4)$$

The formulation above is enough to compute the CPT of Y conditioned on its predecessors $X_1, X_2, \ldots, X_n$.

Applying the Noisy-OR logic would lead to a significant reduction in the probabilities required to quantify the above-mentioned cause-effect interaction. In this instance, the model needs n probabilities, whereas the unrestricted model requires 2^n probabilities (Adedigba et al., 2016a; Heckerman and Breese, 1996).

To illustrate how to apply Noisy OR and Leaky Noisy OR logics as a part of CPT, Auxiliaries failure has been chosen as simple example.

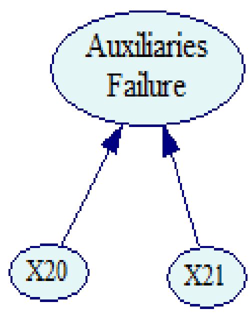

Figure 4-3: Bayesian network for causes of Auxiliaries Failure

Figure 4-3 shows an example of the BN that presents the causes of Auxiliaries failure of a system, based on the failure probabilities given by Table 4-3.

Table 4-3: Safe and failure probabilities of causes of Auxiliaries Failure

No	Causes of Auxiliaries Failure	Failure probability (T)	Safe probability (F)
1	Failure due to long term usage (X20)	3.000×10^{-4}	9.997×10^{-1}
2	Design fault of auxiliaries (X21)	1.000×10^{-5}	1.000×10^{1}

The Noisy-OR logic can be expressed as in the following table.

Table 4-4: Probability of Auxiliaries Failure for Noisy-OR Logic.

State	Failure due to long term usage	Design fault of auxiliaries	True	False	Conditional Probability of Auxiliaries Failure for Different States
1	*F*	*F*	0	1	$0\times9.997\times10^{-1}\times1.000\times10^{1} = 0$
2	*F*	***T***	2×10^{-1}	8×10^{-1}	$2\times10^{-1}\times9.997\times10^{-1}\times1.000\times10^{-5} = 1.999\times10^{-6}$
3	***T***	*F*	7×10^{-1}	3×10^{-1}	$7\times10^{-1}\times3.000\times10^{-4}\times1.000\times10^{1} = 2.10\times10^{-3}$
4	*T*	*T*	7.6×10^{-1}	$2.4\times10^{-1} = 3\times10^{-1}\times8\times10^{-1}$	$7.6\times10^{-1}\times3.000\times10^{-4}\times1.000\times10^{-5} = 2.28\times10^{-9}$

The probability of Auxiliaries Failure is the sum of all states= 2.10×10^{-3}

4.2.1.3 Leaky Noisy-OR Logic

Leaky Noisy-OR logic is an extension of binary Noisy-OR logic, and is useful in conditions where the effect variable in a subsystem can be True despite the causes being False. Leaky Noisy-OR logic is typically applied in scenarios where a model cannot express all of the potential causes of effect Y (Oniśko et al.,2001) ; Adedigba et al., 2016a). In Leaky Noisy-OR logic, the combined effect of the causes of effect is referred to as leak probability l. This leak probability(l) is the probability that effect Y will occur spontaneously (True), despite its causes being absent (False) (Oniśko et al.,2001; Adedigba et al., 2016a; Zagorecki and Druzdzel, 2004). The equation for Leaky Noisy-OR logic for calculating the probability of effect Y based on the subset X_p of Xi, which is True, is given by:

$$\Pr\left(Y\middle|X_p\right) = 1 - [(1 - l)\prod_{i:X_i \in X_p}(1 - P_i)] \qquad (4\text{-}5)$$

The Leaky Noisy-OR logic can be expressed as follows:

Table 4-5: Probability of Auxiliaries Failure for Leaky Noisy-OR Logic.

State	Failure due to long term usage	Design fault of auxiliaries	True	False	Conditional Probability of Auxiliaries Failure for Different States
1	*F*	*F*	1×10^{-2}	9.9×10^{-1}	$1\times10^{-2}\times9.997\times10^{-1}\times1.000\times10^{1} = 9.997\times10^{-2}$
2	*F*	***T***	2.08×10^{-1}	$7.92\times10^{-1} = 8\times10^{-1}\times9.9\times10^{-1}$	$2.08\times10^{-1}\times9.997\times10^{-1}\times1.000\times10^{-5} = 2.08\times10^{-6}$
3	***T***	*F*	7.03×10^{-1}	$2.97\times10^{-1} = 3\times10^{-1}\times9.9\times10^{-1}$	$7.03\times10^{-1}\times3.000\times10^{-4}\times1.000\times10^{1} = 2.11\times10^{-3}$
4	*T*	*T*	7.6×10^{-1}	$2.4\times10^{-1} = 3\times10^{-1}\times8\times10^{-1}\times9.9\times10^{-1}$	$7.62\times10^{-1}\times3.000\times10^{-4}\times1.000\times10^{-5} = 2.29\times10^{-9}$

The probability of Auxiliaries Failure is the sum of all states= 1.02×10^{-1}

In Tables 4-4 and 4-5, the terms True and False indicate the following: (True) means the system fail, and (False) means the system will not fail.

To clarify how CPT has been calculated in Noisy-OR logic and Leaky Noisy OR logic, an example is presented using Auxiliaries Failure. See Tables 4-4 and 4-5.

According to the example, Noisy-OR logic and Leaky Noisy OR logics have two failure probabilities, which should be found and then contributed to the calculation of other values.

4.3. Application of Methodology

To demonstrate the suitability of the proposed methodology, a subsea pipeline leak is considered as the hazard. Despite having a higher associated risk of an accident, a subsea pipeline is a major means of transporting hydrocarbons in many countries (Dey et al., 2007). Underwater pipelines are subject to numerous vulnerabilities, such as buckling (Liu and Yan, 2014), fatigue crack (Zhang et al., 2016), corrosion (Yang et al., 2017), problems with gas hydrates (Mokhatab et al., 2007), vibrations caused by a pipeline's internal fluid contents (Reda et al., 2014) and leaks (Hu et al., 2013).

4.3.1. BT of Subsea Pipeline Leak

A BT model is constructed which captures all the possible causes and consequences for a leak in a subsea pipeline. A subsea pipeline leak is the connecting point for the FT and ET of the BT diagram. Prior knowledge of the failure mechanism has been utilized to develop the FT and ET. FTA is used to evaluate the failure probability of safety barriers. The aim of using safety barriers is to reduce the severity of an undesired event (Xue et al., 2013). Three safety barriers (monitoring or Inspection barrier, emergency shutdown barrier and human factors and organizational barrier) are employed to minimize the damage due to a subsea pipeline leak. A total of 44 basic events have been used to construct the BT model, while 21 basic events are employed to build the FT of the subsea pipeline leak. The rest of the basic events are utilized to construct the FT for three safety barriers.

The prior probabilities for the basic events were obtained from three major reference sources (Yang et al., 2017; Li et al., 2016; Rathnayaka et al., 2012). Expert judgment has also been used to assign values of probabilities based on their subject knowledge and experience. The data provided in Table 4-6 and Table 4-7 are presented as examples of some of the elements used in the modeling process.

The FT is constructed showing probable factors that can cause a subsea pipeline leak. A leak can occur due to a number of factors, such as corrosion, natural hazards, external loading failure and defects in the pipe. Corrosion can occur in both external and internal surfaces. External corrosion is mainly caused by external coating failure and cathodic protection failure, while internal corrosion arises from the presence of corrosive gas and unwanted substances inside the pipe, as well as from irregular pigging, internal coating failure and the absence of a corrosion inhibitor. Natural hazards include earthquakes, seabed movement, hurricanes and freezing. External loading failures are caused by excessive external pressure, seabed soil erosion, the impact of a dropped object, anchoring work and offshore construction. Defects in the pipe may be due to weld-seam defects, material defects or auxiliaries failure. Weld-seam and material defects are caused by design faults and are mostly due to construction and manufacturing defects. Such defects may cause pipeline leaks if external forces come into play. Auxiliary failures due to long-term usage and design faults can also cause leaks.

A complete accident scenario has been developed to build the ET. In this scenario, safety barriers play a crucial role in determining the consequences. When functioning as intended, monitoring or inspection is able to note any alterations from normal work conditions in the pressure and flux in pipelines. Should such changes such as leakage be perceived, there would be immediate implementation of emergency shutdown procedures, which usually involves cutting off the globe valves and stopping the pump. However, under certain conditions, there may be no stoppage of the pump or cutting off of globe valves, or only partial stoppage or cutting off.

One barrier that can affect the entire process of leakage accident evolution is human and organizational factors. These factors can change the procedure by triggering the monitor, alarm and emergency shutdown, or by finding alarm signals and judging and verifying the leakage's occurrence. Five possible consequences – safe (A), near miss (B), incident (C), accident (D) and catastrophic accident (E) – are identified and depend on the number of safety barrier failures. The consequences for subsea pipeline leaks are defined below.

Safe: There was a leak, but it was monitored and identified, the emergency shutdown system was activated and human response action was taken. As a result, the leak did not have any impact.

Near miss: A leak was monitored and the emergency shutdown system was activated; a delayed human response was observed. As a result, a minor loss was recorded.

Incident: One safety barrier malfunction. However, major loss was avoided due to proper action of the other two barriers.

Accident: Some safety barriers failed. As a result, there was significant loss.

Catastrophic accident: All safety barriers failed. As a result, loss of life, serious injury, a huge financial, and environmental impacts occurred.

The FTs and ET are integrated to construct the BT. The developed BT is shown in Figure 4-4.

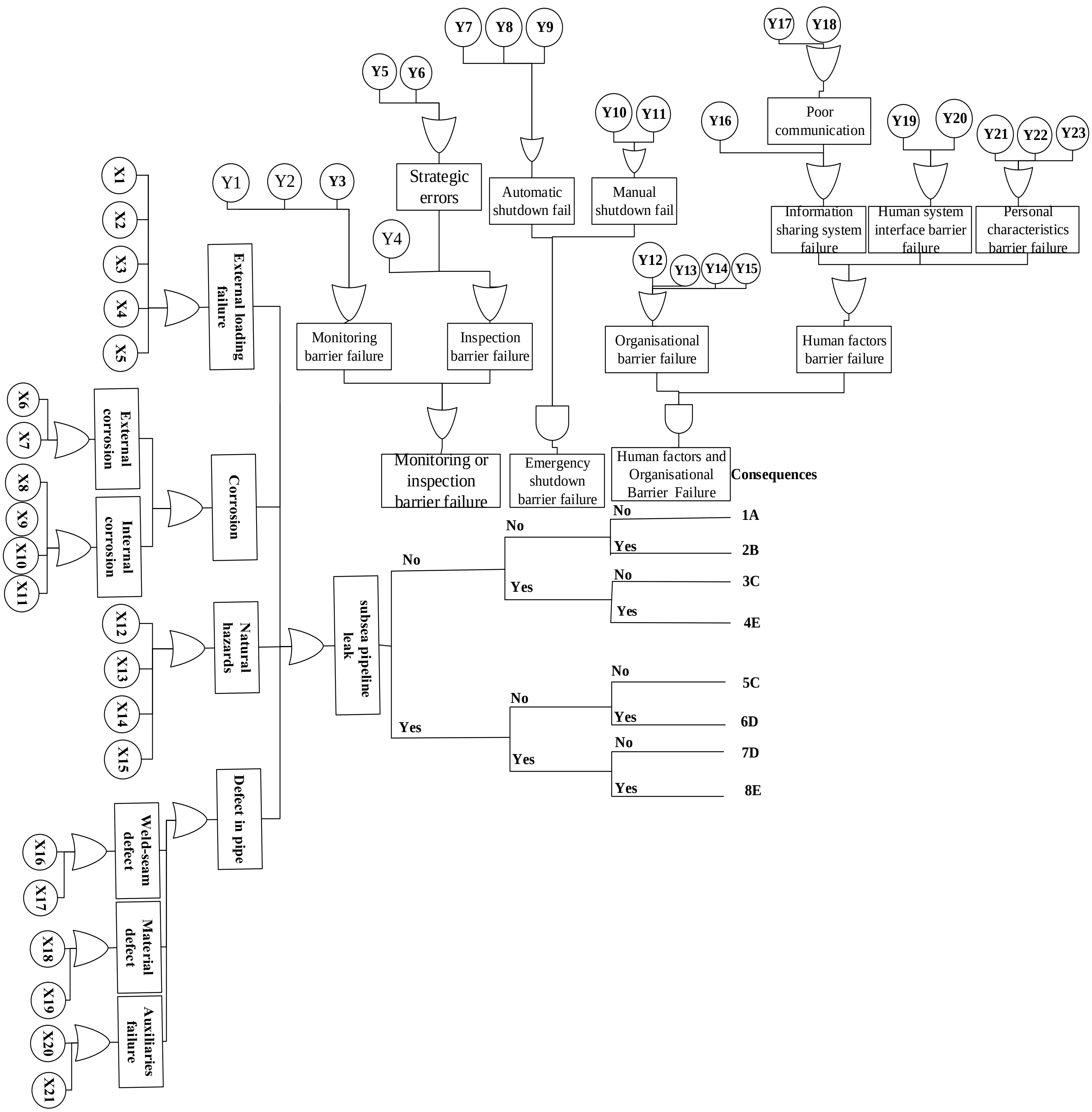

Figure 4-4: BT of subsea pipeline leak

Table 4-6: Basic Events of Subsea Pipeline Leak

Symbol	Basic Events	Prior Probability	Posterior Probability		
			OR	Noisy OR	Leaky Noisy-OR
X1	Excessive external pressure	5.62×10^{-6}	4.20×10^{-4}	3.25×10^{-4}	3.85×10^{-4}
X2	Seabed soil erosion	6.00×10^{-3}	5.21×10^{-1}	4.50×10^{-1}	4.90×10^{-1}
X3	Dropped object impact	1.50×10^{-4}	1.05×10^{-2}	1.01×10^{-3}	3.38×10^{-3}
X4	Anchoring work	2.00×10^{-4}	1.40×10^{-2}	1.32×10^{-3}	1.10×10^{-2}
X5	Offshore construction	5.00×10^{-5}	3.54×10^{-3}	3.30×10^{-4}	2.75×10^{-3}
X6	External coating failure	5.00×10^{-4}	3.50×10^{-2}	5.62×10^{-3}	3.34×10^{-2}
X7	Cathodic protection failure	2.70×10^{-4}	1.89×10^{-2}	2.83×10^{-3}	1.22×10^{-2}
X8	Presence of corrosion gas and unwanted substances	1.00×10^{-3}	7.01×10^{-2}	3.99×10^{-3}	6.60×10^{-2}
X9	Absence of corrosion inhibitor	1.10×10^{-4}	5.50×10^{-3}	9.00×10^{-4}	4.30×10^{-3}
X10	Irregular pigging	2.00×10^{-4}	1.20×10^{-2}	1.70×10^{-3}	1.11×10^{-2}
X11	Internal coating failure	7.74×10^{-4}	5.43×10^{-2}	8.70×10^{-3}	3.36×10^{-2}
X12	Earthquake	6.30×10^{-6}	4.00×10^{-4}	3.00×10^{-4}	3.60×10^{-4}
X13	Seabed movement	2.00×10^{-3}	1.54×10^{-1}	1.35×10^{-1}	1.45×10^{-1}
X14	Hurricane	3.70×10^{-5}	2.35×10^{-3}	4.00×10^{-4}	2.02×10^{-3}
X15	Freezing	2.00×10^{-5}	4.55×10^{-4}	2.00×10^{-4}	4.15×10^{-4}
X16	Design fault of weld- seam	2.30×10^{-4}	1.61×10^{-2}	4.00×10^{-4}	4.81×10^{-3}
X17	Defect due to construction	6.50×10^{-4}	4.56×10^{-2}	3.70×10^{-3}	3.14×10^{-2}
X18	Design fault of material	8.40×10^{-4}	5.89×10^{-2}	2.45×10^{-3}	2.50×10^{-3}
X19	Manufacturing defects	9.70×10^{-4}	6.80×10^{-2}	1.90×10^{-3}	2.20×10^{-2}
X20	Failure due to long term usage	3.20×10^{-4}	2.24×10^{-2}	8.00×10^{-4}	8.28×10^{-3}
X21	Design fault of auxiliaries	1.00×10^{-5}	4.00×10^{-4}	1.85×10^{-5}	7.63×10^{-5}

Table 4-7: Basic Events of Safety Barrier Failure

Symbol	Basic Events	Prior Probability
Y1	Programmable logic controller (PLC) failure	5.00×10^{-4}
Y2	Signal transmission failure in the line	2.00×10^{-4}
Y3	Sensor failure	2.40×10^{-2}
Y4	Harsh subsea environment	1.00×10^{-3}
Y5	Delayed inspection	1.00×10^{-2}
Y6	Inspection overload	2.00×10^{-2}
Y7	Programmable logic controller (PLC) failure	5.00×10^{-4}
Y8	Emergency shutdown valve failure (ESD valve failure)	1.30×10^{-2}
Y9	Hydraulic control failure	1.32×10^{-1}
Y10	Emergency shutdown valve failure (ESD valve failure)	1.30×10^{-2}
Y11	Operator response to active manual ESD failure	6.00×10^{-2}
Y12	Lack of communication	5.00×10^{-2}
Y13	Insufficient safety program	1.00×10^{-2}
Y14	Inadequate supervision	3.40×10^{-2}
Y15	Lack of training	2.50×10^{-2}
Y16	Insufficient work instruction	2.50×10^{-2}
Y17	Lack of communication	5.00×10^{-2}
Y18	Failure of communication	2.50×10^{-2}
Y19	Warning display failure	5.00×10^{-2}
Y20	Warning alarm failure	2.00×10^{-2}
Y21	Physical disability	5.00×10^{-2}
Y22	Failure of operator dexterity improvement program	2.00×10^{-2}
Y23	Failure of regular operator training	3.40×10^{-2}

4.3.2. Mapping of BT into BN

The mapping algorithm presented by (Khakzad et al., 2013b) has been used to map the BT into a BN. Figure 4-5 shows the developed BN. As can be seen, the FT is based on the causal relationships among primary and intermediate events. The safety barriers in the tree-mapping process are represented as safety nodes, while the consequence node with five states related to the end-state are represented with the event tree.

First, the BN has been constructed for the OR logic, while Noisy-OR and Leaky Noisy-OR logics have been used to reconstruct the BN. The graphical network software (GeNIe) is used to do the simulation.

By using OR logic in the BN, the probability of a subsea pipeline leak is estimated as 1.43×10^{-2}, This is identical to the FT calculation. However, when including the CPT amendments Noisy-OR and Leaky Noisy-OR, the probability of a subsea pipeline leak increases to 3.75×10^{-3} and 5.12×10^{-2}, respectively. As an example, the estimated values using non-amended CPT (i.e., 1.43×10^{-2}) can be applied to calculate the occurrence probabilities of consequences. The probabilities of end-states are calculated and shown in Table 4-9. It is worth noting that the results of the occurrence probabilities of consequences are slightly different than those in the Bow-Tie model. This is due to conditional dependencies among top events of the FT and safety barriers being considered.

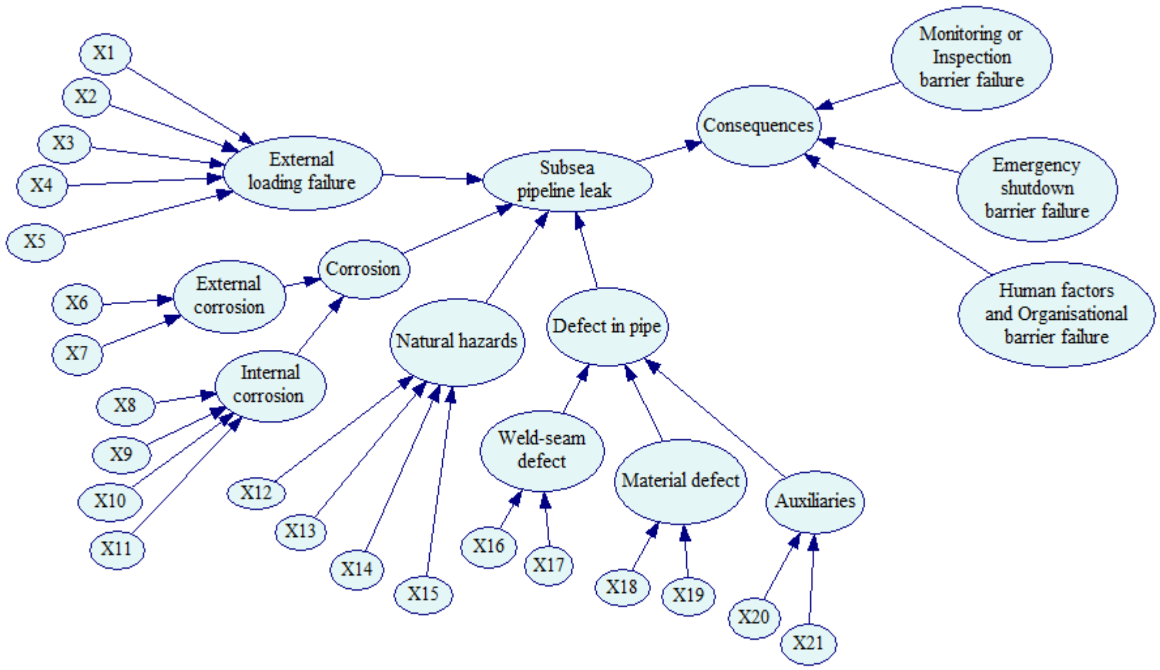

Figure 4-5: Bayesian Network mapping from Bow-Tie

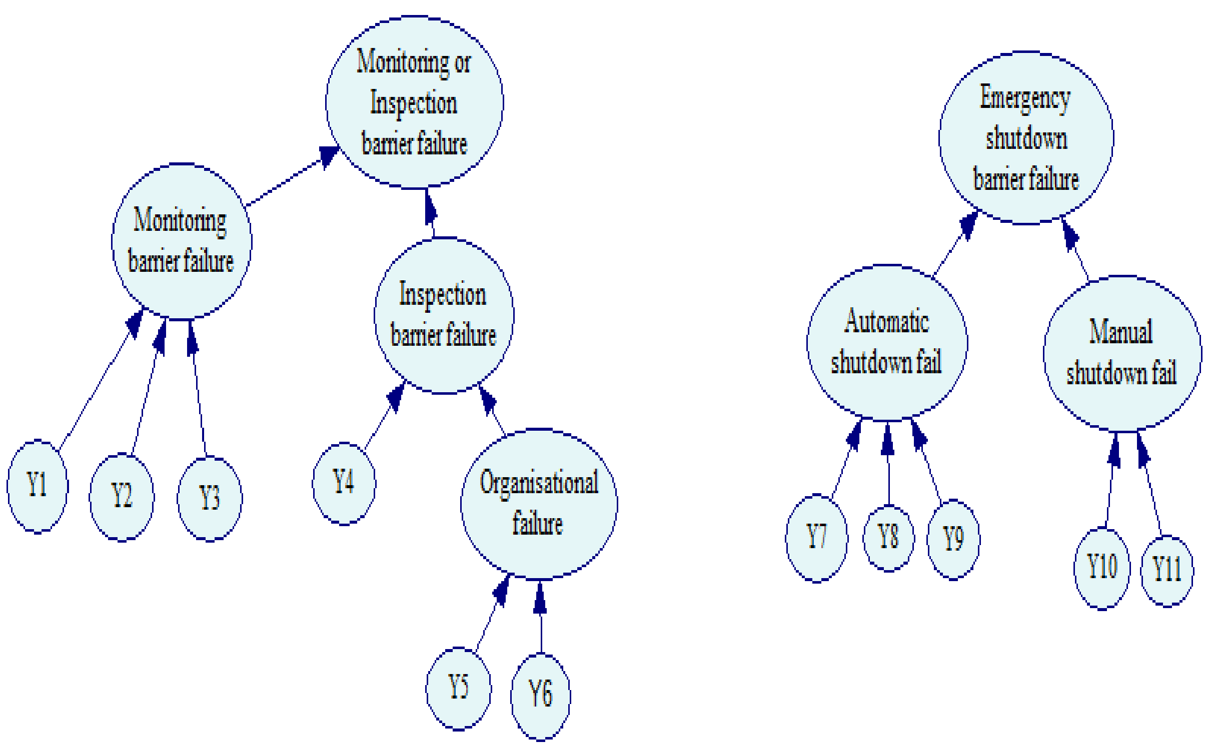

Figure 4-6: BN for monitoring or inspection barrier failure and emergency shutdown barrier failure

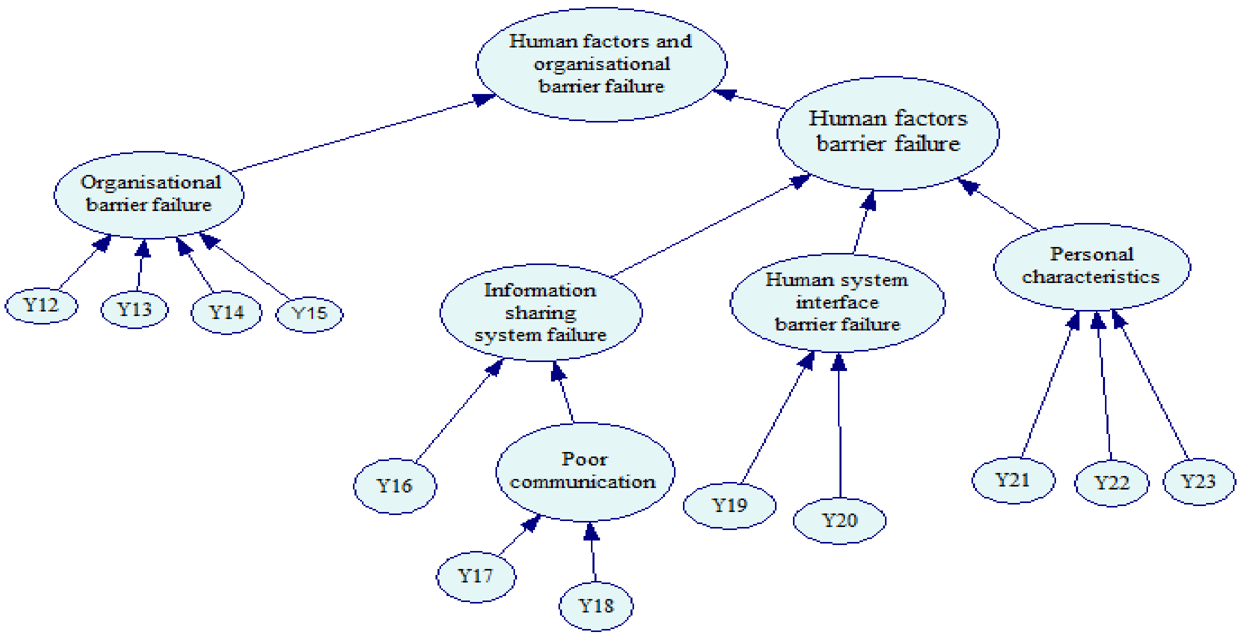

Figure 4-7: BN for human factors and organisational barrier failure

As shown in Figures 4-6 and 4-7, the top events include: monitoring or inspection barrier failure, emergency shutdown barrier failure and human and organisational failure barrier. The values of the top events are calculated for BN with OR, Noisy-OR and Leaky Noisy-OR logics after assigning the CPTs. Table 4-8 shows the probability of different top events.

Table 4-8: Failure probabilities of Subsea Pipeline and its Safety Barriers Calculated with Bow-Tie and Bayesian Network Using Different Logic.

Top events	**BT Analysis**	**BN Analysis**		
		OR	Noisy-OR	Leaky Noisy -OR
Subsea pipeline leak	1.43×10^{-2}	1.43×10^{-2}	3.75×10^{-3}	5.12×10^{-2}
Monitoring or inspection barrier failure	5.47×10^{-2}	5.47×10^{-2}	1.35×10^{-2}	3.40×10^{-2}
Emergency shutdown barrier failure	1.04×10^{-2}	1.04×10^{-2}	7.24×10^{-2}	9.01×10^{-2}
Human factors and organisational barrier failure	2.78×10^{-2}	2.78×10^{-2}	5.34×10^{-2}	7.89×10^{-2}

From Table 4-8, it can be seen that for the BN analysis, the failure probability of all the safety barriers is lower for OR and Noisy-OR logics compared to that of Leaky Noisy-OR logic. This might be due to the uncertainties of the conditional dependencies among the linked nodes in the BN. Further, lower conditional probabilities were assigned compared to the case in which the OR and Noisy OR logics were used. In instances where the Leaky Noisy-OR logic was applied to the BN, a higher failure probability for all the prevention barriers is observed. At the same time, the failure probability of the top event (i.e., subsea pipeline leak) was lower for OR and Noisy-OR compared to Leaky Noisy-OR, which was 5.12×10^{-2}. These results show that the active failures of the assigned prevention barriers were instrumental in contributing to the accident. In fact, preventive measures could have been applied to avoid the failure of the safety barriers if proper and appropriate inspection and maintenance procedures had been followed.

Table 4-9: Failure Probabilities of Different Consequences Calculated with Bow-Tie and Bayesian Network

Index	**Consequences**	**BT Analysis**	**BN Analysis**		
			OR	Noisy-OR	Leaky Noisy -OR
1	A: Safe	1.30×10^{-2}	1.30×10^{-2}	3.25×10^{-3}	4.15×10^{-2}
2	B: Near miss	3.71×10^{-4}	3.71×10^{-4}	1.83×10^{-4}	3.55×10^{-3}
3	C:Incident	8.87×10^{-4}	8.87×10^{-4}	2.98×10^{-4}	5.57×10^{-3}
4	D:Accident	2.94×10^{-5}	2.94×10^{-5}	5.98×10^{-6}	2.69×10^{-4}
5	E: Catastrophic Accident	4.13×10^{-6}	4.13×10^{-6}	1.45×10^{-5}	3.65×10^{-4}

From Figure 4-4, eight consequence probabilities have been obtained that represent a combination of similar consequences.

Table 4-9 presents the results of the consequence analysis. As can be seen, there is a sizeable difference in the range of occurrence probability. For instance, in Leaky Noisy-OR, the occurrence probability rises to the order of 10^{-04}, meaning that it significantly heightens the risk involved, while for the other approaches, the occurrence probability ranges from 10^{-05} to 10^{-06}. In case of "safe", increases to the order of 10^{-02}, and for the other approaches, the occurrence probability is 10^{-03}. In case of "near miss", "incident" and "accident", in Leaky Noisy-OR, the occurrence probability grows to the order of 10^{-03} and 10^{-04}, while for the other approaches, the occurrence probability ranges between 10^{-05} to 10^{-06}.

4.4. Importance Analysis

Updating the mechanism of a BN in the presence of certain evidence allows for the performance of importance analysis. This can identify the most vulnerable root causes of a leak, which eventually helps to develop adequate safety precautions to mitigate the frequency of the causes. The important root causes can be ranked based on the percentage increase in the renewed priors from the actual ones. To do so, evidence is provided to the BN that a leak has occurred and renewed prior probability for all the basic events is observed.

First, importance analysis for the BN with the OR Logic is conducted. The updated BN identifies seabed soil erosion as the most important root cause of the subsea pipeline leak, showing an increase of 85.78%. Seabed movement shows an increase of a 76.11% failure probability in the updated BN. This suggests that the geology should be studied well before designing the pipeline track. Excessive external pressure has almost the same importance. Irregular pigging, design faults of auxiliaries and the absence of corrosion inhibitors show less importance, which is an indication of proper maintenance and sufficient safety measures in the design and manufacturing stages. Freezing has the lowest impact among natural calamities. A different outcome would be obtained if the pipeline were designed to serve in arctic regions, which would have a significant impact on the importance analysis.

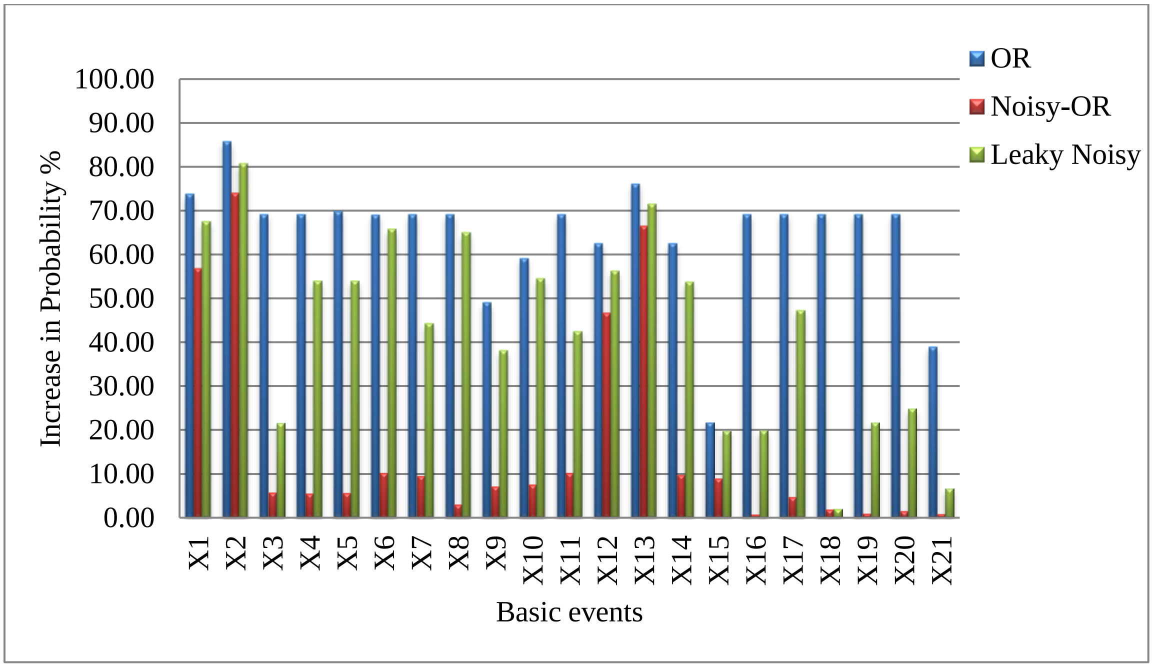

Figure 4-8: Importance analysis of subsea pipeline leak

One of the key aspects of this paper is examining the performance of a BN when there is insufficient data by using Noisy-OR and Leaky Noisy-OR logics. Analysis of the updated BN for these two logics shows that seabed soil erosion and seabed movement are the most important factors in a subsea pipeline leak. For the use of Noisy-OR logic, excessive external pressure is the third most important factor in a subsea pipeline leak, as with the OR logic. Design faults, manufacturing defects and failure due to long term usage have the lowest importance in Noisy-OR logic. Results from Leaky Noisy-OR logic also suggest that design faults make only a small contribution to a leak. In general, Leaky Noisy-OR Logic gives better results than Noisy-OR logic, using the OR logic results as a standard. Furthermore, these two logics can identify the most important root causes. Figure 8 shows the comparative importance analysis for all three logics using a BN.

4.5. Conclusion

In this paper, an approach was presented that demonstrates how risk analysis can be performed in the absence of complete data. A BN can handle uncertainty robustly, and the use of Noisy-OR and Leaky Noisy-OR logics improves its uncertainty handling capacity and limits the exhaustive data requirement. A subsea pipeline leak was considered as the case study. A BT was developed which captures all the possible failure causes of a leak and shows the potential consequences as a result of a leak in the subsea pipeline. The BT was then converted to a BN for OR, Noisy-OR and Leaky Noisy-OR logics.

This study indicates that a BN can be a useful tool in risk analysis, even when limited data are available. Although the failure probabilities of leak and safety barriers vary for BT and BN, it is more reasonable to consider the BN to be a more intuitive approach, as it can capture the uncertainty and complex dependencies among root failure causes. The results obtained for the three different logics also varied. Usually, results obtained from Noisy-OR have similarities with the use of OR logic. A higher probability value is generally observed for the Leaky Noisy-OR logic. However, a certain deviation in outcome is to be expected when there is data uncertainty. The results pertaining to importance analysis also support the conclusion that a BN constructed with Noisy-OR and Leaky Noisy-OR is effective in risk analysis as well as in the identification of critical root causes.

The main contribution of this work is to reduce the data requirement by applying the BN in risk analysis using Noisy-OR and Leaky Noisy-OR. It can be applied to any complex system. However, this technique first needs to be validated using real precursor data from industries. Future work may include detailed construction of the FTs of a subsea pipeline leak and safety barriers. A BN inference mechanism for Noisy-OR and Leaky Noisy-OR logics needs to be more robustly informed to better understand the message propagation behaviour.

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Chapter 5

Summary, Conclusions and Recommendations

5.1 Summary

The present study has illustrated failure analysis of the offshore process component considering causation dependence. In this study, two case studies were presented which are fire in compressor unit and heat exchanger tubes failure. A sensitivity analysis was conducted in each case to determine the most critical components to failure. This part demonstrated that the use of detailed causal analysis rather than failure rate summary data such as that provided by OREDA database or OGP failure rate data resulted in an improvement in completeness and an increase in probability estimation for fire scenario on offshore compression unit from $5\times10^{-3}$to 7.32×10^{-3}, an increase by 46% and increase in probability estimation of heat exchanger tube failure from $4\times10^{-3}$to 7.32×10^{-3}, an increase by 75%. The values of probability are high because not all the aspects contributing the probability was captured. Further a technique to map a Bow-tie (BT) to Bayesian Network is presented. This is necessary because of the limitations of BT in handling uncertainty and interdependency among events. Also, The Bayesian Network was studied in terms of its suitability in safety analysis with an application to subsea pipeline. This study highlights how limited data can be incorporated in a BN by using Noisy-OR and Leaky Noisy-OR logics. Failure probabilities of Subsea Pipeline and its Safety Barriers were calculated with Bow-tie and Bayesian Network using OR, Noisy- OR and Leaky Noisy OR Logics. Failure Probabilities of different consequences were calculated with Bow-Tie and Bayesian Network. Finally, importance analysis was performed for 21 basic events using OR, Noisy- OR and Leaky Noisy OR Logics to determine which elements are important.

5.2 Conclusions

In this study, the sensitivity analysis is performed in the case of dependency between the root causes and the case of independency. The approach adopted for conducting the sensitivity analysis is that, the percentages of each root cause representing a parameter have been increased from 0% to 100% by a step of 10%. Then based on the BN model, the percentage change on the probability of the top event is reported. To find out which of the basic events has more impact on the undesired event, a comparative study is performed based on the generated data. Further, this study used a mapping algorithm from bow-tie approach into a Bayesian network. Although the conventional Bow-tie (BT) technique has been applied extensively in safety and risk analysis. It suffers from severe limitations including static structure and inability to handle uncertainty. A Bayesian Network (BN) approach is a good tool to capture uncertainty and representing interdependency among events. The FT developed is based on the causal relationships among primary and intermediate events. The safety barriers in the tree-mapping process are represented as safety nodes, while the consequence node with five states related to the end-state are represented with the event tree.

First, the BN has been constructed for the OR logic, while the Noisy-OR and Leaky Noisy-OR logics have been used to reconstruct the BN. The graphical network software (GeNIe) is used to do the simulation. An importance analysis was also carried out to identify the most vulnerable root causes of a leak, which eventually helps to develop adequate safety precautions to mitigate the frequency of the causes. The important root causes can be ranked based on the percentage increase in the renewed priors from the original ones. To do so, evidence is provided to the BN that a leak has occurred and renewed prior probability for all the basic events is observed.

5.2 Future Works

Future work may include detailed construction of the FTs of a compressor unit, heat exchanger tubes failure, a subsea pipeline leak and safety barriers. A BN inference mechanism for Noisy-OR and Leaky Noisy-OR logics needs to be more robustly informed to better understand the message propagation behavior. In addition, the data uncertainty is still depending on the subjective expert judgment and difficult to rely on this for decision making. Further research to solve these issues would be important.

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