University of Strathclyde

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Dynamic Safety Analysis of Decommissioning and Abandonment of Offshore Oil and Gas Installations

By

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A thesis presented in fulfilment of the requirements for the degree of Doctor of Philosophy

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Declaration of Authenticity and Author's Rights

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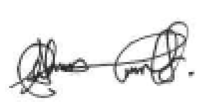

Ahmed Oyeyinka, Babaleye

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Research Outputs

The following research outputs have been published as part of this research work.

Data-in-brief

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Journal Publications

Babaleye, A., Kurt, R.E., & Khan, F., 2019. Hierarchical Bayesian model for failure analysis of offshore wells during decommissioning and abandonment processes. *Process Safety and Environmental Protection*, 131, 307-319. https://doi.org/10.1016/j.psep.2019.09.015

Babaleye, A., Kurt, R.E., & Khan, F., 2019. Safety analysis of plugging and abandonment of oil and gas wells in uncertain conditions with limited data. *Reliability Engineering and System Safety*, 188, 133-141. https://doi.org/10.1016/j.ress.2019.03.027

Babaleye, A. and Kurt, R.E., 2019. Safety analysis of decommissioning operation through Bayesian network. *Ships and Offshore Structures,* 15 (1), 99-109.

Navas de Maya, B., Babaleye, A.O. & Kurt, R.E., 2019. Marine accident learning with fuzzy cognitive maps (MALFCMs) and Bayesian networks: *Safety in Extreme Environments,* 2, 69-78.

Conference

Babaleye, A.O., Khorasanchi, M., & Kurt, R.E., 2018. Dynamic risk assessment of decommissioning offshore jacket structures. In: Proceedings of the ASME 2018 37th International Conference on Ocean, Offshore and Arctic Engineering. ASME 2018-78635, Madrid, Spain.

Navas de Maya, B., Babaleye, A. & Kurt, R.E., 2019. Marine accident learning with fuzzy cognitive maps (MALFCMs) and Bayesian networks: a case study on maritime accidents. In: 4th workshop and symposium on safety and integrity management of operations in harsh environments. St. John's Canada.

Poster Contribution

Babaleye, A.O., Khorasanchi, M., & Kurt, R.E., 2017. Dynamic risk-based safety analysis of permanent well plugging and abandonment operations. In: SPE ICoTA 23rd European well intervention conference. Aberdeen, United Kingdom.

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Abbreviations and Nomenclature

Abbreviaitions

AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
APD	Accident Precursor Data
ARO	Asset Retirement Obligation
BAJ	Brent Alpha Jacket
BIM	Birnbaum Importance Measure
BN	Bayesian Networks
BML	Below Mudline
BT	Bowtie
CA	Comparative Assessment
CE	Causal Event (used interchangeably with primary/basic event)
CIM	Criticality Importance Measure
CPT	Conditional Probability Table
CREAM	Cognitive Reliability, Error and Analysis Method
DAG	Directed Acyclic Graph
DECC	Department of Energy and Climate Change
DECOM	Decommissioning
DID	Decommissioning Incident Database
DISA	Dynamic Integrated Safety Analysis
DPRA	Dynamic Probability Risk Analysis
DREAM	Drivers Reliability, Error and Analysis Method
EAM	Epidemiology Accident Model
ERA	Economic Risk Assessment
ETA	Event Tree Analysis
FMEA	Failure Modes and Effects Analysis
FRAM	Functional Resonance Accident Model
FTA	Fault Tree Analysis
FFTA	Fuzzy Fault Tree Analysis
FVM	Fussell-Vessely Measure
GBS	Gravity-Based Structure
GoM	Gulf of Mexico
HPHS	High Probability High Severity
IE	Intermediate Event

ILN-OR	Imprecise Leaky Noisy-OR
IMs	Importance Measures
IMO	International Maritime Organisation
IOGP	International Association of Oil & Gas Producers
IPM	Improvement Potential Measure
JIP	Joint Industry Project
LPHS	Low Probability High Severity
LN-OR	Leaky Noisy-OR
LOPA	Layer of Protection Analysis
MCDA	Multi-Criteria Decision Analysis
MCMC	Markov Chain Monte Carlo
ML	Mudline
MODU	Mobile Offshore Drilling Unit
MSL	Mean Sea Level
MTTF	Mean Time To Failure
NCS	Norwegian Continental Shelf
N-OR	Noisy-OR
OGA	Oil and Gas Authority
OSPAR	Oslo and Paris Convention
P&A	Plugging and abandonment
PDF	probability density function
PLL	Potential Loss of Life
PPM	Predictive Probabilistic Model
PSA	Probabilistic Safety Analysis
PRA	Probabilistic Risk Analysis
QRA	Quantitative Risk Assessment
RAW	Risk Achievement Worth
RRW	Risk Reduction Worth
RUL	Remaining Useful Life
SAM	Systemic Accident Model
SLV	Single Lift Vessel
SPJs	Steel Piled Jackets
TE	Top Event
UKCS	United Kingdom Continental Shelf

Nomenclature

ϕ	Parameter of Interest
y_i	Dataset
$\omega_0(\alpha, \beta)$	First-Stage Prior Distribution Function
α, β	Hyper-parameters (α = shape function; β = scale function)
$g_0(\alpha, \beta)$	Second-stage or Hyper-Prior Distribution
$g_1(\alpha, \beta \vert y)$	Posterior Distribution
$L(y \vert \alpha, \beta)$	Likelihood Function
$\omega_1(\phi \vert y)$	Posterior Predictive Distribution
$\omega_1(\phi \vert y^*, y)$	Informative Prior Distribution
$n_{i,j}$	Number of Successive Branches
M	Failure Probability of Safety Barrier
N	Success Probability of Safety Barrier
$p(C_i)$	Consequence Probability
SB_i	Safety Barrier
$p(TE)$	Top Event Probability
$p(y_i)$	Joint Probability Distribution
$p\left(y_{i:N_t}^{i:N}\right)$	Joint Probability Distribution with N_t Time Slice
$P(y_i^t)$	Joint Probability Distribution with State Variable y_i
$\mu(i)$	Parent of Variable Node i
$P(E)$	New Evidence Probability
m_i/μ_i	Group Slope
N_i	Number of Trials or Demands
$E\left(y_{ij}\right)$	Average Population Growth
c_i/γ_i	Intercept
$\alpha_c, \beta_c, \tau_\alpha, \tau_\beta, \tau_c$	Independent Noninformative Priors
l	Leak Probability
x	Modality Probability
R	Total Potential Uncertainty Reduction
$IM_{B_j}^{FV}$	Fussell-Vesely's Importance Measure Metric
Γ	Gamma Function
σ^2	Variance of the Distribution
$\bar{T}$	Weibull Mean Life

Abstract

The global oil and gas industry have seen an increase in the number of installations moving towards decommissioning. Offshore decommissioning is a complex, challenging and costly activity, making safety one of the major concerns. The decommissioning operation is, therefore, riskier than capital projects, partly due to the uniqueness of every offshore installation, and mainly because these installations were not designed for removal during their development phases. The extent of associated risks is deep and wide due to limited data and incomplete knowledge of the equipment conditions. For this reason, it is important to capture every uncertainty that can be introduced at the operational level, or existing hazards due to the hostile environment, technical difficulties, and the timing of the decommissioning operations. Conventional accident modelling techniques cannot capture the complex interactions among contributing elements. To assess the safety risks, a dynamic safety analysis of the accident is, thus, necessary.

In this thesis, a dynamic integrated safety analysis model is proposed and developed to capture both planned and evolving risks during the various stages of decommissioning. First, the failure data are obtained from source-to-source and are processed utilizing Hierarchical Bayesian Analysis. Then, the system failure and potential accident scenarios are built on bowtie model which is mapped into a Bayesian network with advanced relaxation techniques. The Dynamic Integrated Safety Analysis (DISA) allows for the combination of reliability tools to identify safety-critical causals and their evolution into single undesirable failure through the utilisation of source-to-source variability, time-dependent prediction, diagnostic, and economic risk assessment to support effective recommendations and decisions-making.

The DISA framework is applied to the Elgin platform well abandonment and Brent Alpha jacket structure decommissioning and the results are validated through sensitivity analysis. Through a dynamic-diagnostic and multi-factor regression analysis, the loss values of accident contributory factors are also presented. The study shows that integrating Hierarchical Bayesian Analysis (HBA) and dynamic Bayesian networks (DBN) application to modelling time-variant risks are essential to achieve a well-informed decommissioning decision through the identification of safety critical barriers that could be mitigated against to drive down the cost of remediation.

Keyword: Decommissioning, dynamic safety model, hierarchical Bayesian analysis, plugging and abandonment,

Chapter 1: Introduction

1.1 Outline

This introductory Chapter presents the background motivation for the increasing need for decommissioning offshore oil and gas installations. It also establishes the challenges associated with decommissioning and the need for the development and adoption of dynamic safety model. Furthermore, the structure of the research is presented to demonstrate the relevance, credence, and permanence of the thesis to the readers.

1.2 Overview

Decommissioning in the oil and gas industry has been attracting both industrial and research talents and will continue to do so for the foreseeable future – the need to decommission offshore assets has become an actual business driven by regulations and asset integrity issues. Many of the assets have reached their design and economic lives for which maintenance and asset life extension activities have become infeasible. The extent of depletion of the reservoir, which tends to increase the cost of production through inefficient enhanced oil recovery, thereby leading to economically unviable activity also contributed to the need for decommissioning.

Many of the offshore installations around the world have been in service for over 30 years and were put in place without consideration for their removal after they have reached the intended design life. There exist associated challenges with each subsystem of an oil and gas field, from subsea to topside. For example, in the case of a well plugging and abandonment (hereafter, well P&A), every well differs from every other well both in design, configuration and hydrocarbon type (oil well or gas well). Furthermore, every layer of a well is dissimilar to the layers before and after it, making it overly complex to model a one-size-fits-all solution for every well P&A operation. Moreover, due to the long years of service of the structures, it is often difficult to ascertain the remaining useful life (RUL) of an ageing facility due to incomplete or lack of inspection and maintenance records, in some cases. In addition, the presence of hidden flaws and structural degradation of the platform can further introduce additional unknowns to the integrity concerns.

Typically, decommissioning activity is a technically extensive and hazardous operation, posing risk to on/offshore personnel due to their direct exposure, the environment because of the impact of dumped disused structures or hydrocarbon release, and economic risk. The cost of decommissioning offshore installations is huge and usually estimated by forecast through Asset Retirement Obligation (ARO) with associated uncertainties. Generally, the exact cost of decommissioning a platform cannot be explicitly determined as the seabed clean-up and pipework removal costs are often shared between many linked installations. The overall removal operation precludes a return on investment, making safety one of the core areas of interest both to operators and stakeholders alike. Safety assessment of decommissioning operations is often interpreted in terms of risk. The risk is, generally, characterised by three categories: risk to on/offshore personnel, environmental risk, and economic risk.

Risk is described as a measure of accident likelihood and consequence of its occurrence (Aven and Heide, 2009). Although, there has been no recorded fatalities in the North Sea, during the decommissioning operations till date. However, near misses and accidents are a norm rather than exceptions during such a time-dependent and complex activity. Due to the cost of remediating catastrophic scenarios during- and/or post-decommissioning, it becomes overly necessary for operators to ensure absolute safety. For illustrative purpose, the quantitative risk assessment carried out on the Ekofisk I field estimated the potential loss of life (PLL) of decommissioning 13 steel piled jackets (SPJs) for both the leave-in-place and complete removal scenarios to be 8% and 29%, respectively (ConocoPhillips, 1999). This result revealed that the probability of a catastrophic event for the complete removal scenario outweighs that of the leave-in-place scenario. Furthermore, these probabilities represent the sum of all risks over the entire decommissioning activity and do not represent the accident evolution over time.

1.3 Decommissioning and Abandonment Uncertainty

The nature and stages of operations required to completely remove offshore installations from the field are complex and involve several activities. Some of the activities include site preparation, lifting operations, and severance of risers, conductors, and substructures as shown in Figure 1-1. Some of the major challenges are the unknown conditions of the structural and/or material state and the sparsity of data that may lead to unplanned accidents. To address these challenges, the complete inspection and repair (I&R) records must be studied, and an appropriate obsolescence mitigation and management plan implemented. However, both the I&R records and the obsolescence strategies are either incomplete or lacking. In addition, the physical, chemical, and mechanical failures associated with the operations need to be captured in their entirety to aid in the safety assessment analysis. These failure modes and evolving reservoir condition are all variables of uncertainty.

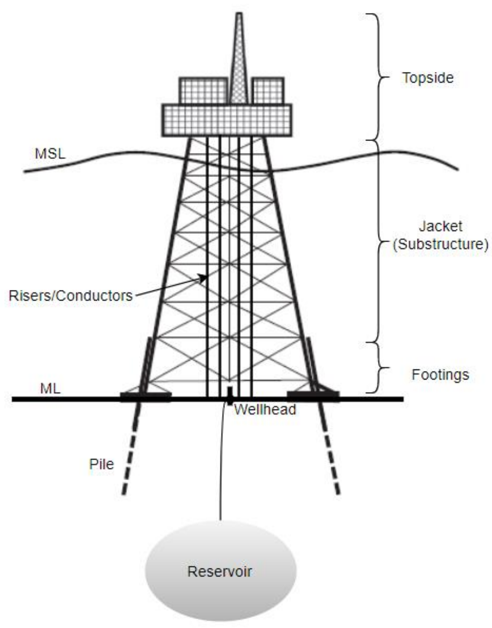


Figure 1-1 A typical steel jacket platform.

1.4 Need for Dynamic Safety Analysis

Decommissioning activity is known to be as expensive, risky, and complex as a capital project. According to the Oil and Gas UK decommissioning survey report, the total anticipated expenditure for decommissioning operations on the United Kingdom Continental Shelf (UKCS) between 2015 and 2024 is £16.9 billion primarily due to the new projects entering the survey timeframe (OGUK, 2020). The cost of getting it wrong goes beyond remediation and liabilities: it could lead to a legal battle between the operators and stakeholders and/or the local authorities. In particular, the cost of removing topsides, steel pile jackets and subsea infrastructure alone accounts for about 18 percent or £3 billion of the total decommissioning expenditure forecast over the next 10 years. Figure 1-2 depicts the forecasted well decommissioning activities "making safe" in the North Sea.

For this reason, it is important to ensure the safe removal of all offshore installations in a manner that will strengthen operators' reputation and stakeholders' trust. The activity is often the last of the available options pursued by producers after all other options such as late-life extension and opportunity for re-use have proven infeasible. Due to regulation demands, an oil and gas conduit is expected to be made safe through flushing and cleaning to the extent possible, all risers and conductors severed and retrieved as required, and the site returned to its original state. Many of the offshore installations have been exposed to the harsh environments for over 30 years which is exceedingly above their usual design life of 25 years. This, in turn, introduces additional uncertainty to the associated risks of decommissioning. In addition, due to weather fluctuations and other time-dependent factors such as setting of cement plugs during well P&A, a dynamic safety model is required to capture, assess, and reassess the likelihood of an undesirable occurrence. The dynamic safety model is based on incorporating statistical methods through Hierarchical Bayesian Analysis with Bayesian networks to conduct comprehensive probabilistic risk analysis on the accident model.

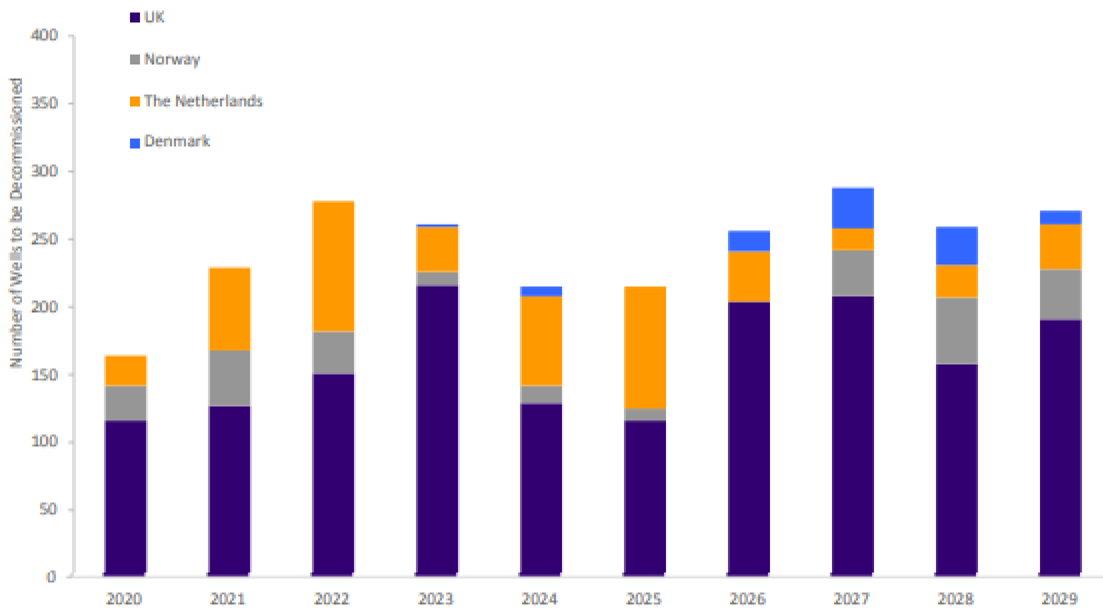


Figure 1-2. Forecasted well decommissioning activity in the North Sea (OGUK, 2020).

1.5 Research Motivation

One of the notable challenges of probabilistic risk analysis is the sparsity of failure data required as input to examine the potential occurrence of a futile decommissioning operation. The current industrial practice is to obtain failure data from analogous industries such as mining, aerospace, and even drilling operations to quantify the failure events using probabilistic risk analysis. This is due, in part, to the lack of complete historical data and mainly because decommissioning operations are dictated by many factors across regions. Some of the factors include operators' internal policies, well and platform types, fluid severity, among others. To this end, it is necessary to develop a framework that can aggregate the available failure data in the form of a distribution with considerable confidence level as input in the probabilistic risk analysis. It is worth mentioning that the focus of this thesis is to develop the proposed model and validate its applicability through real life case studies. The proposed approach has not been adopted in the decommissioning analysis thus far.

1.6 Thesis Structure

This thesis is written in a chronological format. The outlines of the succeeding Chapters are as presented below:

Chapter 2 presents the aim and objectives of the research work to the safety and risk analysis of offshore oil and gas decommissioning programme with respect to a complete removal operation.

Chapter 3 discusses the critical review of literatures relevant to the research work. These include a comprehensive description of decommissioning processes, well plugging and abandonment operations and probabilistic risk analysis.

Chapter 4 introduces the failure analysis framework development which consists of the accident scenarios analysis and evolution model including Bayesian network problem formulation, mapping techniques and probability updating and adapting analysis. This Chapter is presented and published in: the Proceedings of the 38th International Conference on Ocean, Marine and Arctic Engineering, OMAE2018-68375, Spain, Madrid.

Chapter 5 presents the failure analysis of decommissioning and abandonment and introduces the Hierarchical Bayesian Analysis model incorporated with Bayesian network with appropriate relaxation strategies to account for the effects of uncaptured hazards, parameter modelling and overall model uncertainty. This Chapter is published in the *Journal of Process Safety and Environmental Protection.*

Chapter 6 presents the dynamic risk analysis of well plugging and abandonment under uncertain condition and limited data. Fault tree model is developed for the permanent well P&A operation and mapped into a corresponding Bayesian network to investigate the most probable cause of failure through diagnostic, prognostic, and sensitivity analyses. This Chapter is published in the *Journal of Reliability Engineering and System Safety.*

Chapter 7 presents relevant case studies based on published technical documents and lessons learned through the Elgin well plugging and abandonment operational failure.

Chapter 8 demonstrates the applicability of the proposed methodology in its entirety using presented case studies in Chapter 7. The accident models are analysed and verified through sensitivity analysis. The framework for the decommissioning operations covering the focused area of this thesis is presented in Figure 1-3 below.

Chapter 9 presents the application of the safety model for estimating the economic risk values of causations using field-specific design parameters to develop a multi-factor regression model. It further discusses the conversion method of failure probabilities into loss values and validated the risk profile by way of an integrated dynamic-diagnostic analysis.

Chapter 10 presents the discussion following from the obtained results. It discusses the novelty and contribution of the research work particularly focusing on how it benefits both the academic community and the industry, the strength of the proposed methodology including the constraints and limitations supporting the safety design philosophy.

Chapter 11 summarises the findings of the research, proposes recommendations for future research based on objective quality evidence from observed results and suggested the future work to be carried forward from this research by the wider scientific community.

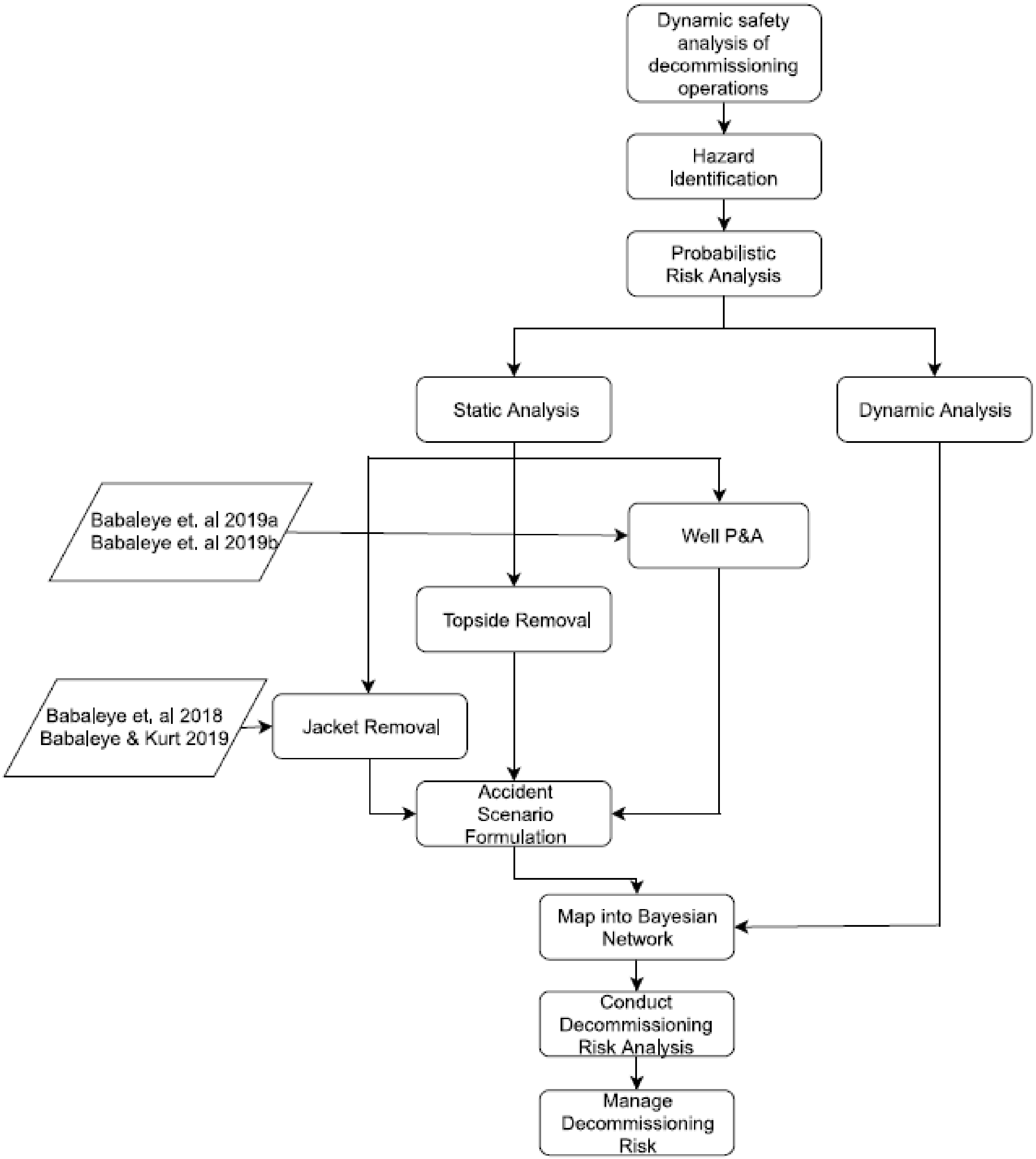


Figure 1-3. Framework of Decommissioning Operations.

Chapter 2: Main Aim and Objectives

2.1 Outline

This Chapter outlined the aim and objectives of this research in terms of the scope and the pathways to achieving the intended goals. It also presents the areas of unanswered questions and how those areas have been thoroughly explored including own contributions to the wider applicability of decommissioning operation.

2.2 Research Scope

The scope of this research covers the complete decommissioning of offshore oil and gas installations and extends to the model development of a combined safety assessment algorithm from well plugging and abandonment operations to jacket structures removal.

2.2.1 Research Question

Safety of personnel, the environment and oil and gas producers' reputation are all important when planning for decommissioning. Although, the risk associated with humans should not be limited to numbers alone due to many interacting factors such as technical, safety, environmental and socio-economic considerations that must be balanced. It is, however, pertinent to develop a strategy for which metrics can be used to assess the extent of safety available to decommissioning in its entirety. Both qualitative and quantitative risk analysis have been extensively adopted to proffer solutions to health and safety challenges. However, the quantitative risk analysis can better support the estimation of decommissioning figures in terms of cost and risk. Many of the activities involved in decommissioning an oil and gas field are not directly related to well established planning templates and some infrastructures are shared between different platforms, making it especially difficult to determine the actual economic risk of decommissioning.

Therefore, this thesis set out to answer the following research question: Can all the attributes of planned and evolving uncertainties, encountered during decommissioning and abandonment operations, be modelled using advanced logic formalisms and dynamic integrated safety assessment framework?

2.2.2 Research Aim

The aim of this thesis is to develop a complete and comprehensive dynamic safety framework for decommissioning operations such as jacket substructures and well plugging and abandonment. This will facilitate the identification of both planned and unplanned (evolving) risks, because many of the risk assessment methodologies applied in the offshore decommissioning industry have focused on static (planned) risks and the anticipated hazards are experience-driven involving subjective failure data. To capture the overall inherent hazards, a dynamic safety and risk assessment model is highly necessary.

2.2.3 Research Objectives

The primary objective is to develop a dynamic safety assessment model using prior and posterior failure probabilities rather than static failure probabilities. To this end, the primary objective is sub-divided into the following:

(i) To identify gaps in the literature by examining the current state of knowledge related to offshore decommissioning and oil and gas well plugging and abandonment.

(ii) To demonstrate the applicability and suitability of a gamma distribution function using Hierarchical Bayesian Analysis as a tool for estimation of failure data with 95% confidence level (Addressed in Chapters 4 and 5).

(iii) To develop a safety analysis based on Hierarchical Bayesian Analysis (HBA) model to quantify the failure probabilities of offshore installations decommissioning operational hazards and demonstrate the applicability of the proposed model on a permanent abandonment case study. (Addressed in Chapter 6).

(iv) To develop a probabilistic risk analysis for offshore well plugging and abandonment operations built on advanced logic formalism to address the issues of uncertain reservoir conditions and limited failure data (Addressed in Chapters 6 and 7).

(v) To develop dynamic risk-based sensitivity analysis model that can be applied to each phase of decommissioning and abandonment operations subject to time-dependent accident evolution (Addressed in Chapter 8).

(vi) To develop a dynamic economic risk analysis based on multi-factor regression model and failure probability to forecast the future value of money in terms of loss values incurred from impact of failure. (Addressed in Chapter 9).

(vii) To summarise the main findings, concluding remarks from obtained results, research contribution, and propose potential outlook for further research. (Addressed in Chapters 10 and 11).

For objective (i), the results are envisaged to be achieved through critical review of literature consisting of decommissioning and abandonment operational sequence and probabilistic safety analysis related topics with emphasis on academic publications found on ScienceDirect, Scopus, Taylor & Francis and Google Scholar, technical reports from decommissioning industry, regulatory bodies, and Joint Industrial Project, JIP (ABB, 2017) reports. The quality of the critical literature review outcomes is validated through peer review process in scientific journals and remarks from integrity, safety, and risk engineering experts.

For objective (ii), the results are envisaged to be obtained through the mathematical model governing the Gamma distribution function and are coded in MATLAB due to its numerical complexity and unknown parameters that need to be adequately represented. The quality of the gamma distribution model is embedded in the Hierarchical Bayesian Analysis (HBA) and the recommendations taken from industry experts (Decom World). Although, Weibull distribution is used to compare the relevance of the HBA in this work, it was not presented in the published paper.

For objective (iii), the system description leading to the hazard identification analysis are envisaged to be developed through comprehensive and systematic review of literature, wellbore schematic, and technical documents on the permanent abandonment of oil and gas wells. The dynamic safety model formulation, governing equations, boundary conditions, parameters introduced, and assumptions are validated through comments from industry professionals (for example, Shell UK decommissioning managers) during OMAE 2018 conference, academic and research community via article peer-review processes, and process safety experts at the Center for Risk, Integrity, and Safety Engineering (C-RISE) research group in Canada.

For objective (iv), the appropriate relaxation strategies are envisaged to be built on the premise that reservoir condition is unknown at the time of cessation of production due to a number of reasons such as the lack of maintenance records or insufficient documentation of lessons learned during maintenance, inspection, and repair over the service life of the well to be abandoned. In addition, relevant inputs are obtained from source-to-source including but not limited to wellbore schematics, technical documents, published papers, decom world and oil and gas authority's (OGA) databases depending on the methodology requirements. The results emanating from the case study adopted to justify the applicability of the developed safety analysis model are reviewed by the research partners at C-RISE and by the reliability engineering and system safety journals peer reviewers. The second part of this objective focused on the development of link and leak probabilities to model the effect of limited failure data on the result accuracy. The link probability is directed towards ignorance modelling, since the underlining assumption is that the reservoir condition is uncertain, and the degree of belief must account for this uncertainty. The leak probability, on the other hand, strive to account for the potential occurrence of an accident even when there is no accident contributory factor present. One instance when this scenario occurs is when all the accident causals have not been completely captured or an indirect causal has not been modelled. To that end, the model response is improved through the implementation of sensitivity analysis to control key performance parameters based on Accident Precursor Data (APD).

For objective (v), all inputs are envisaged to be obtained from preceding objectives and experiential learning based on Bayesian inference is applied to the matured model to investigate the identified key performance parameters and their influence on the responsiveness of the accident scenarios. Safety critical analysis is examined, and the quality of the developed model is validated through peer-reviewed comments and remarks from safety exert partners at the C-RISE research group. It is worth to mention that the accuracy of the developed dynamic safety model herein depends on the quality of results obtained from the previous objectives in their entirety. Therefore, the comprehensive reviews of each preceding objective by experts at C-RISE invariably confirm the credence of objective (v).

For objective (vi), the accident model, top event failure estimation and economic risk analysis formulation including the mathematical model used to obtain the cost data to perform dynamic-diagnostic forecast are envisaged to be validated through a parameter-driven sensitivity analysis. In addition, the HBA results used to obtain the failure probabilities was similar to those obtained from objective (ii).

For objective (vii), the correctness of the conclusions drawn from the research are envisaged to be validated through the summary of main findings emanating from the analysis of the developed framework.

Chapter 3: Critical Review Of Literature

3.1 Outline

This Chapter outlined the relevant literature, addressing the current state of knowledge. It provides the width and depth of the decommissioning of offshore oil and gas installations processes and options. The elements of well plugging and abandonment strategies and steel piled jackets (SPJs), are also discussed including a comprehensive presentation of the dynamic safety analysis techniques.

3.2 Decommissioning Processes

Decommissioning is defined by the International Association of Oil & Gas Producers (IOGP) as the cessation of production of hydrocarbons, making safe the well reservoir and the removal of offshore installations and the subsequent site remediation to its original state (IOGP, 2018). The decommissioning process involves several stages, typically sequential – from well plugging and abandonment, structural (topside and jackets or concrete substructures) removal, to the severance of pipes, risers and conduits connecting the platform to the oil and gas treatment facility subsea. The process is experience-driven, requiring sophisticated removal techniques and dedicated barges or cranes to ensure safety to the personnel, assets, and the environment. The structures to be decommissioned are characterised by complexity and hydrocarbon-containing, with interacting subsystems. These interactions among the subsystems are often dynamic in nature, for example, the setting of cement during plugging and abandonment operation, weather windows or degradation of mechanical plugs, among others. To a large extent, noncompliance due to human factors (Song et al., 2016), cutting and lifting operations, and equipment failure are imminent during decommissioning operation, making the process susceptible to accidents (Abdussamie, 2018). From the decommissioning incident database (DID) through the Joint

Industry Project guidance for safety case management (ABB, 2017) findings, lack of failure data and comprehensive lessons learned, a significant level of decommissioning incidents from recent projects revealed that no life has been lost so far from a total of 562 logged incidents (OGUK, 2020). However, 22 incidents were considered to have been potentially fatal and another 11 was reported to have resulted in permanent injury. 22 incidents are associated with lost time injuries, 33 medical treatments with another 34 cases of medical aid, 159 near misses and 313 involving structural flaws with potential catastrophic condition (Figure 3-1).

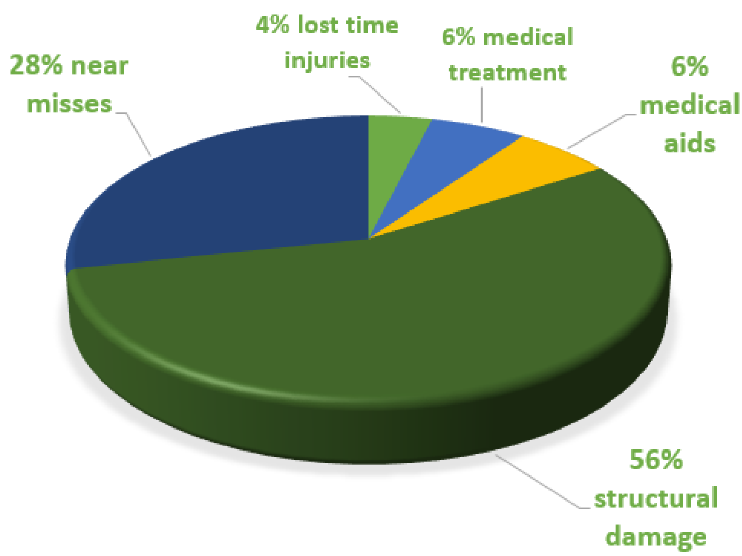


Figure 3-1. 562 decommissioning incidents from 2005-2015 (OGUK 2015).

In recent decades, many high-level decommissioning and abandonment accidents have been recorded. For example, the plugging and abonnement (P&A) operation in the G-4 well of the Troll Field on the Norwegian Continental Shelf (NCS) operated by Statoil, and the Elgin well plugging, and abandonment operational failure operated by Total are notable cases where cascading of events have resulted in economic and assets losses (Fam et al., 2020; Total, 2013). In addition, lifting, cutting, and towing operational accidents such as the Bohai number 2 oil rig, the mobile offshore drilling unit (MODU) ROWAN GORILLA I and, the West Gamma accommodation jackup rig incident were considered some of the catastrophic accidents in the oil and gas industry. In the latter scenario, structural failure, loss of towline and flooding were identified as the main causes of the accident (Vinnem, 2007). More recently, Fang and Duan (2014) reported a typhoon experienced on the CNOOC Offshore Oil 298 project during transportation resulted to 68 fatalities in 2006. For this reason, it is necessary to develop a probabilistic safety model capable of assessing risks prior to incidence occurrence. Probabilistic Safety Analysis (PSA) is a standard technique for evaluating the safety of complex and critical engineering systems. This technique is applicable to all phases of the offshore decommissioning life cycle – from cessation of production, well P&A, topside and substructure removal to transportation onshore. The primary objective of safety assessment techniques is the identification, quantification, and evaluation of all potential hazards to prevent them and subsequently mitigate the residual risk. It is important to integrate management oversight and engineering analyses to formulate a comprehensive and systematic approach to effectively manage complex system risks (Fam et al., 2021a; Fam et al., 2021b; Johnson et al., 2021; Cepin & Mavko 1997). Decommissioning safety primarily focuses on prevention and mitigation of major accidents emanating from personnel exposure, assets losses and environmental hazards. The key steps in the safety assessment of decommissioning operation are hazard identification, failure analysis, risk assessment and management. Hazard identification steps primarily identify all potential hazards associated with the decommissioning activities and may analyse how these hazards interact and evolve into accidents (Rathnayaka et al., 2010).

Risk can be used as a parameter to measure offshore decommissioning safety and it is quantitatively expressed as a product of probability and its corresponding consequences (Fam et al., 2021a; Fam et al., 2021b). Risk management involves the techniques to systematically work with the risk information to prevent, control and mitigate the associated losses due to personnel exposure. The aggregated processes of risk quantification and estimation, risk evaluation, risk-based decision-making, and design improvement (Khan et al. 2015; Modarres 2006), all constitute risk management. To objectively quantify and estimate the risks associated with decommissioning, an accident scenario modelling technique has proven effective (Nichol et al., 2000). The accident scenario modelling helps to develop an appropriate preventive measure focusing on the overall elements of a decommissioned platform – from causations to safety barriers and consequence modelling.

Accident models give detailed conceptualisation of the characteristic accident, and essentially display the relationship between causes and effects in its entirety. They are risk assessment technique to explain the causes of accidents (Sarvestani et al., 2021; Zhang et al., 2021; Qureshi, 2007).

3.3 Substructure Decommissioning Strategies

3.3.1 Opportunities for Re-Use.

The cost of decommissioning is as high as those of capital projects. For this reason, options to extend the life of an asset or re-use often come ahead of decommissioning. The legal obligations also put pressure on the operator, in terms of prohibiting the dumping and leaving offshore installations wholly, or in part, on the sea (OSPAR, 1998). Due to technical difficulties associated with the removal of offshore jacket footings, the decommissioning team must explore every possible non-oil and gas applications for the platform. The re-use opportunity involves the detailed review and examination of the feasibility of other options. The lack or insufficient maintenance data may introduce uncertainty into the review, and this can influence the decision to re-use or decommission the installations. The remaining useful life (RUL) of these structures are often analysed using appropriate stress analysis software tools such as SACS, ANSYS, and Abaqus amongst others (Varde et al., 2014) and experiment-based approach (Ahmadzadeh and Lundberg, 2013). For instance, Ramirez-Ledesma et al (2021) modified the RUL equation for offshore platforms pipes and plates through characterisation of their chemical compositions, microstructures, and mechanical properties. Qin et al (2021) predicted the RUL intervals based on constant stress accelerated life test data. The prediction interval was assessed using Monte Carlo simulation.

3.3.2 Partial Removal.

The partial removal involves the separation of the upper part of the jacket structure from the footings. The re-use of jacket structure is associated with its own risk, but the cost and safety aspects of partial and complete removal are relatively higher. This is expected as the partial removal involves cutting through the jacket legs including the pontoon and diagonal bracings. The depth at which the jacket is severed depends on existing local and international regulations. OSPAR 98/3 recommends the nominal depth of cut to be approximately 51.2 m above the seabed to avoid cutting through external and internal piles including the layers of grout associated with it (OSPAR, 1998; IMO, 1989; Shell, 2017).

3.3.3 Complete Removal.

The complete removal of jacket structure can be performed using reverse installation method or single lift vessels (SLVs). The reverse installation is a method of re-floating and towing to shore. This is, typically, the most acceptable option for removal by all concerned stakeholders. However, the risk associated with this method is higher than for other options. It is classified into stage-wise operation: Offshore preparations, attachment of additional buoyancy, towing and dismantling. The offshore preparations involve completely severing all the conductors and making safe the internal buoyancy chambers. It is worth mentioning that the seals must be fit-for-purpose and checked rigorously to avoid unplanned surprises. The high-pressure air pump is used to displace all seawater in the legs and flooded members and consequently de-ballasted and held in place by its own weight on the seabed. The additional buoyancy attachment is to compensate for the heavy weight of the jacket due to the presence of steel piles and grout around the piles and inside the pontoon legs. The towing and dismantling stages are carried out accordingly depending on the exact disposition of buoyancy and flooded compartments. The SLV, on the other hand, has a more technical advantage than the reverse installation method due to its proven feasibility to remove the whole jacket in one piece. The SLV is considerably expensive to hire but proven to satisfy the technical, engineering, safety and environmental impacts assessment when compared to the reverse installation option (Ahiaga-Dagbui et al., 2017; Shell, 2017; Rassenfoss, 2014).

3.4 Well Plugging and Abandonment

The need to permanently plug and abandon a well after it has reached the end of its life cycle is driven by several factors, some of which are economic reasons and extent of formation fluids depletion in the reservoir, among others. The primary objectives of a Well P&A operation are to prevent the discharge of formation fluids to the environment through leakage pathways, and also to create a barrier between formation fluids and fresh water (Johnson et al., 2021; Nicot, 2009). To protect operator’s planned financial commitments, permanent well abandonment operation is often carried out with the intent that the well will remain sealed forever. However, plugging a well permanently without failure due to degradation over time is not realistic (Miyazaki, 2009) and a difficult engineering standard when compared with the 30- to 40-year design life expected of most oil and gas installations. For this reason, inspection and remediation are as important as adequate plugging and abandonment.

3.4.1 Well P&A Categories

Well P&A operations are categorised as shut-ins, temporary or permanent. In a shut-in scenario, the well is typically plugged for economic reasons and can be side-tracked when the appraisal proved worthy. The temporary abandonment is done with the intention to re-enter the well in the foreseeable future, and the well is often referred to as a ‘suspended’ well. The design intent of a permanent well abandonment operation is such that the well cannot and should not be re-entered. Permanently plugged and abandoned wells represent the worst-case scenario attributed to all or most of the current and future P&A operations in terms of (i) the subsea environment (ii) the unknown nature of the reservoir, and (iii) wellbore dynamics. As a result, permanent P&A is a suitable case study for analysing the safety risks. To that end, the plugged and abandoned well is designed to maintain an everlasting integrity, so the well barriers and mechanical plugs put in place during P&A operations are intended to be permanent. The plugging material employed should ensure an integrity period that is, as a minimum, twice the planned abandonment period (NORSOK, 2004).

The procedure for permanently plugging and abandoning a well is such that mechanical or cement plugs are set in the wellbore at specific intervals to disallow hydrocarbon-containing fluid flow. The P&A process often requires a workover rig and cement is pumped into the wellbore. The P&A operation duration is dependent on the number of plugs planned to be set within the well.

3.4.2 Critical Nature of Well P&A

During decommissioning, it is important to isolate the oil and gas well(s) from the production facilities and careful compliance with the national regulations, operator’s standards, and contractor’s code of practice, to avoid surprises that may lead to a chain of undesired events. Due to ageing, the plugging and abandoning of aged wells come with several risks, which could range from low- to high-levels of risk. One of the major challenges is that every well differs from every other well, even within the same field, in design and construction. Similarly, due to operational completions and interventions carried out on the well over time, proper documentation is often lacking, or even misleading in some cases. It is not uncommon that every layer of a depositional formation bears no resemblance to the layers above and below it (King and King, 2013). These uncertainties necessitate robust and comprehensive risk reduction techniques to tackle the incident-prone and hazardous operation.

3.5 Well P&A Techniques

The plugging and abandonment of oil and gas wells often require that oilfield cement (or resin, which is currently under study) is injected into the wellbore and mechanical plugs are strategically placed at specific intervals to prevent gas migration and/or oils from leaking through various failure modes within the wellbore as shown in Figure 3-2. The bottom plugs are first set while the tubing is retrieved uphole. This is followed by placing stopped plug for the rig-based or balanced plug for the rigless method. The casings are then cut to a certain depth – usually 5m Below Mudline (BML). The need to ensure the integrity of permanent well P&A is driven by the desire to protect the environment. Although, the offshore industry regulation in the 20th century was focused on the need to protect the oil and gas resources and not the environment (NPC, 2011). The requirements and regulations governing well P&A operations vary for different countries due to contrasting geological formations, pressure levels in the wellbore and well geometry. Typically, a common requirement is that minimum of one permanent well barrier must be placed between well surface and a potential source of flow (Schoenmakers, 2014). Wells are designed and constructed as pressure vessels whose primary function is to contain and allow the flow of formation fluids. Well P&A is, therefore, a process of plugging the well using cement and mechanical plugs to prevent leakage of formation fluids at various but specific locations in the wellbore. There are currently two techniques used for plugging and abandoning wells, that is, the rig-based and the rigless methods (Rassenfoss, 2014; Schoenmakers, 2014; Kirby et al., 2004). The rigless method is further divided into the coiled tubing (CT) and the through-tubing (TT) categories. The plugging and abandonment selection criteria are largely driven by economics, type of well, accessibility, regional and national regulations, and associated risks.

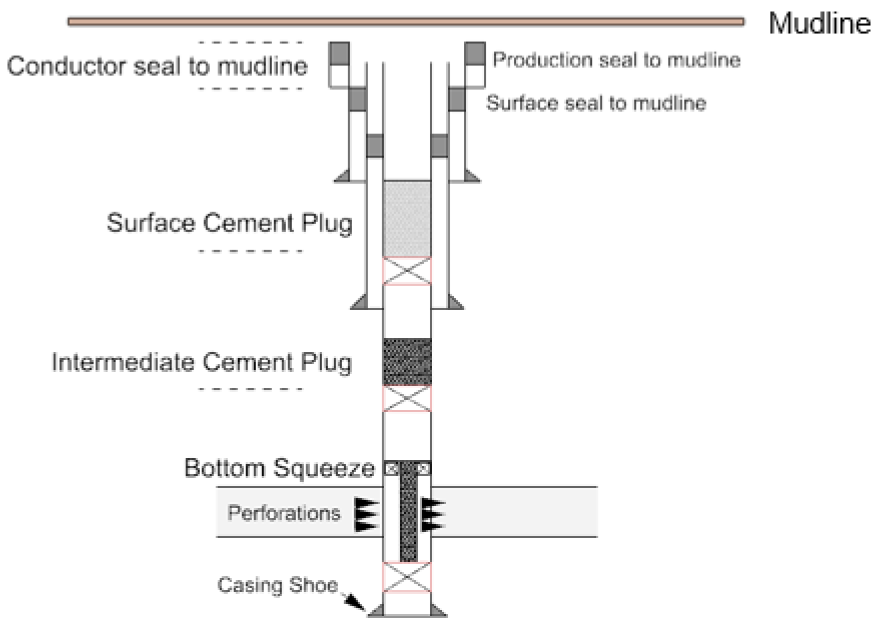


Figure 3-2 Permanent Well P&A Schematic

3.5.1 Rig-Based method

The rig-based method involves plugging the well with cement and mechanical plugs, severing and retrieving the tubing using either an existing platform or mobilising a new one. The operation is more convenient and relatively flexible but can be overly expensive, especially in the case of mobilisation, because of the cost of daily hire. This method, however, is applicable to all wells because it can handle pressure surges or highly deviated wellbore (Kierans et al., 2004).

3.5.2 Rigless method

The rigless method involves a series of remotely controlled steps to permanently plug a well. It can be achieved with the help of coiled tubing, CT or through-tubing, TT techniques. For the CT, the kill-weight fluid, which is intended to counterbalance the wellbore pressure is delivered down the CT (Rudnik et al., 2013; Kirby et al., 2004). The CT is similar to the rig-based due to its capability to retrieve tubing and circulate cement downhole, although the energy required to perform the operation is high and can be relatively expensive when compared to TT. CT is widely adopted the world over but often required in specialised and or exceptional scenarios where wells remediation has to be done before abandonment (Kirby et al., 2004; Kaiser, 2017). The TT, on the other hand, involves pumping kill-weight fluid and cement downhole through the existing tubing. This method is the most efficient and cost effective but, not applicable to all wells (Rudnik et al., 2013). This is, especially due to the risk of formation damage inherent in killing the well.

From the foregoing, the concept of Design for Decommissioning (DfD) is the current best practices in the offshore decommissioning industry. The DfD holds that any assets removal operation offshore must satisfy the Comparative Assessment (CA) policy. The CA allows for the comprehensive balance between technological, safety, economic, social and environmental impact assessment prior to a decision to adopting a selected decommission strategy. This objective selection effort does not permit oil and gas producers to decide at will without satisfying both regional and international conventions. Based on this, Figure 3-3 illustrates all aspects that need to be considered when designing for offshore decommissioning, but only the highlighted areas (in red) are considered in this thesis. For instance, a balance between technological, safety, environmental, social, and economic considerations of a decommissioning project must be ensured to provide a complete turnkey operation. To achieve this, advancements in technology for the removal, reuse and recycling of the retrieved assets must be explored. Safety consideration deals with data validation and uncertainty management. In the context of environmental consideration, sites and facilities characterisation should be accorded considerable level of effort. The decontamination strategy for the sites seeks to address social impact while adopting the least expensive methods for decommissioning the installations. To that end, the operation is constrained by strict guidelines and regulations by both regional and international bodies, and an environmental impact assessment developed where the benefit of adopting selected decommissioning methodology is laid bare including the case for hierarchical choice – that is, whether to extend assets life or to decommission.

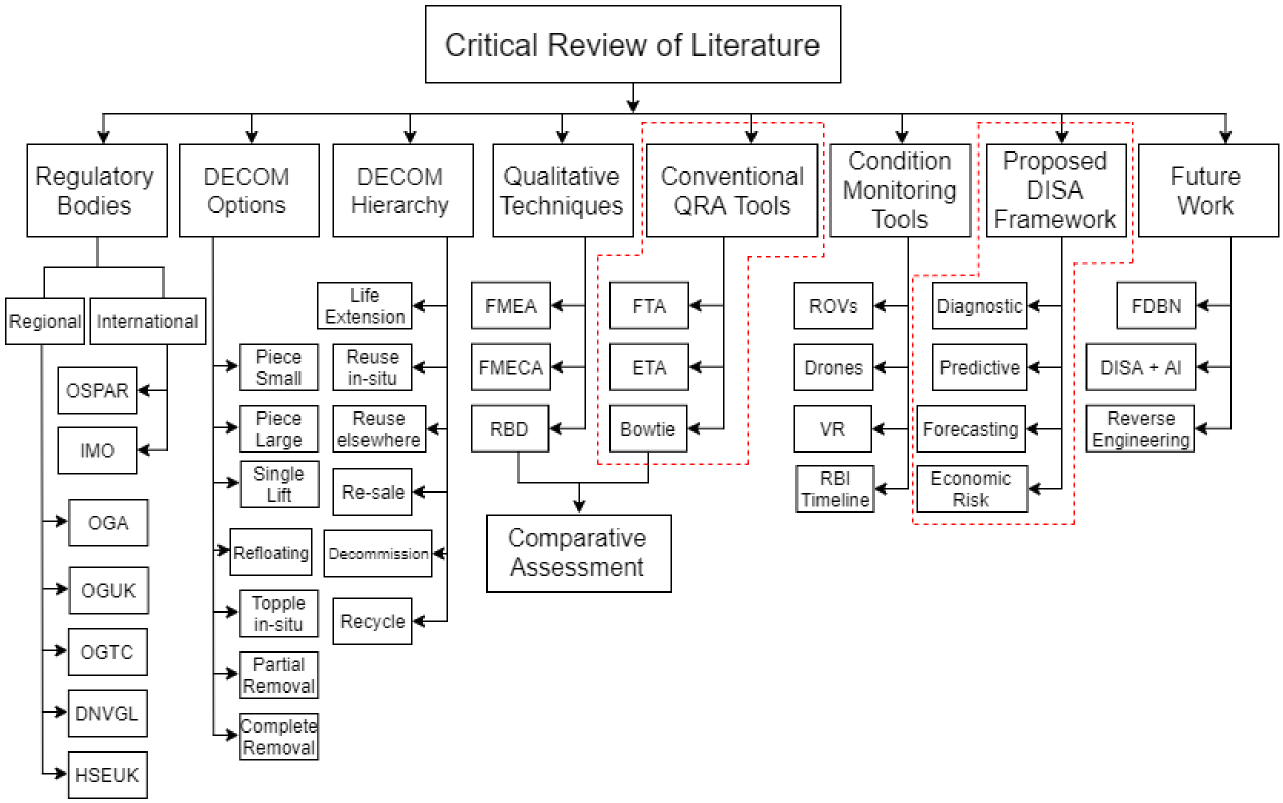


Figure 3-3 Review Framework for Decommissioning and Abandonment.

3.6 Current Industrial Approach to Safety

3.6.1 State of Knowledge

Decommissioning and abandonment safety focus mainly on the prevention and mitigation of accidents to offshore personnel, loss of assets and contamination of the environment. The evolution of such accidents can lead to hydrocarbon release, fire, and explosion when an ignition source is present. To tackle the decommissioning and abandonment accidents effectively, it is necessary to develop the overall accident scenarios model. A comprehensive accident scenarios model provides an exhaustive formulation of accident characteristics, and fundamentally depicts the cause-consequence relationship among the contributory factors (Fam et. al, 2021a; Qureshi, 2007).

However, several accident scenarios models have been developed to address the causes and consequences of complex engineering systems. For example, fault trees (FT), event trees (ET), critical path model, petri nets and Bayesian networks are common forms of such models (Kamil et al., 2019; Abimbola et al., 2016; Adedigba et al., 2016; Khakzad et al., 2013). These models are built on cascaded events emanating into an undesired occurrence in systematic hierarchies rather than causations from single chain of events (Khan et al., 2021; Ding et al., 2020; Hollnagel, 2002; Hollnagel and Goteman, 1982). The concept of cascading of events, generally referred to as the Domino Effect Theory, was widely adopted in diverse industries to investigate the cause-consequence relationship in an accident scenario (Kamil et al., 2019; Ding et al., 2019). It thrives on the idea that an accident cannot occur if any causation factor is disconnected or eliminated from the chain of events leading to the accident. The strength of the Domino Effect Theory is in its ability to model simple to complex sequential accidents. It is not able to handle nonlinear interactions among accident causations.

A suitable model for illustrating the causes of accidents in complex engineering systems are called “epidemiological accident models (EAM)” (Zhang et al., 2021). The model describes the evolution of accidents and uncaptured but unavoidable hazards occurring concurrently in space and time. The EAM is based on the argument that the occurrence of an accident is dictated by the combined interaction of accident-induced agents and environmental elements capable of compromising safety. The EAM provides the basis for which complex engineering systems safety are addressed, a process beyond the capability of the sequential accident models. One of such EAMs is the Swiss Cheese Model (SCM) used to demonstrate how the human element and organisational failure independently contribute to the accident evolution process with associated multi-attribute causations (Underwood and Waterson, 2014).

The SCM is especially, suited to the prevention of accidents emanating from human factors. The structure of the SCM is such that the primary cheese slices are sequentially positioned along the accident causation path. The cheese slices depict the safety barriers put in place to prevent the accident, and the holes on the first and through the cheese slice represent the uncaptured or hidden hazards. The holes on the last cheese slice represent unsafe acts that can compromise the overall integrity of the relevant safety barriers (Rathnayaka et al., 2011; Katsakiori et al., 2009). The holes change as the failure mode changes. If the holes are aligned, all protective safety barriers would have failed, making the occurrence of an accident imminent.

Modern accident models have been developed to address the overall system characteristic performance rather than focusing on the individual cause-consequence and EAM formulations discussed above. One of such models is the systemic accident model (SAM), which holds that accident evolution is as a result of variation in the system (Stroeve et al., 2009). The SAM assumes that engineering systems constitutes various elements constantly interacting in dynamic equilibrium through information and control in a feedback loop. Hollnagel (2002) and Qureshi (2007) established that accident occurs due to flaws in the complex interactions among contributing elements involving human, organisational, physical and software system components. Some notable SAM have been developed and implemented to address hierarchical socio-technical framework (Rasmussen, 1997) and the systems theoretical accident model and processes (STAMP) that views the occurrence of accidents as a function of inadequate control and implementation of relevant safety barriers connected with system constraints captured at the planning, development, design, and operational phases rather than individual component failures (Rathnayaka et al., 2011a; Leveson, 2004).

Other SAMs include CREAM (Cognitive Reliability, Error and Analysis Method); FRAM (Functional Resonance Accident Model) and DREAM (Drivers Reliability, Error and Analysis Method) (Leveson, 2020; Leveson, 2004). The CREAM utilizes the cognitive characteristics of human element as causation factors for assessing the end consequences of system reliability and safety. The FRAM models the resonance behavior of a dynamic component of the system and how it induces hazards that can initiate series of interconnected chain of events leading to an accident. The DREAM model is an extension of the CREAM, particularly, developed to address the drivers peculiar to traffic systems accidents (Hollnagel, 2004; Hollnagel, 1988). It is worth mentioning that the SAMs are generally suited for dynamic and nonlinear interactions among accident contributory factors, including where potential safety issues may arise due to resonance.

More recently, efforts have been made to numerically assess the cause-consequence relationship among interacting factors that influences the system safety under changing conditions. To that end, probabilistic theory has been developed and adopted in diverse industry to study the cause and consequence of failures in the system based on the theory of causality. For example, Pearl (2000) modelled a structural causal formalism to indicate the accident evolution and describe the probabilistic causal model as a binary possibility of occurrence and non-occurrence.

Many of these models – EAM, SAM and their forms – rely on the availability of failure data and cannot thrive where data sparsity is a norm as is the case with offshore decommissioning and abandonment operations. To address this issue, fuzzy set and evidential theory have been developed, adopted, and applied to sizeable numbers of industrial safety issues aimed at providing an analytical method of obtaining failure probabilities from expert judgement. For instance, Lin and Wang (1997) combined fuzzy set theories using experts elicitation to evaluate the failure probability of events causation for a robot drilling system. Their work was built on the triangular and trapezoidal fuzzy numbers. The fuzzy set was incorporated with fault tree, in a term referred to as Fuzzy Fault Tree Analysis (FFTA), to calculate the failure probabilities with fault tree analysis (FTA) (Tyagi et al., 2010) and implemented for analysing oil and gas transmission pipelines safety risks (Yuhua and Datao, 2005). Sahin and Kum (2015) proposed a model to investigate the marine accident in arctic and harsh environment using FFTA and

Lavasani et al (2015) utilised the same FFTA to quantify the risk analysis of leakage in abandoned oil and natural-gas wells. Forms of FFTA has been combined with the Analytic Hierarchy Process (AHP) to conduct risk assessment during a fire and explosion accident for steel oil storage tanks in the process industry (Shi et al., 2014). While fuzzy set and evidence theory have proven to be promising in estimation of failure probabilities where there are lack of historical data or sufficient knowledge of system uncertainty, it cannot provide the needed precision in estimation due to the subjective nature of expert elicitation. The expert elicitation introduces additional uncertainty to the accident model and is not suited for decommissioning and abandonment application. The existing accident models, able to address accident causations acting sequentially and non-sequentially, cannot (i) objectively estimate failure probabilities with considerable confidence level, where sufficient failure data is lacking; (ii) capture evolving hazards as operational conditions change over time; (iii) model dependencies among interacting causations without considerably extending the accident model with additional advanced logic gates.

3.6.2 Research on Risk Analysis and Cost of Decommissioning Operations

In accordance with the existing comparative assessment framework presented in Figure 3-3, an extension from conventional probabilistic risk analysis to robust uncertainty modelling is required to capture the accident contributory factors of the decommissioning and abandonment operations in their entirety. This extension ensures that the planned and unplanned hazards can be accounted for and consequently enable a safer operation. In addition, a case-specific risk profile is implemented for interpreting the susceptibility of decommissioned platform to prevent any potential single failure that may culminate in a futile operation (Faber et al., 2002). In their study, Faber et al (2002) introduced the application of belief networks to addressing decommissioning of fixed offshore platforms. Their work focused on demonstrating the wider application area of uncertainty modelling using gravity-based structure (GBS) as case study. The work relied on guesstimates to estimate the risk profile of ascent and/or descent of a GBS during removal operation. Their results were case-specific and could not be extended to diverse on/offshore installations, and the belief networks model was static as it thrived on the conventional AND/OR logic gates. It is also worth mentioning that the accident model used in their analysis could not be validated to have been entirely capable of representing practical scenarios. In addition, several recent studies focused on the quantitative risk and cost assessment of the fixed offshore structural removal and wellbore plugging and abandonments. The assessment of the approaches implemented with respect to their effectiveness on addressing the safety analysis requirements for decommissioning and abandonment operations is presented in Table 3-1.

Abdussamie et al. (2018) studied the hazards associated with the lifting operations and transportation of offshore structures and attempted to quantify the risk due to mechanical and structural failures. The work proposed the application of fuzzy set theory using rule-based fuzzy logic models to estimate the risk values including sensitivity analysis for the purpose of ranking the failure modes. The focus of their research was on transport barges and Heavy Lift Vessels (HLVs) during load-out and or float-off operational phase, making it an installation-oriented effort rather than decommissioning. A commonality established in their work is that no exact and off-the-shelf failure probabilities currently exist for this technically challenging installation and decommissioning activities and methodologies to develop these risk values is crucial to delivering safe offshore operations.

Lavasani et al. (2015) presented the application of Fuzzy Fault Tree Analysis (FFTA) to address the lack of failure data to assess the risk of well plugging and abandonment hazard. The work assumed that the well P&A operation was successful but sought to estimate the failure probability to conduct static risk analysis. They assumed the failure probability values reported in the Mineral Management Services (MMS) risk analysis of abandoned wells report and applied FFTA to estimate other causal events of interest. However, the empirical formula and estimation effort cannot be justified to encourage oil and gas producers to adopt this methodology. In addition, the question of how efficient FFTA approach to uncertainty modelling without introducing uncontrollable unknowns into the modelling still holds, within the wider offshore decommissioning community.

Kaiser, M.J. (2017) argued that over 11000 wells have been plugged and abandoned in the federal waters of the Gulf of Mexico between 2004 and 2015, but no studies exist on the operational reliability and the frequency of remediation activity. The work proposed a means to estimate the probability that a dry tree well abandoned using rigless methods requires remediation after initial operations are completed. A margin of error approach was adopted from a population mean of wells investigated. A random sample of 502 platform wells in water depth below 400 ft were tracked for five years to identify bubbling or leaking events and observed that 9 of those 502 wells required remediation after operations were performed with estimated probability of 0.018 at 95% confidence interval at [0.006, 0.03]. While the research output was a step in the right direction, the method of probability estimation is static in nature, did not account for the nonlinear and nonsequential events interaction, and the focus was on the Guld of Mexico without flexibility to adapt the approach to other regions with benign or harsher environments than the Gul of Mexico.

Tan et al. (2018) investigated the simultaneous dismantling of topsides of multiple offshore platforms with focus on module lift planning. They formulated the lift planning optimization problem and developed a web system integrating Building Information Modelling (BIM) and Geographical Information System (GIS) to address the module lifting challenges. Three heuristic algorithms were implemented and compared to obtain the module layout with the minimum total lift time, and the algorithms were integrated into a developed BIM/GIS-based web system. While the work paved way for a structured lifting planning operations on topsides, it did not offer additional insight into the risks associated with overall removal and site remediation in the event of failure.

Kaiser, M.J. (2015) presented the application of settled liability data to infer private information on the cost of decommissioning in the Gulf of Mexico (GoM). The article thrived on the normalisation of cost from 17 public oil and gas companies and estimate was performed on a regional basis and by operator category from 2008 to 2012. The established that the average cost of asset removal is approximately $6.4 million USD in water depth less than 200 ft and $15.6 million USD in over 200 ft. Average cost statistics were also suggested as a market index for decommissioning activity in the GoM. Although, this cost values provided basis for further analysis, but the estimate was based on a specific field and region, making the results untenable for other regions.

Kaiser and Liu (2014) adapted the work decomposition algorithms developed by Proserv Offshore to estimate the cost for well plugging and abandonment, conductor severance and removal, pipeline abandonment, umbilical and flowline removal, and platform removal for the 53 Deepwater fixed platforms and compliant towers in the GoM. The cost decomposition thrives on the development of multi-factor regression analysis for each of the installations to be decommissioned and were presented by stage and operators. While this was a comprehensive analysis, the amount of data needed for such analysis would require non-disclosure agreements and thereby limit publication of results in its entirety. In addition, the regression model is field-specific and would require significant modification to suit other regions. The work also did not account for the future value of money, inflation rates, and Assets Retirement Obligation (ARO).

Li and Hu (2021) motivated their research by questioning the evaluation method of regression method applicable to offshore decommissioning such as that presented by Kaiser and Liu (2014). To that end, they conducted a review of many Multi-Criteria Decision Analysis (MCDA) models and their applicability to offshore decommissioning. The work focused on the comprehensive review of the cost assessment model including the general framework and methodology of the cost assessment model and associated accuracy. The authors established that current cost regression model is flawed due to the lack of basic data and the incomplete MCDA method used.

Despite the credible argument raised and the proposal to adopt MCDA in cost assessment, the authors did not consider the critical drivers of decommissioning cost and, the importance of dynamic cost model formulation since a futile decommissioning operation has a knock-on effect on the overall cost.

More recently, Fam et al. (2020) developed a dynamic safety analysis model to assess the risks inherent in a well plugging and abandonment operation. The work thrived on the introduction of common cause failures and human reliability model to assess the failure probability of the top event failure within a dynamic Bayesian network. They utilised two sets of data in their analysis: one obtained from human reliability factor model; and the other from literature. However, the source of the data used for common cause failure was not identified, making it necessary to have a common method for generating and processing failure data.

For this reason, several statistical tools exist for the estimation of sparse failure data. However, the collection and capturing of such failure data often occur at a multi-stage level since the data are obtained from analogous operations. Among the applicable techniques to tackle the multi-stage data analysis, Hierarchical Bayesian Analysis (HBA) appears to be the most suitable. The HBA is able to incorporate a diverse category of information sources and types and build upon its multi-stage parameter handling capabilities. HBA has been widely adopted in various fields to cater for the variabilities associated with source-to-source uncertainty through the development of a multi-stage priors for the parameter of interest such as unreliability, time-to-failure, failure rate or failure probability (Siu and Kelly, 1998; Kelly and Smith, 2009; Yan and Haimes, 2010; Kelly and Smith, 2011). For example, Martz and Bryson (1984) applied a form of Bayes' theorem to combine and compute five dissimilar sources of data to estimate low probability – high consequence events. Kaplan (1983) applied the two-stage Bayes' approach to incorporate three different data sources for modelling plant-to-plant variability, a method . The model was driven by the need to address data sparsity within the heavy machinery industry (Siu and Kelly, 1998).

Traditionally, the HBA model has been adopted in major accident probabilistic risk analysis modelling using Accident Precursor Data (APD) as input to predict the most probable cause(s) of failure (Yang et. al., 2015; Khakzad et al., 2014a; Khakzad et. al., 2014b; Yang et. al., 2013).

Table 3-1: Safety assessment methods from literature

Literature	Static PRA	FFTA	MCDA	BN	DBN	Cost	Comment
Abdussamie et al. (2018)	×	✓	×	×	×	×	To assess structural and mechanical failures during lifting and transportation of offshore structures. No failure data collection incorporated in approach.
Faber et al. (2002)	×	×	×	✓	×	×	BN of Gravity-Based Structures (GBS) to assess ascent/descent risk profile. Failure date were guesstimates.
Lavasani et al. (2015)	×	✓	×	×	×	×	Applied FFTA on well plugging and abandonment system to estimate failure probability of accident contributory factors. Accident model on a very high level and dynamic nature of interacting events not accounted for in analysis.
Kaiser, M.J. (2015)	×	×	×	×	×	✓	Applied settled liability on cost of decommissioning. No safety metrics assessed or estimated.
Kaiser, M.J. (2017)	✓	×	×	×	×	×	Applied margin of error approach to estimate mean probability of failure. Method did not account for the nonlinear and nonsequential events interaction.
Kaiser and Liu 2014	×	×	×	×	×	✓	Work decomposition algorithm to estimate cost. Applied on well plugging and abandonment and other subsea installations. No safety metrics estimated.

Tan et al. (2018) BIM/GIS-based web system.	×	×	×	×	×	×	Algorithm developed based on module lift planning. No safety or risk metrics considered.
Li and Hu (2021)	×	×	✓	×	×	✓	Multi-Criteria Decision Analysis to assess decommissioning cost. Study is semi-qualitative.

3.6.3 Uncertainty in accident modelling

The interactions between accident causals in complex engineering systems are nonlinear and nonsequential due to several factors that may be present concurrently (Adedigba et al., 2016). This nonlinearity is due to the cascade of failure which are induced in no particular order because complex engineering systems and especially decommissioning and abandonment operations are rare accident events with the capability to be resilient to planned hazards. In the event of unplanned hazards within the complex systems, the modelled response to accidents is compromised and further exacerbated by the time-variant accident causals which are often underestimated during the planning and cessation of production phases. This challenge can be addressed by incorporating advanced logic formalism into existing and proven accident model that can represent the effects of uncaptured or unplanned hazards and integrated with time-dependence safety models. The concept of incorporating advanced logic gates within accident models to tackle uncertainties in accident scenarios formulation was introduced in the 1980s (Jensen and Nielson, 2007; Bearfield and Marsh, 2005; Bobbio et al., 2001), for example, used in diagnosis of liver disorders (Onisko et al., 2001). While there have been sizable numbers of studies emanating from this early research, the focus of the present work is on the most recent publications, discussing the mapping of conventional probabilistic risk analysis into uncertainty models incorporating advanced logic gates to elicit conditional dependencies, and closely related to offshore operations or process systems.

Fam et al. (2021a) incorporated Human Reliability Analysis (HRA) with dynamic accident modelling to predict the risk profile of well plugging and abandonment as a long-term monitoring tool. The long-term monitoring is extended to capture a group of oil and gas wells clustered within the same field and linked by common dependencies. A Noisy-OR gate was developed for capturing multi-variable dependencies among accident contributory factors. A dynamic Bayesian network was adopted to reflect temporal effect to forecast the compromised integrity of the plugged and abandoned well over a decade. While this approach allowed for the prediction and diagnosis of a wellbore leakage in the rare accident system studied, the estimation of the safety critical nature of interacting causal events has not been demonstrated.

Wang et al. (2021) used the K2 structure learning algorithm and a Bayesian network parameter learning method to develop a Dynamic Bayesian network for the Escape, Evacuation and Rescue (EER) plan on an offshore platform. In this study, the K2 structure learning algorithm was used for establishing a reliability prediction model, the Bayesian network parameter learning was used for the safety assessment and the development of the Dynamic Bayesian network structure. The developed safety model relied on a transition probability which was determined through a Markov method. The primary contributory factors leading to evacuation failure was estimated using diagnostic reasoning as well as providing insights for the development of cost effective EER strategies. However, the accident model did not consider the effect of uncertainty in the modelling parameters and/or the degree of belief.

Abimbola et al. (2016) transformed a bowtie into a Bayesian network for assessing the reliability of offshore well integrity during casing and cementing operations. The bowtie was used to analyse failure scenarios and the Bayesian network for modelling the conditional dependencies and to perform probability updating. The conditional dependencies were developed based on the Noisy-OR formalism to account for the occurrence of a single top-level failure where a leak probability is present. Then, the estimated safety metrics were used to assess the strength of influence of the accident contributory factors. Through a diagnostic analysis, the key elements to ensuring the integrity of cementing operation were identified and relevant risk control measures established to improve well integrity operations.

Bobbio et al. (2001) comprehensively demonstrated the mapping of fault trees into Bayesian networks including the need for advanced relaxation strategies such as Noisy-Or and Leaky Noisy-OR and extended to multi-state variables modelling to handle the time-consuming elicitation of failure probabilities commonly inherent within the conditional probability tables in a Bayesian Belief Network. The permanence of their work was tested on a generic multiprocessor system and was based on the assumption that failure of systems or subsystems is sequentially dependent. This need not be true in practical terms as cascading of failure is not uncommon in complex engineering systems like decommissioning and abandonment operations.

Khakzad et al. (2013) extended the work of Bobbio et al. (2001) to map bowtie into Bayesian network to address the modelling issues relating to causal events dependency. Their work was illustrated with a process accident from the U.S. Chemical Safety Board as case study. The methodology presented benefitted from the many modelling capabilities of dynamic safety analysis. However, this paper did not incorporate advanced logic gates to account for uncertainties in modelling parameters or address the critical nature of decommissioning operations.

Many solutions have been proffered by researchers for the development of multi-factor systems to address decommissioning activities (Sommer et al., 2018; Fam et al., 2018; Akinyemi et al., 2019; Zagonari, 2020, Rouse et al., 2018; Zhang et al., 2021). However, these diverse solutions focused on the different areas of consideration – such as environmental, technical, safety, social and economic – in the decommissioning and abandonment domain, rather than the activity in its entirety.

The presented studies indicates that all currently explored probabilistic safety analysis have not explored complex and/or integrated safety model thus far. For example, Fam et al. (2021a) did not develop the accident model beyond the extent of this present work for well plugging and abandonment failure and relied on analogous data that has not been processed; Wang et al. (2021) used Dynamic Bayesian network but did not take the effect of statistically dependent events into account. Abimbola et al. (2016) and Khakzad et al. (2013) used uncertainty models capable of depicting multi-state variables and built the accident cause-consequence in a bowtie but did not consider the effect of data paucity in the respective systems studied. Bobbio et al. (2001) mapped FTA into its corresponding Bayesian networks and applied it on a simple system. Lavasani et al. (2015) used Fuzzy Fault Tree Analysis (FFTA) on a simplified well plugging and abandonment system. A notable observation from all these studies revealed that only Fam et al. (2021a) and Lavasani et al. (2015) used a plugged and abandoned well as a case study, others were applied to systems outside the decommissioning and abandonment domain.

Table 3-2: Analysis of research studies on uncertainty modelling

Literature	Static PRA	FFTA	MCDA	BN	DBN	Cost	Comment
Fam et al. (2021a)	×	×	×	✓	✓	×	Applied Dynamic Bayesian network on well plugging and abandonment operations. Safety metrics estimated.
Wang et al. (2021)	×	×	×	✓	✓	×	Applied Dynamic Bayesian network on EER strategies on offshore platforms. Safety metrics estimated.
Abimbola et al. (2016)	✓	×	×	✓	×	×	Applied to well integrity operations using advanced logic gates. Safety metrics estimated.
Bobbio et al. (2001)	✓	×	×	✓	×	×	Developed based on elicitation complexity. Applied to a generic multiprocessor.
Khakzad et al. (2013)	✓	×	×	✓	×	×	BT-to-BN mapping of process plant accident. Applied to U.S. Chemical Safety Board accident. Safety metrics estimated.

3.7 Current Research Direction

Following from the analysis of the current state of knowledge evident by the reviewed literature, several research gaps and potential roadmap for further research were identified as shall be seen below.

With respect to the failure data collection methods in the existing study:

1. Decommissioning and abandonment activities have not benefitted from operation-specific failure data and common data analysis methods across the industry. Improvement in the data collection, processing and utilisation methods to foster completeness and unification of the accident scenarios analysis need to be promoted.
2. The implementation and incorporation of such collected failure data could be improved through a dedicated decommissioning and abandonment Accident Precursor Data (APD) database to reduce the reliance on experts' subjective judgements.
3. Analogous data from similar operations such as drilling, mining and/or aerospace could be collected and aggregated using source-to-source variability techniques.
4. Permanence of source-to-source data collection and statistical processing of the inherent variability could also be investigated.

With respect to the accident scenarios modelling methods:

5. Development of nonlinear accident model where each accident contributory factor is not statistically independent of the other, could be explored.
6. Development of non-sequential accident model where cascading of failure is a probable scenario could be investigated.
7. Development of a finitely complex cause-consequence model where failure outcomes of interest could be evaluated in both forward and reverse direction could be considered.

8. Integration of conventional PRA/QRA with modern probabilistic safety analysis methods to benefit from both capabilities could be trialed.
9. Application of time-dependent safety analysis methods to well plugging and abandonment operation.
10. Incorporation of robust safety analysis model to capture both planned and evolving hazards could be considered.

With respect to accident parameters uncertainty modelling:

11. Introduction of parameter uncertainty models built into the safety analysis to reduce the influence of unknowns such as uncertain reservoir conditions and limited failure data, could be considered.
12. Incorporation of accident models into real-time monitoring device to capture planned and unplanned incidences could be explored.

With respect to well plugging and abandonment operations safety assessment:

13. Integration of statistical methods for small-sized data analysis and robust safety assessment could be considered.
14. Application of dynamic safety assessment capable of long-term monitoring of plugged and abandoned wells.

With respect to the steel piled jacket removal

15. Application of safety assessment, in terms of, economic risk to forecast the future value of decommissioning could be investigated.
16. Incorporation of dynamic safety model with parameter uncertainty models for ascertaining the safety of complete assets removal operation.

3.8 Identification of Research Gap

As can be inferred from above, decommissioning and abandonment operations are technically intensive requiring specialised skills and the overall knowledge of the operational phases. To conduct probabilistic safety analysis of these complex engineering systems, both planned and unplanned hazards associated with the process in its entirety need to be captured. One major and notable challenge identified above, is the sparsity of failure data required to quantify and assess the single, most probable failure capable of leading to a futile decommissioning operation. Typically, failure data are usually obtained from analogous activity and this approach often introduce additional uncertainty to the safety risk analysis.

In this PhD thesis, the following research gaps emanating from the analysis of current state of knowledge presented in Section 3.7 culminated in the selections discussed below.

3.8.1 Research gaps 1, 3, 4 and 13

The accuracy of a quantitative risk assessment is as important as the reliability of failure data used in the estimation. Since the identified research gaps emphasised the lack or sparsity of such data, developing a systematic approach to collect and process the data to a considerable confidence level becomes necessary, so that all source-to-source data variability are adequately addressed. The focus will be on statistical improvement of small-sized data cleaning methods, in specific Hierarchical Bayesian analysis (HBA), with application to decommissioning and abandonment system.

The HBA method has been considered an invaluable method for aggregating the failure probabilities of accident contributory factors to overcome the challenges of small-sized failure data often encounter during decommissioning and abandonment operational risk assessment. Furthermore, the HBA has the potential to estimate probabilities at a multi-stage level with acceptable confidence interval in which a stage under consideration is statistically dependent on the prior stage, making the method more beneficial compared to single-level modelling methods. Therefore, it would be advantageous to adopt a new method that can incorporate the HBA. However, the complete safety assessment would require an appropriate model for the HBA, and for this, Weibull distribution (a single-stage modelling method) can be investigated and compared with Gamma distribution (a multi-stage modelling method) to allow for an objective quality method selection.

3.8.2 Research Gaps 7-8

The Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and bowtie (BT) can be effective and proven methods for capturing the interrelationships and dependencies that exist between interacting accident contributory factors. These PRA/QRA tools, albeit conventional, are well suited for analysing the modellable failures (Khakzad et al., 2014). Although, FTA is simple to formulate and can be applied to any finite system, however, other tools capable of addressing common cause failures and time-dependencies could be preferred for handling rare accident systems such as decommissioning and abandonment operations (Khakzad et al., 2011). To benefit from its simplicity, FTA can be used to develop the accident causation model and transform into other models for further analysis. The ETA thrives on events consequence modelling emanating from the identification of a single point failure and associated multi-point failures resulting from lack of containment within the investigated system (Adedigba et al., 2016). While Ramos et al (2020) proposed a dedicated Event Sequence Diagram (ESD) for depicting consequence modelling, ETA method is selected in this work, due to simplicity in its formulation. The BT thrives on the combinatorial strength of both FTA and ETA to develop a robust cause-consequence relationship for the interacting accident elements. While the BT offers the advantages of both tools in its constituents and associated simplicity, it cannot adapt to the dynamic nature of complex engineering systems (Khakzad et al., 2013) such as decommissioning and abandonment operations.

For these reasons, the conventional PRA/QRA tools would be developed to support the accident scenarios modelling effort. However, the BT model would be mapped onto other methods capable of uncertainty, common cause failures and dynamic modelling.

3.8.3 Research Gaps 5, 9-11 and 14

The past and current research studies on decommissioning and abandonment safety analysis have focused on the conventional PRA/QRA approaches. Although, these tools are invaluable for static safety assessments, they are not able to account for the often-encountered changes in the cementing job or pressure buildups within the system. Research in the process systems industry have shown that uncertainty and long-term monitoring of assets are possible through the formulation of advanced reliability models such as Artificial Neural Networks (ANN), Bayesian networks (BNs), Dynamic Bayesian Networks (DBNs) and Fuzzy Bayesian Networks (FBN) (Shi et al., 2018; Abimbola et al., 2016; Shi et al., 2014; Khakzad et al., 2013).

Since ANN is computation intensive requiring elicitation of multitude data points to monitor the condition of assets and noting that, decommissioning is not an investment. Motivating the offshore community to adopt ANN would require a level of effort disproportionate to the time available for this study. In addition, fuzzy set theory has been discounted in Section 3.6.2 due to its computation effort that cannot be justified for the purpose of this research work. Therefore, by developing the accident models from the PRA/QRA tools and mapping these into Bayesian networks and consequently, the dynamic Bayesian networks to conduct safety risk analysis it is envisaged that the rigour of the time-dependent analysis will be significantly enhanced. The transformation into BN and DBN will enable the model to be finitely complex without considerably impacting the computation effort, improve the dependency among interacting elements, capture planned and evolving hazards and tackle the temporal effect of key performance events from all interacting events. Table 3-3 illustrates the merits and demerits of BN and establishes the benefit of adopting dynamic BNs for the purpose of accommodating time-dependent events.

By incorporating the HBA, the PRA/QRA tools and the BN and DBN into an integrated framework the challenges identified in each method would have been improved at every stage in the formalism. The combined framework (Dynamic Integrated Safety Analysis (DISA)) will provide insight into the optimisation of rare accident models and will be capable of addressing the overall decommissioning and abandonment challenges, in relation to risk profile predictions.

Table 3-3. Merits and demerits of BNs

Strengths	**Weaknesses**
BNs can handle complex and nonlinear interactions among accident contributory factors, which are norms in the context of decommissioning and abandonment operation.	Elicitation of prior marginal probabilities is a complex task with no well-defined guidelines on the computation of the conditional probability tables.
Can accommodate variety of relaxation strategies within its conditional probability tables.	Elicitation of the dependence among events' marginal probabilities depend strongly on the degree of belief.
Can handle complex engineering models considerably well even when data is limited or sparse.	Data paucity can introduce additional uncertainty in the estimated outcomes.
BNs can update prior probabilities when new information becomes available.	BNs cannot adapt to variations in events as a function of time. Hence, the incorporation of DBNs.
Can adapt prior probabilities to update events through experiential learning.	BNs are believed to be capable of handling complex models but the degree of complexity remains unknown.

3.8.4 Research Gaps 15 and 16

This thesis will also focus on the integration of economic risks and uncertainty parametric modelling within the DISA framework, as potential resilience in accident modelling is beneficial to rare accident models. More specifically, considering the complex nature of the decommissioning and abandonment operations, decision-makers will benefit from a robust computational framework that is able to yield reliable failure probabilities and predict the future value of money on demand. The DISA framework, being made up of several tools and parameters enhancement, can incorporate captured hazards, evolving hazards and current market data to estimate the probability of system failure and the cost of actualising the failure. Therefore, it would be an invigorating learning experience to investigate how the DISA results could be utilised to develop and predict the long-term monitoring of decommissioning and abandonment operations and how hazards could be spotted shortly before they manifest into undesirable events.

3.8.5 Rationale for Research Gaps 6 and 12 Exclusion

Although the main reason for excluding these research gaps in the analysis is the time-bound PhD duration. However, additional reasons are offered below:

Research gap 6. The development of a detailed and comprehensive non-sequential accident model for decommissioning and abandonment operations do not currently exist. The level of efforts required to verify and validate such models would require case-specific data which may lead to collaboration with the industry. This will not only limit publication of results but also consume time.

Research gap 12. The development of real-time monitoring device to capture planned and unplanned incidences would demand considerable level of effort in the investigation of the device in terms of fit, form and functionality. It would, therefore, be prudent to first improve the existing accident models and gain insight into the DISA framework and its effectiveness prior to developing the real-time device.

3.9 Concluding Remarks

Based on the foregoing, this PhD thesis will develop a Dynamic Integrated Safety Analysis (DISA) framework for conducting safety analysis based on HBA and DBN probabilistic tools. The DISA framework will be used to reduce parameter uncertainty modelling and consequently, estimate both risks and cost models for the decommissioning and abandonment of offshore oil and gas installations.

3.10 Chapter Summary

HBA is a statistical method that can address the issue of small-sized failure data that is typical of decommissioning operation. The current research direction focused on how to improve the existing static method of conducting probabilistic risk analysis by incorporating several tools such as the HBA with DBN to predict the risk profile and cost of remediation. Several research studies conducted to date focused on the static safety analysis of decommissioning and abandonment systems, dynamic safety modelling of process systems and on the development of dynamic safety analysis of well plugging and abandonment without addressing the issue of data paucity. Despite this progress, there exist sizable number of research gaps in relation to dynamic safety assessment, parameter uncertainty modelling and economic risk assessment. Through the incorporation of HBA with other methods such as BT (with its FTA and ETA constituents) and mapping into its corresponding BN and DBN equivalents, it is envisaged that some of the data paucity and uncertainty challenges will be relaxed.

This integrated safety framework can be considered the primary novelty this PhD thesis contributes to the wider research community. Other secondary contributions emanating from this thesis can be considered an extension of the application of the DISA framework to decommissioning accidents, since no such method currently exist in the decommissioning and abandonment domain, thus far.

Chapter 4: FRAMEWORK DEVELOPMENT

4.1 Outline

This Chapter presents the methodology adopted in this thesis aimed at developing and demonstrating a framework to conduct a probabilistic risk analysis for the decommissioning and abandonment operation of oil and gas installations. First, a comprehensive hazard identification analysis is developed to capture all possible causal events that may lead to a single accident-initiating hazard. The evolution of identified hazard into accidents including the relevant safety barriers and their associated failure mode is also developed and depicted in a bowtie. The bowtie is then mapped onto a Bayesian network, where quantified failure data are fed for assessing the risk. The failure data are then obtained through source-to-source variability techniques using Hierarchical Bayesian Analysis model. Consequently, explanation is proffered on the combinations of proposed methods in specific sequence and scenarios. The steps involved in the framework development are also presented.

4.2 Justification for Method Steps

Following on from the discussion in Chapter three (3), the conventional probabilistic safety analysis methods are inadequate for performing risk analysis of rare accidents. In addition, the hazard identification methods commonly adopted can fallshort to capture salient but imperceptible hazards which may introduce uncertainties into the accident model. More specifically, the failure data needed as inputs for the estimation of the top-level risk are often lacking or insufficient due to the unique nature of the decommissioning and abandonment systems. Therefore, it proposed to integrate a Hierarchical Bayesian Analysis (HBA) and Dynamic Bayesian Networks (DBN) with advanced relaxation strategies, in specific Noisy OR gate, leaky Noisy OR gate and imprecise leaky Noisy OR gate, to form a Dynamic Integrated Safety Analysis (DISA) framework, which can proffer a more comprehensive insight into the accident scenarios analysis. The justification for the selection and the anticipated benefits were provided in Section 3.8, however, same is extended below to establish the rationale for the sequential application of proposed framework.

4.3 Dynamic Integrated Safety Analysis (DISA) Framework

The dynamic risk assessment technique is based on the framework shown in Figure 4-1. This methodology follows a systematic solution step as presented below:

- *Step 1*: Accident scenarios analysis are conducted through system- and subsystems-level definition, hazard identification, and operational phases failure analysis.
- *Step 2*: A cause-consequence relationship is developed to visualise the accident evolution, in the form of BT – combining the strengths of FTA and ETA. The constructed BT is then transformed into its corresponding BN as discussed in Section 4.4.
- *Step 3*: The failure data used in the probabilistic risk analysis asinput to estimate the single failure capable of initiating the undesirable end consequences are then computed in this step. The computation algorithm is a statistical approacj based on HBA method to aggregate the small-sized data into a mean distribution at 95% confidence interval.
- *Step 4*: Uncertainty modeliing is formulated in this step to handle potential uncertainty that can be introduced into the model. This type of uncertainties can emanate from the parametric modelling assumptions, small-sized data aggregation and the effect of uncaptured hazards. The family of uncertain models adopted is the advanced logic gates for overcoming or relaxing the identified limitations of static PRA/QRA models.

- *Step 5*: The BN is further translated into DBN using appropriate formalism incorporating uncertainty and time-based conditional probability modelling. Within the formulated DBN, Probabilistic risk analysis and dynamic safety analysis are performed using the failure data obtained through HBA in step 3.
- *Step 6*: Model validation using the three-step analysis in Section 4.9 is performed and risk control measures proposed for selected case study. This model validation exercise is essential to test the applicability, credence and permanence of the DISA framework.
- *Step 7*: Economic risk modelling is introduced to interpret the safety risks in terms of the financial implications of failing to capture and remediating any hazard or combination of hazards that can culminate into catastrophe.

Summarily, the proposed method introduces a dynamic integrated safety analysis incorporating Hierarchical Bayesian Analysis (HBA) with Bayesian networks (BNs) to address the identified gaps. The HBA is adopted to address the issue of data sparsity. HBA is especially capable of aggregating the small data size and present the probability of failure as a mean of distribution with 95% confidence level. The BNs is used to flexibly adjust the failure data to reflect real-time observations as more information about the uncertainty become available. The time dependency of operations is also accounted for using the BNs robust computation engine, and further transition into dynamic state modelling based on the Markov chain. The proposed DISA framework has not been adopted in the offshore decommissioning and abandonment operations thus far. The DISA results are used to support the development of risk control measures, monitor, and control the decommissioning and abandonment process to enhance safety while saving the cost of remediation. The method steps must be applied sequentially and the DISA step is discussed in more detail in the succeeding sections to cover the application of methodology in its entirety. Step 3 is exclusively discussed in Chapter 5 since the data collection approach is a standalone and an important input to the DISA framework. The subsequent Chapters present the application of developed steps to selected case studies.

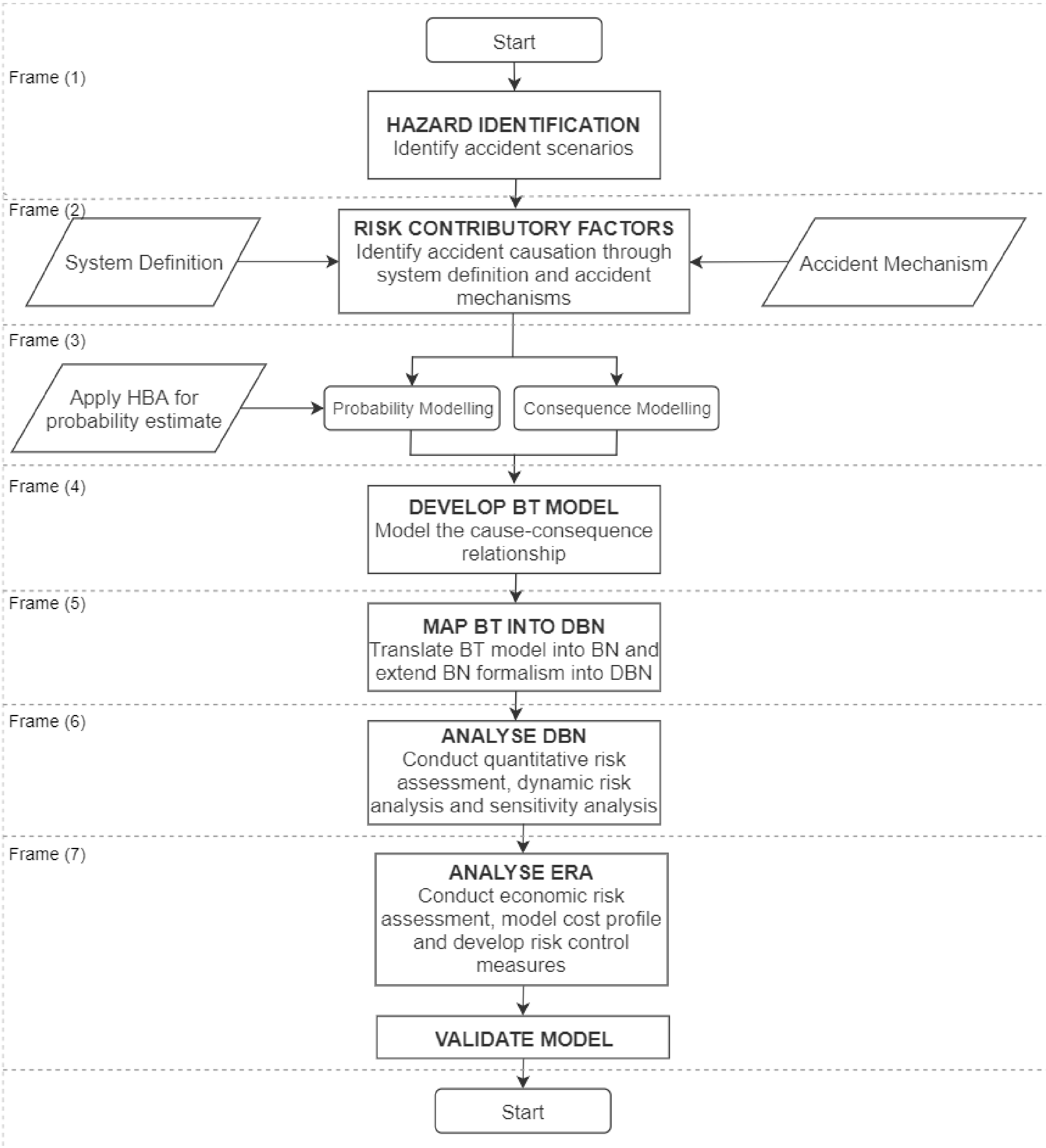


Figure 4-1 Dynamic Integrated Safety Analysis Framework.

Figure 4-1 is the overall framework and the steps in frames 1, 2 and 3 satisfy the objectives (1)-(3).The steps in frames 4 and 5 satisfy the objectives (4) and (5), which further provide the basis for accomplishing objective (6) and objective (7) built on the observed trends from model responses of all obtained results.

4.4 Hazard Identification (Step 1)

Hazard identification (HAZID) is a technique used to examine the operational sequence of a system and evaluate the potential of any of the system components to cause harm (Leveson, 2020; Johansen and Rausand, 2014; Qureshi, 2007; Leveson, 2004). The HAZID belongs to the family of risk assessment tools for investigating the root causes and failure modes of complex systems. Risk assessment is conducted following a thorough HAZID analysis including risk factors capable of initiating accidents. Risk analysis is the process where the identified risks associated with the hazards are analysed and evaluated – typically, quantitatively. As part of a comprehensive risk management, the final step is a risk control process where measures are put in place to eliminate or mitigate the hazard.

4.5 Accident Evolution Model (Step 2)

4.5.1 Fault Tree Analysis (FTA)

Fault tree analysis is one of the widely adopted techniques for safety, risk, and reliability assessments. It is a deterministic and deductive logic gate used to depict the relationships between causal events of an undesired scenario and their criticalities. The constituents of an FT comprise of basic event, intermediate event, and top event. The basic events are the minimum faults that can initiate a potential fault or harm to the subsystems of a component. The intermediate events are sets of faults in the subsystem capable of causing a potential accident. The top event is the most critical hazard that can initiate major accidents especially when the safety barriers implemented are insufficient or deteriorate over time. The top event represents the highest-level incidence in the accident model hierarchy and fleshes out into various scenarios called fault or intermediate events until the primary causals or basic events are completed identified and captured within the FTA model (Crowl and Louvar, 2002). FTAs are better represented and constructed only when event trees have been developed and the initiating (top) event identified (Khakzad et al., 2011). The FT can only handle binary state for events and each event is assumed to be statistically independent of the other. It also relies on logic gate operations to formulate the relationships among interacting events, without the possibility of accommodating intermediate state for events i.e., either true or false; yes or no; success or failure etc. The most commonly used logic gates are the OR-gate and the AND-gate (Rausand and Hoyland, 2004). The OR-gate is characterised by serial connection of the interacting events such that the failure of any single component or subsystem results to the failure of the system in its entirety. On the other hand, the AND-gate is used to represent the interaction of components or subsystems in parallel such that the overall system failure requires the simultaneous failure of all components. Equations (4-1) and (4-2) represent OR-gate and AND-gate, respectively.

$$p(C_i) = \prod_{i \in C_i}^{n} (1 - p_i) \tag{4-1}$$

and

$$p(C_i) = \prod_{i \in C_i}^{n} p_i \tag{4-2}$$

The FT can represent accident scenarios in both qualitative and quantitative models. In the qualitative model, the logical relationship among events leading to the top event is illustrated explicitly. It depicts the possible combination of events, termed Minimal Cut Sets (MCS) that must be present for the accident initiating hazard to occur. In the quantitative model, the failure probability of the top event is estimated from the Boolean algebraic combination of basic events through the intermediates to the top event (Nivolianitou et al., 2004). However, the application of FT in the analysis of complex systems is undermined by its associated significant error margin.

In addition, its assumption of statistical independence of events limits its use in modelling mutually exclusive events, common cause failures or complex dependency events. The presence of generic and imprecise failure data adds to the uncertainty in the results obtained from FTA. Its binary state limits its application in multi-variable and multi-state events (Khakzad, et al., 2011; Bobbio, et al., 2001). To that end, efforts have been made to reduce the uncertainties in FTA through the development of fuzzy set and evidence theory-based FT analysis (Ferdous et al. 2009; Markowski et al. 2009) and hybrid FTA (Liu et al., 2013; Lin and Wang, 1997).

4.5.2 Event Tree Analysis (ETA)

The event tree is a widely adopted tool for consequence scenarios modelling. It is an inductive technique which begins with an initiating event and terminates at a loss which may be major, minor or a near miss. Each of the possible outcome is referred to as, a consequence or an end event. Like the FT, it can represent accidents qualitatively and quantitatively. Qualitatively, it provides the logical relationship of how a failure can occur and quantitatively, the probability of occurrence can be estimated. An event tree can capture accident scenarios including the inherent safety functions implemented to prevent the occurrence of an accident in a sequence of events. The structure of an ET is rather progressive and inductive. The progressive outlook ensures that end consequences are initiated by a single hazard (initiating event). It combines all possible scenarios of implemented safety barriers functioning or otherwise. The safety barriers are systematically positioned within the ET to demonstrate that one barrier effectiveness must have deteriorated for the succeeding barrier to be activated. It is also possible to activate two barriers concurrently in some complex engineering systems. However, it also suffers from the use of generic and imprecise data. Meel and Seider (2006) advanced the use of ET through the development of plant-specific dynamic assessment methodology which utilizes Accident Precursor Data to predict the frequencies of end-states abnormal events. In the same vein is the work of Kalantarnia et al. (2009) in which the posterior failure probabilities of safety barriers is determined by Bayesian updating mechanism. Further application of ET methodology to process accident modelling and an offshore drilling accident, utilizing FT principle for safety barriers and Bayesian updating mechanism using accident precursors was conducted by Rathnayaka et al. (2011b, 2013).

The occurrence probabilities of the end consequences given that the implemented safety barriers have failed are often assumed to follow the binomial distribution function given below.

$$p(C_i) = \prod_{i:j \in SB_i} M^{n_{i,j}} N^{(1-n_{i,j})} \quad (4\text{-}3)$$

Where M and N are the failure and success probabilities of safety barriers, respectively; $n_{i,j}$ is the number of successive branches prior to failure occurrence of the end consequences. Typically, $0 \leq n_{i,j} \leq 1$. SB_i is the safety barrier at the instant i.

4.5.3 Bowtie Model

The bow-tie technique is a complete safety risk modelling tool whose constituents are the FT and ET. The FT is depicted as the input, with its top event as the initiating event of the ET. The ET is the output end of the bowtie. The combination of both FT and ET especially, makes the bowtie a systematic and robust risk analysis technique. Here, both the cause of an accident, barriers to ensure safety and the consequence of such accident can be visualised in its entirety and optimised accordingly. Bowtie is widely adopted in the diverse field of analysis due to its capability to offer the advantages of FT and ET. For example, bow-tie has been applied in a Layer of Protection Analysis (LOPA) (Markowski and Kotynia, 2011; Pasman and Rogers, 2013) and dust explosion accident (Khakzad et al., 2013; Yuan et al., 2015). Detailed information on the construction and analysis of risk within bowtie can be found in the literature (Ferdous et al., 2013; Khakzad et al., 2012; Mokhtari et al., 2011). It is worth mentioning that bowtie, despite its potentials, is also limited in its ability to adapt to dynamic accident scenarios and interdependencies among complex interacting events.

Consequently, the identified hazards can be fully represented on an FT and the accident-initiating hazard, often referred to as the top event, becomes the initiating event of an ET. The accident evolution presents the logical relationship among causes of hazard, called primary events (PE_S) and how they manifest into faults, expressed as intermediate events (IE_S) through to the top event (TE), all on the FT side. On the ET side, the safety barriers (SB_i) put in place to prevent or mitigate the hazard evolving into an accident and the potential consequences (C_i), should the implemented barriers fail. For example, Figure 4-2 illustrates an accident scenario and its corresponding evolution into end consequences for which probabilities of C_1 and C_3 can be expressed as

$$p(C_1) = p(TE).p(\overline{SB}_1).p(\overline{SB}_2).p(\overline{SB}_3) \qquad (4\text{-}4)$$

and

$$p(C_3) = p(TE).p(\overline{SB}_1).p(SB_2) \qquad (4\text{-}5)$$

Where $p(TE)$ is the top event occurrence probability obtained from the Boolean algebraic operands of the primary and intermediate events, $p(PE_i)$ and $p(IE_i)$. $p(SB_i)$ and $p(\overline{SB}_i)$ are the occurrence and non-occurrence probabilities of the safety barrier i.

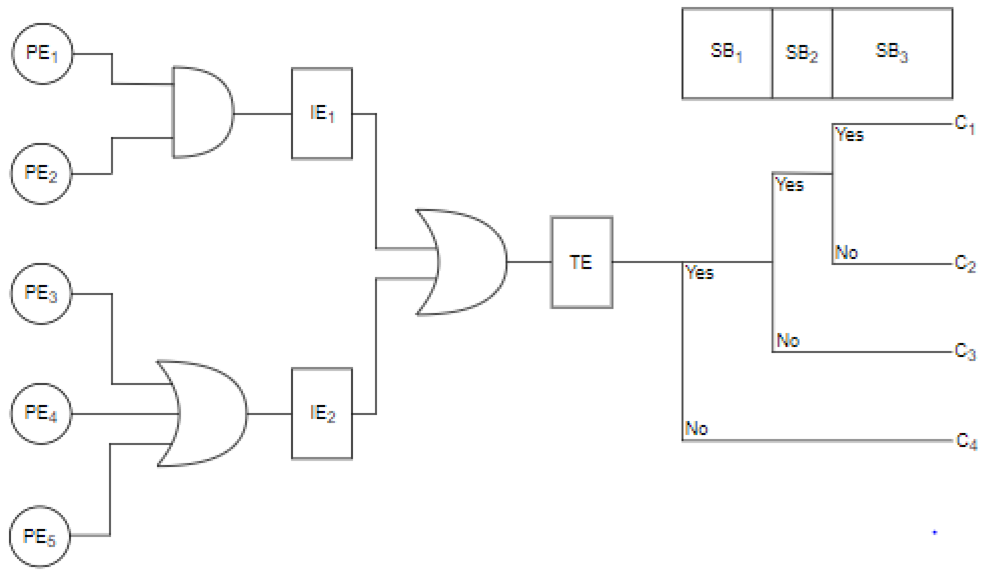


Figure 4-2 Accident Evolution in BT model.

Estimation of the occurrence probabilities of end-consequences makes it feasible to evaluate the Potential Loss of Life (PLL). However, the failure probabilities of primary or causal events are rarely available, making it necessary to adopt a suitable statistical method with acceptable confidence level. In addition, as BT has its strength in cause-consequence visualisation, it cannot be used to address time-dependency of events and complexity of connected engineering systems such as decommissioning and abandonment installations. To tackle the latter issue, the BT structure will be mapped into its corresponding BN equivalent, as shall be seen in subsequent Section.

4.5.4 Bayesian Networks (BNs)

The Bayesian network (BN) is a graphical technique for representing a set of conditional dependencies among discrete random variables. BN is a probabilistic methodology for risk prediction under uncertainty due to its flexibility and transparency. It offers the potential to construct complex interacting and nonlinear events and is capable of handling multi-variable systems and their dependencies under uncertainty. It consists of both qualitative and quantitative constituents. The qualitative part is a Directed Acyclic Graph (DAG) with nodes representing discrete random variables and arcs depicting direct causal relationships among interacting nodes. The quantitative part represents the relationships between the interacting variables which are specified within Conditional Probability Tables (CPT) to indicate the strength of influence among the interacting nodes. The elicitation of the prior marginal probabilities is key to the accuracy of the estimated failure probability for the parameter of interest, in this case, the top event. The Conditional Probability Table (CPT) used to specify the conditional probabilities comprises sets of values for the parent nodes. Consider Figure 4-3 with set of variables $Y_{i.}$ Y_1 and Y_2 are the root nodes; Y_3 and Y_4 are the intermediate nodes; and Y_5 is the leaf node. The root nodes corresponding to basic events in an FT are assigned marginal prior probabilities. The intermediate and leaf nodes are given CPTs based on the level of influence of their parent nodes. The theory and practice of BN is not the focus of this thesis but its applicability to the task under consideration. Comprehensive information regarding BN can be found in the literature (Bobbio et al., 2001; Jensen and Nielsen, 2007).

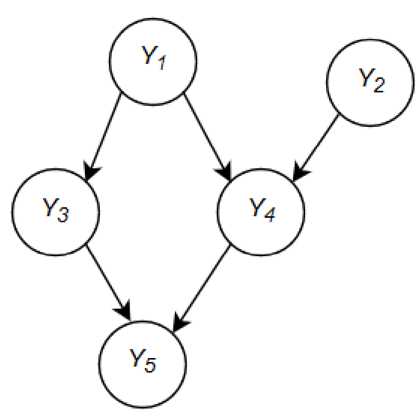


Figure 4-3 A typical BN structures

Each state of Y_i is represented by binary outcomes y_i and $\bar{y}_i$. The BN joint probability distribution follows the product rule as given in Equation 4-6.

$$P(y_i) = \prod_{i=1}^{5} P(y_i | y_{\mu(i)}) \quad (4\text{-}6)$$

Where $P(y_i)$ is the joint probability distribution of the state variables y_i. $\mu(i)$ is the parent of variable node i. Equation (4-6) can be expanded according to the product rule as:

$$P(y_i) = P(y_5|y_4, y_3) \cdot P(y_4|y_2, y_1) \cdot P(y_3|y_1) \cdot P(y_2) \cdot P(y_1) \quad (4\text{-}7)$$

Equation 4-6 can be extended to accommodate large but finite number of variables with combination of states, making BN well suited to handle complex and nonlinear systems. Given the availability of new evidence, E, the posterior (updated) probabilities of Figure 4-3 can be obtained by:

$$P(y_i|E) = \frac{P(E, y_i)}{P(E)} \quad (4\text{-}8)$$

4.5 Mapping BT to BNs

The main purpose of mapping a bowtie into BNs is to make numerical elicitation using advanced logic gates possible. The notable logic gates which BNs can accommodate include noisy-OR, noisy-AND, leaky noisy-OR, etc. Another purpose of such transformation is due to the robust computation engine of the BN to accommodate different combinations of sequential and non-sequential accident causal factors. The BNs like the BT, offer the benefit of representing accident models qualitatively and quantitatively. In the qualitative mapping algorithm for the FT side, the Basic or Causal Events (CEs), Intermediate Events (IEs), and the Top Event (TE) become the root nodes, intermediate nodes, and leaf node of the BN, respectively as depicted in Figure 4-4. The leaf node is often referred to as a pivot node in the case of a fully developed BT.

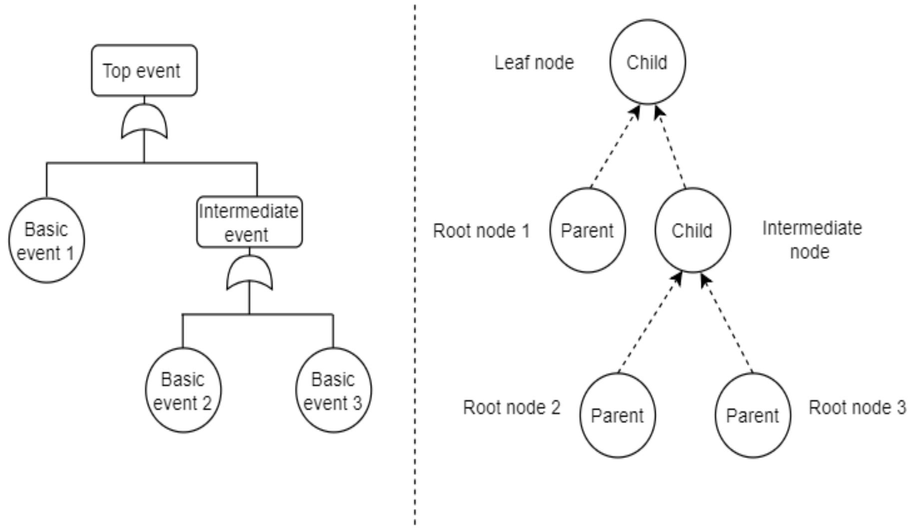


Figure 4-4 FT-to-BNs similitude mapping

The logic gates connecting the events of the FT are represented by directed arcs. On the quantitative part, the failure probabilities of the primary events become the marginal prior probabilities for the root nodes within the BN. To account for event scenario conditional dependency in the BN model, appropriate logic gates are developed to elicit the failure probability for each intermediate and leaf node. The elicitation is performed within the Conditional Probability Table (CPT) of each node (Bobbio et al., 2001; Bearfield and Marsh, 2005; Lampis and Andrews, 2009; Khakzad et al., 2013a, 2013b) as illustrated in Figure 4-5.

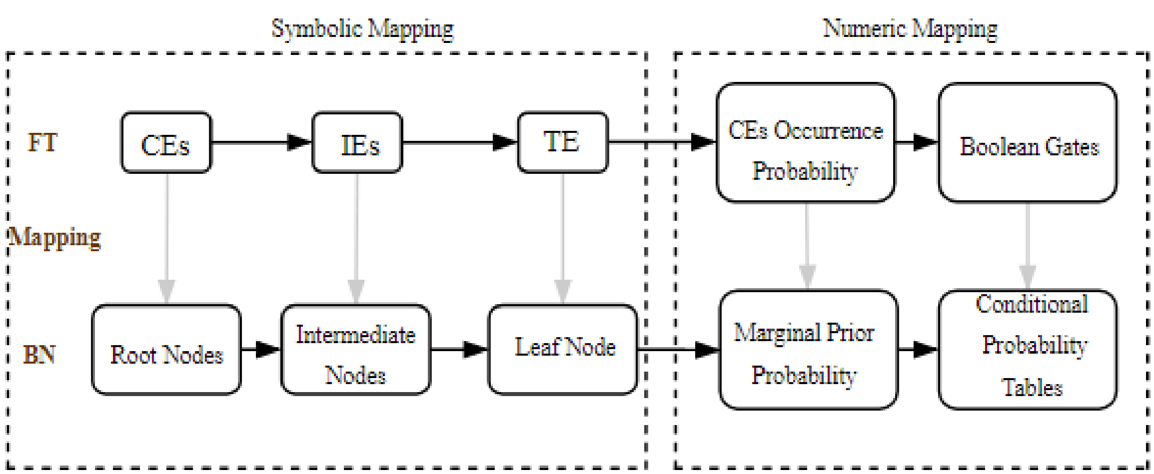


Figure 4-5 FT-to-BN Qualitative and quantitative mapping algorithm

To map ET, on the other hand, the safety barriers are depicted by safety nodes, SB_i and each end consequence becomes a leaf node. When the BT is transformed into the corresponding BN, the top event is expressed as a pivot node linking the FT and the ET. The relationship between the safety nodes and/or between a safety node and the pivot node is such that there must be conditional dependencies before a causal arc can be directed from a preceding node to a succeeding node i.e., from SB_i to SB_{i+1}, or TE to SB_i as shown in Figure 4-6. Where there are safety barriers conditionally dependent on end consequences, the linking process follows the same argument. The elicitation of the end consequence occurrence probabilities is done through their Conditional Probability Tables like the intermediate and pivot nodes discussed in the FT mapping. The failure probabilities of the safety nodes are the inputs in the consequence node CPT. The estimation of the consequence nodes is performed as if the occurrence of safety barriers and pivot node were logically independent.

$$P(SB_i|TE) \neq P\left(SB_i\middle|(1-TE)\right) \quad (4\text{-}9)$$

And

$$P(C_i|SB_i) \neq P\left(C_i\middle|(1-SB_i)\right) \quad (4\text{-}10)$$

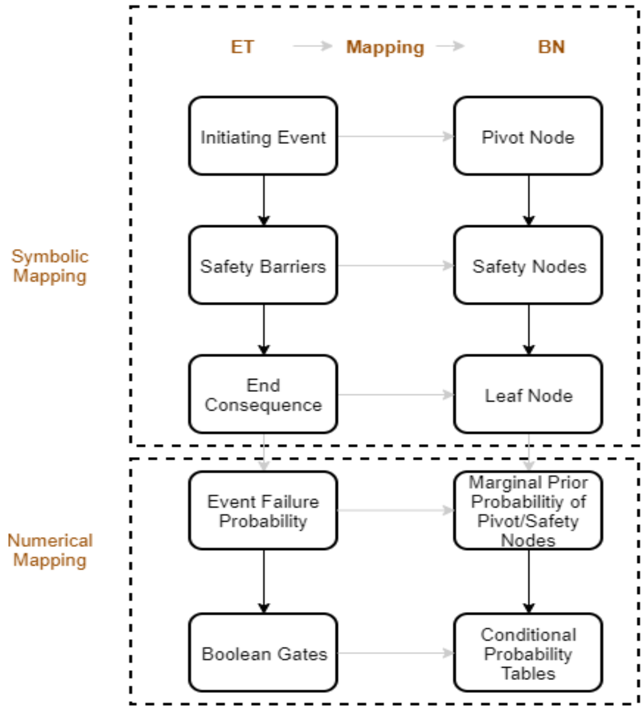


Figure 4-6 ET-to-BN Qualitative and quantitative mapping algorithm

4.6 Modelling Failure Probability (Step 3)

The HBA modelling method, its formulation and applicability to the estimation of failure probabilities of causations with associated confidence interval analysis are discussed below.

4.6.1 Hierarchical Bayesian Analysis (HBA) Modelling

Following the mapping algorithm discussed in Section 4.4, the root nodes need to be assigned marginal prior probabilities. The marginal prior probabilities can only be obtained through aggregation since the failure data are often sparse and affected by the source-to-source variability. The data sparsity necessitates the application of hierarchical Bayesian models, due to their capability in modelling unmeasured or uncaptured failure data structured in groups. Different but statistically related parameters – called non-informative priors – are assigned to predict the mean distribution of each group using intermediate number of parameters. The representation and interpretation of these group-level parameters are then used to describe group-level differences for predictors obtained from related accident sources. The hierarchical Bayesian models are especially suitable for decommissioning and abandonment accidents model where failure data size is infinitesimally small. The benefit of group-level parameters is that there is no independent variability among the grouped dataset but assumes that there exists a constraint bounded by statistical distribution. The distribution – such as Normal, Weibull, Gamma, etc. – is modelled with a pre-defined variance. Hierarchical Bayesian models are particularly used to account for sources of individual- and group-level variability and uncertainty when estimating group-level coefficients, making it superior to classical statistical models which require averaging over individual level variation. The hierarchical models thrive on the strength across groups of datasets while minimizing the effects of small sample sizes. Its modelling algorithm allows random effects to absorb unmeasured variations with high confidence interval leading to significantly low bias in the estimation.

For illustration purpose, given that failure datasets, y_i for decommissioning 20 Steel Piled Jackets (SPJs) failure causals were obtained from different sources over 8 weeks weather window. y_{ij} is the number of SPJ i at week j, and N_i is the number of trials for each decommissioning operational hazard. Table 4-1 shows a typical group dataset that is collected for the observations.

Table 4-1. SPJs failure data obtained from 20 sources.

Source	Number of failures (y_i)	Number of trials(N_i)
1	0	140
2	0	130
3	0	130
.	.	.
.	.	.
.	.	.
.	.	.
18	4	167
19	5	151
20	10	150

The argument here is that each SPJ can be represented by a regression line with own slope m_i and intercept c_i, and all SPJs follow a common distribution with regression line pattern having group slope $m_i = \mu_i$ and group intercept $c_i = \gamma_i$. A conventional distribution would typically be represented by an average population growth line given by $E(y_{ij}) = \gamma_i + \mu_i x_j$. The hierarchical models thrive on the group- and individual-level estimates by assuming that the datasets are distributed over some parameters of interest, often referred to as non-informative priors. The distribution benefits from the strength of various statistical distribution models, as can be seen below:

$$y_{ij} \sim N\left(\alpha_i + \beta_i(x_j - \bar{x}), \tau_c\right)$$

$$\alpha_i \sim N(\alpha_c, \tau_\alpha)$$

$$\beta_i \sim N\left(\beta_c, \tau_\beta\right)$$

Where α_i and β_i are the hyperprior parameters distributed over the mean and variance estimated from the independent non-informative priors $\alpha_c, \beta_c, \tau_\alpha, \tau_\beta, \tau_c$. The choice of selected distribution is dependent on the strength and application area under study (El-Gheriani et al., 2017a; 2017b). Whereas conventional models rely on the independent contribution of data (likelihood) and parameter (prior) model to estimate failure probability of events, the hierarchical models take advantage of the likelihood, prior and hyperprior parameters in its probability estimation, making it a robust and realistic method of probability calculation under uncertainty. In this study, hierarchical model capability is demonstrated to address the offshore decommissioning and abandonment safety issues. For the sake of simplicity, the model can be visualised in the form below:

$$p(\theta_1, \theta_2, \theta_3 | y_1, y_2) \propto p(y_2 | \theta_1, \theta_2, y_1) \quad \text{likelihood}$$

$$\times\, p(\theta_1|\theta_3) p(\theta_2) \quad \text{prior}$$

$$\times\, p(\theta_3) \quad \text{hyperprior}$$

Where θ_j is the mean of j (with j = 1,2,3…) groups dataset with each, collected over N_j trials (demands or observations); y_{ij} is the i^{th} (with i = 1,2,3…) measurement from the j^{th} group of data and σ_j^2 is the variance of each group dataset, often assumed to be known. The group mean μ is then obtained from the mean θ_j estimated for each of the j groups dataset. As shall be seen later in subsequent Chapters, the group mean, and variance will be chosen to be of equal magnitude to condition the distribution in accordance with the strength of the application distribution category (El-Gheriani et al., 2017a). The hierarchical model for given data size y_{ij}

having priors for each sub-group through $p(\beta|\alpha)$ and requiring a hyperprior distribution parameter of interest, $p(\alpha)$ is represented in hierarchy as shown in Figure 4-7.

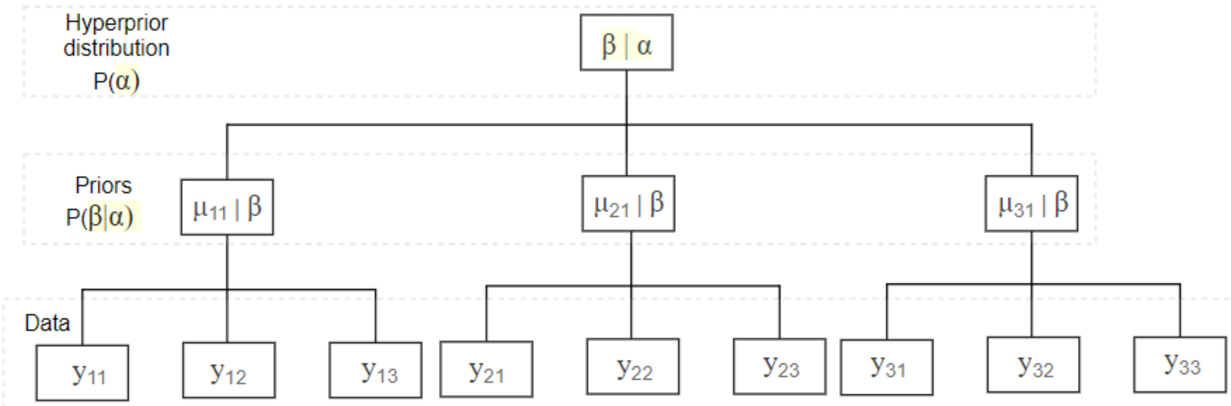


Figure 4-7 Hierarchical Model Representation.

4.6.2 Hierarchical Bayesian Analysis (HBA) Formulation

The HBA is a useful technique in probabilistic risk analysis for scenarios where failure data is lacking or sparse. HBA can incorporate a wide range of information in the estimation process where analogous data from similar operation are available. The analogous data, collected from different activities such as drilling, mining and production are aggregated using source-to-source variability concept (Khakzad et al., 2014; Lunn et al., 2009; Siu and Kelly, 1998). One major concern of any uncertainty modelling is the degree of accuracy in collecting or developing where applicable, an appropriate prior failure distribution. Generally, the two stage Bayesian and empirical Bayes' theorem are adopted in Probabilistic Risk Assessment (PRA) for estimating prior distributions. A multi-stage prior distribution is utilized in the hierarchical model which is very complex to analyse numerically. Recently, the development of Markov Chain Monte Carlo (MCMC) sampling software makes a comprehensive Hierarchical Bayesian Analysis controllable (Kelly and Smith, 2011; 2009). As data sparsity is a common setback in the decommissioning and abandonment industry, there is a need to aggregate the datasets from a variety of sources. The following steps are required to develop such datasets within HBA.

The first step requires that a likelihood function with parameter of interest ϕ be specified for the data set (y). Then an informative prior distribution can be developed for this parameter by considering that the parameter ϕ follows a generic distribution $\phi \sim \omega_0(\phi|\alpha, \beta)$ which represents the first stage prior. The hyper-parameters (α, β) that characterise this prior are also uncertain and are considered to follow a diffusive or non-informative distribution $g_0(\alpha, \beta)$, which is known as a second stage prior or hyper prior distribution.

The data set (y) along with Bayes theorem can be used to update the second stage prior in order to have a posterior distribution for α and β, i.e., $g_1(\alpha, \beta|y)$. It is calculated using the two-dimensional form of Bayes theorem:

$$g_1(\alpha, \beta|y) = \frac{g_0(\alpha,\beta)\, L(y|\alpha, \beta)}{\iint g_0(\alpha,\beta)\, L(y|\alpha, \beta) d\alpha\, d\beta} \tag{4-11}$$

where the likelihood function of α and β, i.e., $L(y|\alpha, \beta)$, is achieved by averaging the likelihood function of ϕ, i.e., $L(y|\phi)$ over all values of ϕ:

$$L(y|\alpha, \beta) = \int L(y|\phi)\ \omega_0(\phi|\alpha, \beta) d\phi \tag{4-12}$$

The posterior of the hyper-parameters (α, β), i.e., $g_1(\alpha, \beta|y)$ will be used to update the first stage prior $\omega_0(\phi|\alpha, \beta)$ to obtain the posterior predictive distribution $\omega_1(\phi|y)$. This distribution is known as the population variability curve (PVC) and can be written as:

$$\omega_1(\phi|y) = \iint \omega_0(\phi|\alpha, \beta)\ g_1(\alpha, \beta|y)\ d\alpha\ d\beta \tag{4-13}$$

This distribution represents the source–to-source uncertainty in ϕ and can be used as an informative prior distribution when more case-specific data become available:

$$\omega_1(\phi|y^*, y) = \frac{\omega_1(\phi|y)\, L(y^*|\phi)}{\int \omega_1(\phi|y)\, L(y^*|\phi) d\phi} \tag{4-14}$$

$$\omega_1(\phi|y^*, y)\ \propto\ \omega_1(\phi|y) L(y^*|\phi) \tag{4-15}$$

4.7 Uncertainty Modelling (Step 4)

Due to the many limitations of the AND- and OR-gates in modelling all potential interactions among causes and their effects, it is necessary to implement more advanced logics to handle the uncertainties associated with causations representation. Although, the theory of reasoning under uncertainty is well covered by Bayesian networks robust computation engine. However, numerous challenges are a commonplace in the problem formulation due to the lack or insufficient knowledge of the precise failure data and the assumptions built into the parameter modelling. To address these uncertainties associated with failure data and model parameters, three relaxation strategies – the noisy-OR (N-OR), leaky noisy-OR (LN-OR), and the imprecise leaky noisy-OR (ILN-OR) are developed and tailored to suit the elicitation issues (Fallet-Fidry et al., 2012; Antonucci, 2011).

4.7.1 Noisy-OR

The N-OR logic gate is part of proven tools widely adopted in the safety and risk analysis of process systems and medical sciences field. The N-OR gate is, especially, popular because of its ability to reduce the dependence elicitation of the conditional probabilities from exponential to linear causals within a Bayesian network. It relies on the assumption that a single causation can trigger the occurrence of an undesired event provided the causal is unhindered, that is, even if a causal is actively present (in its true state), such causal may still not be sufficient to initiate the end event occurrence (Pearl, 1988). This underlying assumption is realistic and often encountered in practice, however, events such as Boiling Liquid Expanding Vapour Explosion (BLEVE) caused by the rupture of a pressurized liquid vessel above its boiling point has been reported to have occurred even when the liquid is not flammable or without notable rupture of the vessel. The BLEVE is one of a rare accidents scenario where the end consequence may occur without the causal being in its true state, necessitating the need to accommodate a 'leaky' probability in the model formulation.

The Noisy-OR gate is one form of canonical interaction that is extensively used in Bayesian networks. The Noisy-OR gate belongs to the category of models widely referred to as being Independent of Causal Influences (ICI). The Noisy-OR gate is applicable when there are numerous possible causes $A_1, A_2, A_3 \dots, A_n$ of an effect variable Y. The model has two assumptions: (1) Each of the causes A_i has a probability p_i strong enough to cause Y, when other causes are absent. (2) Each of the causes A_i influences Y independently from each other. The noisy model requires specification of n parameters p_1, p_2..., p_n. p_i is the probability that effect Y is true given that cause A_i is true and all other causes A_j, $j \neq i$, are false (Oniśko et al., 2001). Therefore, the two outcomes of variable A_i are represented by a_i and $\bar{a}_i$. The probability of y provided a subset A_j of the A_i's that are true is given by the following formula, from which the complete CPT of Y is conditional on its parents $A_1, A_2 \dots., A_n$ can be derived.

$$p\left(Y \middle| A_j\right) = 1 - \prod_{i:A_i \epsilon A_j} (1 - p_i) \qquad \text{(4-16)}$$

The Noisy-OR model benefits from a considerable reduction in the number of probabilities needed to elicit the interactions among causations and consequences within the CPT. The model only requires "n" probabilities, unlike the unrestricted model which needs 2^n probabilities to completely elicit the cause-consequence interactions (Heckerman & Breese 1996).

4.7.2 Leaky Noisy-OR

The leaky N-OR logic gate is an extended form of the N-OR gate developed to account for the possible occurrence of an undesirable event even though none of the causations is actively present (Medina-Oliva et al., 2009; Simon and Weber, 2009). The leaky N-OR thrives on the assumption that an uncaptured hazard with a nonzero probability is independently sufficient to trigger an accident even though all captured causals are inactive (i.e., in their false states). This uncaptured hazard is termed a '*leak probability*'. Since a BN, despite its numerous uncertainty modelling potentials, is a family of parametric models intended to represent problems as close to realistic as possible, it also falls short to completely represent accident practicality. To that end, the application of 'leaky probability' is crucial to represent the uncaptured variables that can influence the outcome of a rare accident event. The leak probability is the probability that the leak scenario exists. The precision of such leaky probability modelling is dependent on the derivation of a probability that the child node could be active (i.e., present) given that each of the causal (parent node) explicitly identified in the Bayesian network was inactive (i.e., absent). Forms of the leaky N-OR gates have been developed as a strategy to relax the conditional probabilities by different researchers as can be found in literatures (Lemmer and Gossnik, 2004; Bobbio et al., 2001; Onisko et al., 2001). From the foregoing, one critical issue that has not been considered in both N-OR and LN-OR is the comprehensive elicitation of the uncaptured probabilities. In addition, the N-OR and LN-OR formalisms describe the uncaptured probabilities in accident scenarios where only a single cause is present, but in practice, many causes may be active concurrently thereby undermining the quantification assumptions and precisions of these models.

Since the Noisy-OR gate does not consider the situation where a subsystem could fail despite that its components are all active and functional. Therefore, the leaky Noisy-OR considers a situation where the consequence variable is true though all its causes are false. The Leaky model presumes a positive probability called leaky probability (l). Leaky probability is the probability that effect Y will occur spontaneously though all its causes are false. The model is applicable where it is impossible to capture all potential causes that could make effect Y occur. The effect of leaky probability could be easily modelled by the influence between A_i and Y that has changed due to the addition of an unknown or uncaptured hazard (Bobbio et al. 2001; Wasyluk 2001; Zagorecki

& Druzdzel 2004). Therefore, the leaky Noisy-OR gate formula that can be used to calculate the probability of Y given the subset A_j of the A_i which are true is expressed as.

$$p(Y|A_j) = 1 - \left[(1-l)\prod_{i:A_i\epsilon A_j}(1-p_i)\right] \qquad (4\text{-}17)$$

The Leaky Noisy-OR (LN-OR) formalism is especially, applicable to decommissioning and abandonment operations where reservoir conditions, the age of the well and platform, mechanical, physical, and chemical damages within the casings of the wellbore are all variables of uncertainty and could be more. The accident contribution from each node A_1, A_2 and A_3 is assumed to be independently capable of leading to the consequence node A_4 when other root nodes are absent. In practice, this need not be true, as there are uncaptured hazardous events not represented in the model that can cause the failure of the system. These uncaptured events are accounted for by introducing an additional parameter l '*leaky probability',* such that $0 \leq l_o < 1$. The leak probability assumes that the occurrence of uncaptured events will adequately provide new knowledge of the consequence event by incorporating another causal variable L, with a *'link probability'*, given by $l_o = P_i$. It is to be noted that this additional parameter, albeit efficient, does not consider the uncertainty associated with leak probability, link probability and the outcomes of the parent variables in the accident model (Antonucci, 2011; Fallet-Fidry et al., 2012; Babaleye et al., 2019). These uncertainties can be parametised using data uncertainty modelling formalism.

4.7.3 Extended Leaky Noisy-OR

To compliment, rather than, phase out the capabilities of the N-OR and LN-OR logic gates, an imprecise leaky N-OR gate is formulated with the view to a wider and realistic representation of the uncaptured probabilities. Antonucci (2011) proposed the ILN-OR formulation to allow for the probabilities to be flexible enough to represent sets of distributions in intervals, as an improvement to the common single probability distributions. Fallet-Fidry et al. (2012) applied this improved probability formulation in their evidential network-based extension to support risk analyses. Three areas of uncertainties are present in the other two models, and these are the prior probabilities, the leak probability used to define the uncaptured hazards, and the link probability associating the parent nodes to their corresponding child node. To put these in context, the prior probabilities are estimated from sparse failure data obtained from source-to-source or exert judgement and are lacking in sufficient knowledge of the overall state or condition of the system to be analysed. The number of uncaptured hazards including their occurrence or nonoccurrence states cannot be ascertained in most cases. Furthermore, the strength of influence of a modelled causal event on its outcome is also a variable of uncertainty. The ILN-OR offer a unique probability modelling advantage referred to as "*ignorance"*. The concept of ignorance model centers around the understanding that accident contributory factors can exist beyond binary states. Often, each causal is represented to be true or false, but no co-existence of states has been thought possible. However, it could be practical to assume that the presence of a single causal may not lead to the failure of its end consequence. This means that the existence of a cause does not imply it is sufficiently capable to cause the end event to fail. To this end, it is realistic to adopt a model that can present this new knowledge or evidence using interval-based probabilities due to its robustness.

Therefore, the extension of the LN-OR – imprecise noisy-OR (ILN-OR) – is introduced to account for the uncertainty associated with elicitation parameters and unknown condition of the reservoir leading to inaccurate failure data state variables estimations in the risk model (Fallet-Fidry et al., 2012). The ILN-OR assumes that occurrence and non-occurrence representation of state variables are not sufficient due to the probability that the state variable may or may not exist. For the sake of simplicity, the leaky probability, and corresponding link probability are assigned a lower and upper bound, such that $l_{min} \leq l_o < l_{max}$ and $P_{i,min} \leq P_i < P_{i,max}$. Such assignments will enable the state variables to be represented as either being true, false, or true-false simultaneously. This is primarily a practical way to obtain failure probabilities in intervals rather than discrete values, to provide the risk assessor enough information to develop a conservative safety mechanism. Thus, an extended CPT for the accident model is given by.

$$p\left(A_i = \{a_i\} \middle| A_{j,j\neq i}\right) = 1 - [(1 - l_{min}) \prod_{i:l_j \epsilon A_j}(1 - p_{i,min})] \tag{4-18}$$

$$p\left(A_i = \{\bar{a}_i\} \middle| A_{j,j\neq i}\right) = [(1 - l_{max}) \prod_{i:l_j \epsilon A_j}(1 - p_{i,max}) \cdot \prod_{i:l_j \epsilon A_{ij}}(1 - p_{i,max})]] \tag{4-19}$$

$$p\left(A_i = \{a_i, \bar{a}_i\} \middle| A_{j,j\neq i}\right) = [(1 - l_{min}) \prod_{i:l_j \epsilon A_j}(1 - p_{i,min})] - (1 - l_{max}) \prod_{i:l_j \epsilon A_j}(1 - p_{i,max}) \cdot \prod_{i:l_j \epsilon A_{ij}}(1 - p_{i,max})]] \tag{4-20}$$

Where l_{min} and l_{max} are the minimum and maximum leak probabilities, $p_{i,min}$ and $p_{i,max}$ are the corresponding link probabilities, $p\left(A_i = \{a_i\} \middle| A_{j,j\neq i}\right)$ is the occurrence probability of A_i given the failure of $A_{j,j\neq i}$, $p\left(A_i = \{\bar{a}_i\} \middle| A_{j,j\neq i}\right)$ is the non-occurrence probability of A_i given the failure of $A_{j,j\neq i}$, and $p\left(A_i = \{a_i, \bar{a}_i\} \middle| A_{j,j\neq i}\right)$ is the probability of ignorance of occurrence or non-occurrence of A_i given the failure of $A_{j,j\neq i}$.

Equations (4-18), (4-19) and (4-20) enable the states of both parent and child nodes to be specified with more than binary states. To incorporate the uncertainty of the states of the parent variables, $a_3, \bar{a}_3$ a modality probability x is assigned. For example, the CPT of A_3 given the causations A_1 and A_2 is as presented in Table 4-2. Imprecise leaky noisy-OR CPT for node $\boldsymbol{A_3}$, where $p_{i,min}$ is assumed to be equal to $p_{i,max}$ and $l_o = l_{min} = l_{max}$.

Table 4-2. Imprecise leaky noisy-OR CPT for node A_3

A_1	a_1			$\bar{a}_1$			$a_1, \bar{a}_1$		
A_2	a_2	$\bar{a}_2$	$a_2, \bar{a}_2$	a_2	$\bar{a}_2$	$a_2, \bar{a}_2$	a_2	$\bar{a}_2$	$a_2, \bar{a}_2$
a_3	$p_1 p_2$	p_1	xp_1	p_2	l_o	xl_o	xp_2	xl_o	$x^2 l_o$
$\bar{a}_3$	$(1 - p_1)(1 - p_2)$	$1 - p_1$	$1 - xp_1$	$1 - p_2$	1	x	$1 - xp_2$	x	x^2
$a_3, \bar{a}_3$	$p_2 + p_1 - 1$	$2p_1 - 1$	$2xp_1 - 1$	$2p_2 - 1$	l_o	$x(l_o - 1)$	$2xp_2 - 1$	$x(l_o - 1)$	$x^2(l_o - 1)$

4.8 Dynamic Bayesian Network (Step 5)

Dynamic Bayesian network (DBN) is a form of BN that thrives on temporal dependencies of accident contributory factors to model the dynamic behavior of localised random variables. DBN is a method used in rare accident scenarios where localised model events evolve over time. Each localised model is represented as a time slice and is connected to other localised models via temporal arcs. Each time slice depicts a static BN at a given time step t, such that a node at the time step $(t+1)$ is conditionally dependent on both the parents of the $(t+1)^{th}$ time slice and the parents of the t^{th} time slice, as shown in Figure 4-8. The temporal arcs linking interacting random variables in different time slices denote a time-variant probabilistic dependence. The DBN thrives under two fundamental assumptions to avert infinite complexities in its computation. The first being that the model must be stationary and the other being that the model must follow the Markov chain formalism. The stationary requirement requires that the laws governing the relationship among interacting events remain constant, although the probability distribution of the events might evolve. The Markov Chain formalism requires implies that the posterior states of interest depend on a finite number of prior states, even though, there are sufficient historical data with infinite prior states.

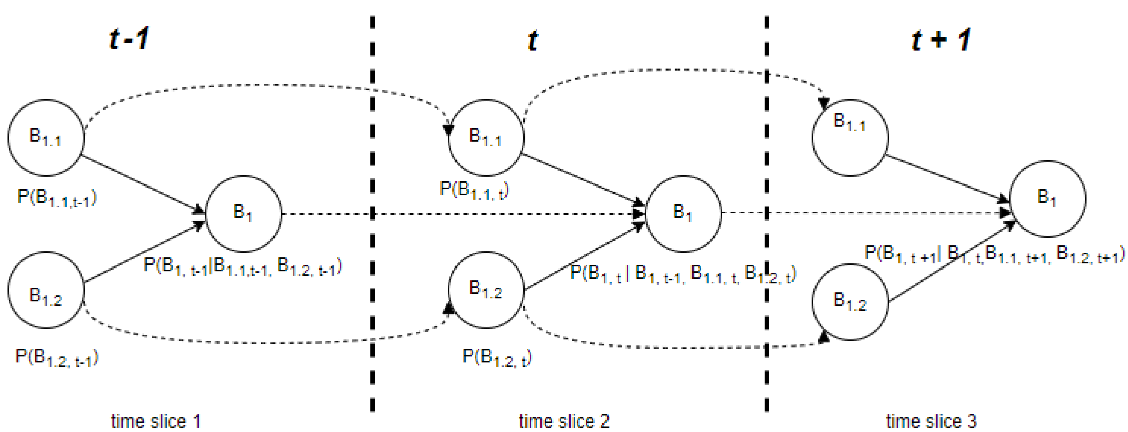


Figure 4-8 DBN model with temporal dependence

The computational robustness of DBN aims to proffer localised model response where accident evolution is imminent, such as is the case with decommissioning and abandonment operation. One additional advantage offered by the DBN is in its capability to model probability distribution over a finite random variable with infinite number of constraints. Consider Figure 4-3 (above),

$$P(y_i^t) = \prod_{i=1}^{5} P(\, y_i^t | y_i^{t-1}, y_{\mu(i)}^{t-1}, y_{\mu(i)}^t) \qquad (4\text{-}21)$$

Where $P(y_i^t)$ is the joint probability distribution of the state variables y_i of the i^{th} node in time-slice t. $\mu(i)$ is the parent of variable node i, which can be at the same time-slice t or the preceding time-slice $(t-1)$.

For a pair of BNs, BN_1 and BN^*, the DBN defines the characteristics of BN_1 with a prior failure probability $p(y_1)$, and defines BN^* as a two-slice temporal Bayesian network with dependencies modelled as a product of the CPTs within the temporal BN. The first node of the two-slice temporal BN is assigned a statistically independent prior state distribution with a node, $p(y_i^{i:N})$ and all nodes in the subsequent time-slice are assigned their corresponding CPTs. The joint probability distribution of a DBN with an N_t slices is given by:

$$p(y_{i:N_t}^{i:N}) = \prod_{i=1}^{N} P_{BN_1}(\, y_i^t | y_{\mu(i)}^t) \times \prod_{t=1}^{N} \prod_{t=2}^{N_t} P_{BN^*}\, (\, y_i^t | y_{\mu(i)}^t) \qquad (4\text{-}22)$$

4.9 Model Validation (Step 6)

This research work is motivated by the scarcity of historical data or literature and where there are such data, it is often sparse due to limited knowledge of the decommissioning and abandonment operational hazards in its entirety. To that end, it is both a necessity and a matter of significance to verify and validate the correctness of the quantitative risk assessment methodology proposed. This is especially required to provide an objective quality evidence with a considerable confidence level in the obtained failure probability results. Therefore, this research work is validated in a series of steps, as discussed below.

(i) *Model Formulation Verification.* In this step, the model is formulated based on the phases of activity needed to decommission and abandon the systems. The potential accident scenarios from each phase are analysed and systematically constructed using appropriate accident scenarios analysis and evolution tool – bowtie, fault tree and event tree – to ensure that the model has been formulated in the most practical and realistic manner. For the sake of reasonable argument, the bowtie developed for the accident scenarios in this thesis were conducted and examined by a combination of reputable academics and industry experts in a technical workshop.

(ii) *Techniques Comparative Analysis.* Conventional quantitative risk assessment - such as FT, ET, and BT – though able to analyse the risks associated with simple to complex engineering systems, they are not capable of modelling common cause failures, dependencies amongst accident contributory factors or dynamic behaviour of events from a time t to $t + \delta t$. The results obtained from the proposed model are examined and compared with those obtained through the conventional QRA. To preserve the confidence in modelling and analysis, similar data obtained through HBA as shall be seen in succeeding Chapter, are used as priors in both the conventional QRA and the proposed dynamic safety model.

(iii) *Sensitivity Analysis.* The degree of response of an infinitesimally small change in the accident contributory factors on the accident itself has been a proven method to examine how sensitive the consequences are to their associated causals. Several methods such as the Birnbaum Importance Measure (BIM), the Improvement Potential Measure (IPM), Risk Achievement Worth (RAW), Risk Reduction Worth (RRW), the Criticality Importance Measure (CIM), Fussell-Vesely's Measure (FVM), and the Shannon's Mutual Information (entropy reduction) method are commonplace within the reliability industry for predicting the safety critical factors (Chybowski et al., 2014;

Verma et al., 2010; Fricks and Trivedi, 2003). In the context of DBN, the entropy reduction sensitivity model is the most robust and widely used measure of safety critical factors during information sources ranking (Kjærulff and Madsen, 2013). It defines the mutual information among sources as the total potential uncertainty reduction, R given the original uncertainty in R_i prior to consulting R_j. The entropy reduction, as a sensitivity measure, enables the reduction of one variable through the knowledge of another related variable as expressed in Equation (4-21).

$$I^{ER}_{(R_i,R_j)} = -\sum_i \sum_j p\left(R_i, R_j\right) log \frac{p(R_i,R_j)}{p(R_i)p(R_j)} \qquad (4\text{-}21)$$

Where

$\boldsymbol{I^{ER}_{(R_i,R_j)}} =$	the importance measure by entropy reduction of root causes $\boldsymbol{R_i}$ and $\boldsymbol{R_j}$
$\left(R_i, R_j\right) =$	root causes R_i and R_j, respectively.
$p\left(R_i, R_j\right) =$	the joint probability distribution function of root causes R_i and R_j
$p\left(R_i\right), p\left(R_j\right) =$	the probability distributions of root causes R_i and R_j, respectively

However, as decommissioning and abandonment operation is not an investment, there is generally no considerable incentive to implement elaborate analysis. As a result, the sensitivity analysis adopted in this study relies on Fussell-Vesely's importance measure metric, $IM^{FV}_{B_j}$. The $IM^{FV}_{B_j}$ is a form of risk reduction worth and is expressed as shown in Equation (4-22).

$$IM^{FV}_{B_j} = \frac{\partial p^{TE}_{(B_i)}}{\partial p_{(B_j)}} \frac{p_{(B_j)}}{p^{TE}_{(B_j)}} = \frac{p^{TE}_{(B_j)} - p^{TE}_{(B_j=0)}}{p^{TE}_{(B_j)}} \qquad (4\text{-}22)$$

Where $\boldsymbol{IM_{B_j}^{FV}} =$ Fussell-Vesely's importance measure metric

$p_{(B_j)} =$ Failure probability of root cause B_j

$p_{(B_j)}^{TE} =$ the parent risk level defined by the top event failure probability

$p_{(B_j=0)}^{TE} =$ the decreased risk level with the basic event of interest optimised or assumed to be active i.e., with 100% reliability or in its true state.

4.10 Economic Risk Modelling (Step 7)

The economic risk model commences after the risk analysis results have been obtained, as discussed from steps 1 to 6. The Economic Risk Analysis (ERA) builds upon the failure probabilities obtained in the dynamic state modelling steps following validations through sensitivity analysis. The tools and techniques from steps 1-6 are also used herein to ensure the assessment is complete, comprehensive and robust. The ERA is developed to account for the future value of money and provide a substitute for the unknown inflation rates and Assets Retirement Obligation (ARO) information. It laid bare the implications of failing to capture hazards before thy manifest into an uncontrollable and undesired event, that may result in heavy financial burden on the Oil and Gas producers in the event of site remediations and clean-ups.

4.11 Research Framework

The framework of this study is aimed at developing a systematic approach to address several identified concerns related to decommissioning and abandonment of offshore well P&A and Steel Piled Jacket (SPJ) removal. One of the major issues is the sparsity of failure data needed to conduct a detailed probabilistic risk analysis. This data paucity forms the basis for developing a statistical method capable of addressing the issues associated with small-sized data analysis in the Chapter 5. The problem of unknown reservoir conditions associated with plugging and abandonment, the influence of time dependence on the model response and method to reduce the associated modelling and parameter uncertainties are as presented in Figure 4-9.

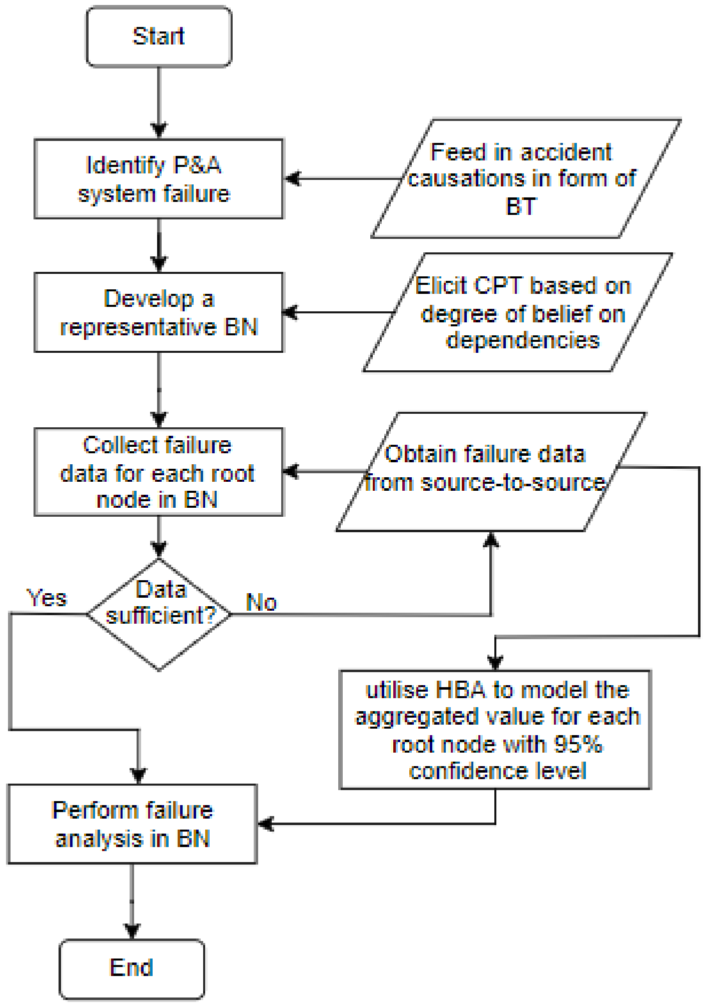


Figure 4-9 Research framework flowchart

Chapter 5: Sparse Data Modelling for Risk Analysis

5.1 Outline

This Chapter demonstrates the application of the Hierarchical Bayesian Analysis to aggregate the failure probabilities of accident contributory factors as a mean distribution with 95% confidence level. The HBA methodology thrive on the statistical models capable of modelling multi-stage data based on the concept of source-to-source variability. Weibull and Gamma distributions are presented in Section 5.3. Section 5.4 presents the application of the proposed HBA models and comparisons are made between both methods using the data obtained in a Design-for-Decommissioning (DfD) workshop. Results and discussions emanating from the analysis are presented in Section 5.5 followed by the concluding remarks on the credence of the proposed methodology in Section 5.6.

5.2 Introduction

Decommissioning and abandonment operations are characterised by inherent and environmental risks. To quantify these risks, a comprehensive quantitative risk analysis must be performed. However, the complexity of the operation and overall knowledge of associated hazards often rely on the personnel's experience. Literature and historical information required to obtain failure probabilities are usually sparse or lacking, altogether. Therefore, it is not uncommon to adopt a variety of information sources from analogous operations such as mining, aerospace, and related offshore drilling hazards. One major issue associated with such approach is the additional uncertainties introduced due to assumptions and dissimilarities of operational sequences. The risk estimation becomes inaccurate leading to consequences capable of endangering personnel lives, the environment, and loss of assets to be decommissioned and/or abandoned.

The primary concern with well integrity assurance during and after abandonment is the release of hydrocarbon-containing fluid which may lead to fire and explosion if ignition source is present.

The accurate prediction of potential release of hydrocarbon-containing fluid is necessary to preserve the safety of complex engineering activities. The consequence of such inaccurate accident prediction can be significant, putting human life and the environment at stake. A parameter of interest (such as failure rate, failure probability, Mean Time to Failure (MTTF) etc.) needs to be defined and calculated to ascertain the risk level associated with major accidents. To address the afore-mentioned issues, it is necessary to develop a considerable risk estimates capable of aggregating sparse failure data for each causal event and yielding acceptable risk value for the parameter of interest. This is, especially, important in order to obtain considerable results with reduced uncertainty and acceptable confidence level. The gathered data from analogous sources with unrelated characteristics emanating from dissimilar operational conditions, geographical location, topology, operational sequence, and subjective expert opinions can be aggregated to obtain the desired estimates through systematic quantitative risk analysis. This approach has become a commonplace in the decommissioning and abandonment industry to address the challenges posed by data availability and sparsity. What is not common, on the other hand, is the standardization of a robust technique required to accurately estimate the failure probability or failure rate of the high-level hazardous event using these partially related group-level data.

Generally, APD is often used as input to the HBA models for conducting probabilistic risk analysis. However, the APD is typically flawed since they are often obtained from variety of source with unrelated complexities, locations, and activities. The implication of implementing such analogous data is that it does not exactly reflect the inherent chain of events leading to the evolution of accident under study, making the risk analysis depending on the APD susceptible to a degree of uncertainty.

In this thesis, a method to aggregate the source-to-source data based on statistical distribution is introduced. In particular, the two-parameter Weibull distribution and the Gamma distribution are compared as viable methods to process the collected data with 95% confidence level. The distribution method yielding the most practical approximation suitable for the type of accident scenarios analysis in this study would then be the primary source of failure data used throughout the rest of this work, as shall be seen later in subsequent Chapters.

5.3 Selection of relevant data distribution method

5.3.1 Weibull Distribution

The empirical Weibull distribution function was developed primarily to describe the reliability of technical products as an extended form of the exponential family of statistical distributions (Rinne, 2008; Weibull, 1951). It has been widely used in numerous industries to obtain reasonable estimates for parameters of interests. For example, in stress and structural analysis where breaking strength data have paucity limitations or in survival analyses (Lawless, 2003) and extreme value prediction (Carter and Challenor, 1983). Duerr and Grashoff (1999) adopted the Weibull distribution function to demonstrate and describe the heat exchanger cleaning-in-place kinetics in the process industry.

Forms of Weibull distribution have been developed by many researchers to address multitude of engineering challenges and peculiar cases similar to those encountered in decommissioning and abandonment operations. For instance, the Weibull distribution is characterised by its survival and hazard functions. The hazard function is often represented by an increasing, constant, and decreasing rate, making it unsuitable for modelling sizable numbers of real lifetime data encountered in practical engineering systems which follow the bathtub-shaped failure rate. The common forms of Weibull distribution ranges from two- to five-parameter. Notable extensions of the two-parameter family are the flexible Weibull distribution (Bebbington et al., 2007) and the truncated Weibull distribution (Zhang and Xie, 2011). The two-parameter form has a Probability Density Function (PDF) given by

$$p(y) = \frac{\alpha}{\beta}\left(\frac{y}{\beta}\right)^{\alpha-1} e^{-\left(\frac{y}{\beta}\right)^{\alpha}} \qquad , p(y) \geq 0, \alpha, \beta > 0 \tag{5-1}$$

Where α and β are the shape and scale parameters, respectively. These hyper-parameters help to characterise the degree of spread amongst the source-to-source data and are related to one another as expressed below

$$\beta^2 = \sigma^2 \left[\left(\Gamma\left(1+\frac{2}{\alpha}\right)\right) - \left(\Gamma^2\left(1+\frac{1}{\alpha}\right)\right)\right]^{-1} \tag{5-2}$$

Where Γ and σ^2 are the gamma function and variance of the distribution, respectively. Equation (5-2) reveals that the scale parameter increases proportionately with the variance in the data and the shape parameter α is associated with the availability of sufficient failure data, that is, a low α-value indicates the presence of data while a high α-value implies data paucity. For the sake of simplicity, datasets with $\alpha < 1$ exhibits a decreasing failure rate over time. Where $\alpha > 1$, the failure rate increases with time and a unity shape parameter indicates a constant failure rate. The gamma function Γ of the distribution shown in Equation 5-2 is expressed as

$$\Gamma\,(k) = \int_0^{\infty} \mathrm{e}^{-\mathrm{y}} y^{k-1} dy \tag{5-3}$$

Generally, the gamma function can be interpreted numerically if the right-hand term converges to a real number such that $\Gamma(k) = (k-1)!$. Given the set of data from source-to-source, the expected Mean Time to Failure (MTTF ($\bar{T}$)) or Weibull mean life for a decommissioning and abandonment accident occurrence is estimated by

$$\bar{T} = \beta\Gamma\left(1+\frac{1}{\alpha}\right) \tag{5-4}$$

Equation (5-4) holds that the MTTF demarcates causations that have the Most Probable Cause (MPC) of failure from causations whose influence on the overall accident scenarios are insubstantial. For example, large values of $\bar{T}$ indicates increased proportion of causations with fitness on the Weibull distribution plot and vice versa.

5.3.1.1 Numerical Estimation of Parameters

In the statistical estimation of a probability distribution of parameters, Maximum Likelihood Estimator (MLE) is the widely adopted method used to maximise a likelihood function such that the observed datasets are the most probable data for the study of interest. The MLE thrive on the assumption that observed data are independent and identically distributed, in practice, this need not be true, making the assumption an additional source of uncertainty especially for very small sample size. Nwobi and Ugomma (2014) compared methods for the estimation of MLE parameters using the Mean Square Error (MSE) and the Kolmogorov-Smirnov (KS) criteria. However, estimation of the failure probability for each accident causations using the Weibull distribution method requires extra effort of interpolating the distribution with relatively less reliable goodness fit. To address this, the MLE of the scale parameter β given the shape parameter α is given by

$$\beta = \left(\frac{1}{N}\sum_{i=1}^{N} y_i^{\alpha}\right)^{\frac{1}{\alpha}} \qquad (5\text{-}5)$$

Where y_i is the dataset and N is the observed number of trials or demands during the decommissioning and abandonment operation. From Equation (5-5), the MLE for α can be obtained numerically from the implicit solution of the function

$$\frac{\frac{1}{N}\sum_{i=1}^{N} y_i^{\alpha} \ln y_i}{\frac{1}{N}\sum_{i=1}^{N} y_i^{\alpha}} - \frac{1}{\alpha} - \frac{1}{N}\sum_{i=1}^{N} \ln y_i = 0 \qquad (5\text{-}6)$$

5.3.1.2 Linearised Estimation of Parameters

The Cumulative Density Function (CDF) of Equation (5-1) is obtained from the unreliability term given by

$$P(y) = 1 - e^{-\left(\frac{y}{\beta}\right)^{\alpha}} \quad , P(y) \geq 0, \alpha, \beta > 0 \qquad (5\text{-}7)$$

The linearised form of the CDF is given by Equation (5-8) below and can be depicted on a Weibull plot which takes the form of the equation of a straight line with slope m and intercept c. Equation 5-7 is resolved with variables change as

$$\ln\left(1 - P(y)\right) = -\left(\frac{y}{\beta}\right)^{\alpha}$$

$$\ln\left(-\ln\left(1 - P(y)\right)\right) = \alpha \ln y - \alpha \ln \beta \qquad \text{(5-8)}$$

Where Equation (5-8) compares with $z = my + c$ from which $m = \alpha$ (the slope or shape parameter) and $c = -\alpha. ln\beta$, the intercept. Since both dependent and independent variables have been linearised in logarithmic forms, a straight-line log-log plot can be used to describe the data characteristics. The interpretation of this linearised model follows that a sparse dataset modelled as a Weibull distribution is expected to yield a linear Weibull plot.

To process the data, an empirical distribution function should be defined to facilitate the estimation of the ordinate axes (unreliability). One of such function is the Bernard's approximation expressed as

$$P(y) = \frac{k - 0.3}{n + 0.4} \qquad \text{(5-9)}$$

Where k is the event failure order and n, the sample size. The approximation assumes that the true probability of failure $P(y)$ value should occur at the k^{th} failure from a sample size n at a confidence level of 50%. Although, this method helps to manually compute the failure probability of an event of interest, it is by no means an easy task due to the amount of effort required.

5.3.2 Gamma Distribution

The gamma distribution is an extended form of several other statistical distributions such as the exponential distribution, the Weibull distribution, the log-normal distribution, the Chi-squared distribution, and the Erlang distribution. It is especially suitable for estimating datasets of interests and estimation parameters. The gamma distribution thrives on the understanding that it is potentially a difficult task to obtain a posterior inference from a prior distribution, which represents the current state of knowledge of the events under study (El-Gheriani et al, 2017a). For example, datasets sourced from a single source of similar group of sources are expected to produce a predictable trend. In practical scenarios encountered among complex engineering systems, this expectation is not usually true. It is not uncommon to observe dissimilarities in the model parameters due to dependency amongst the data, particularly, when the available sample size is quantitatively small. In addition, Gamma distribution has been proven to be well suited for modelling temporal variability in deteriorated assets and for predicting inspection and maintenance intervals due to the informative prior and posterior possibilities (Pandey et al., 2009; Van Noortwijk, 2009). In general, data analysis tools such as regression analysis and/or Monte Carlo simulation would graphically show a unique correlation between the distributions. Independent assumptions from these correlations can immediately invalidate the results obtained through these methods (Seco et al., 2001).

For this reason, Gamma distribution can be adopted to estimate the parameter of dependence using the prior knowledge of the distribution. As a family of the reliability tools, it can be used to model the lifetime of systems or components. For a given random variable y distributed over a standard gamma distribution, the Probability Density Function (PDF) is expressed as

$$p(y|\alpha,\beta) = \begin{cases} \frac{\beta^{\alpha}}{\Gamma(\alpha)} y^{(\alpha-1)} e^{-\beta y}, y > 0 \\ \qquad\quad 0 \qquad , y \leq 0 \end{cases} \tag{5-10}$$

Where $\alpha > 0$ is the shape parameter defining the shape of the distribution, and $\beta > 0$ is the scale parameter representing the spread among the dataset distribution. The mean and variance of the distribution are given by

$$\mu = \alpha\beta = \frac{\left(\Gamma\left(1+\frac{1}{\alpha}\right)\right)}{\beta\Gamma(\alpha)} \tag{5-11}$$

$$\sigma^2 = \alpha\beta^2 = \frac{\left(\Gamma\left(1+\frac{2}{\alpha}\right)\right)\Gamma(\alpha) - \left(\Gamma^2\left(1+\frac{2}{\alpha}\right)\right)}{\beta^2\Gamma^2(\alpha)} \qquad (5\text{-}12)$$

The parameter estimation technique also uses the maximum likelihood estimation approach similar to that discussed for Weibull distribution. One advantage offered by the gamma distribution is its ability to model multi-stage level distribution, making it especially ideal for decommissioning and abandonment scenarios where many factors contribute to the uncertainty. The gamma distribution thrives in the modelling due to its conjugate prior for the precision of a normal distribution. That is, it is a conjugate pair to itself – both the prior and posterior distributions are in the same gamma distribution family. A convenient conjugate pair of the Gamma distribution can be a Poisson or a Binomial likelihood, as the following proof would show. Given a set of data Y_i distributed over λ, a Poisson distribution of the form below is generated

$Y_i \sim Po(\lambda)$

$$P(Y_i \mid \lambda) = \frac{\lambda^{Y_i} e^{-\lambda}}{Y_i!} \qquad (5\text{-}13)$$

For a prior λ distributed over gamma with given shape and scale parameters of interest α and β, then

$$\lambda \sim gamma(\alpha, \beta)$$

$$P(\lambda \mid \alpha, \beta) = \frac{1}{\Gamma(\alpha)} \beta^\alpha \lambda^{\alpha-1} e^{-\beta\lambda} \qquad (5\text{-}14)$$

The primary aim here is to demonstrate that the posterior distribution of λ has a similar form to the right-hand side of Equation (5-14). Since Bayes' theorem is used to estimate under uncertainty, it can be inferred here to justify the proof, thus

$$P(\lambda \mid Y_i) = \frac{P(Y_i \mid \lambda) P(\lambda)}{P(Y_i)} \qquad (5\text{-}15)$$

It can be seen that the denominator of Equation (5-15) does not contain λ and can be excluded from the likelihood expression in comparison with the right-hand side of Equation (5-14). The posterior distribution will be proportional to the likelihood probability of Y_i given λ and expressed as

$$P'(Y_i) \propto P(Y_i \mid \lambda)P(\lambda) \tag{5-16}$$

Assuming $Y_i = \begin{pmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ y_N \end{pmatrix}$ are interchangeable and independent variables, then

$$p(Y_i \mid \lambda) = \prod_{i=1}^{N} \frac{\lambda^{Y_i} e^{-\lambda}}{Y_i!} = \frac{\lambda^{(Y_1+Y_2+\cdots+Y_N)} e^{-N\lambda}}{\prod_{i=1}^{N} Y_i!} \tag{5-17}$$

Similarly, the denominator of Equation (5-17) can be discarded as it does not contain λ term; From which the likelihood function becomes $P(Y_i \mid \lambda) \propto \lambda^{(Y_1+Y_2+\cdots+Y_N)} e^{-N\lambda}$. Noting that the averaging of the random variable y can be expressed as $\sum_{i=1}^{N} y_i = N\bar{y}$. The likelihood function invariably simplifies to

$$P(Y_i \mid \lambda) = \lambda^{N\bar{y}} e^{-N\lambda} \tag{5-18}$$

The posterior distribution can now be formulated such that $P(\lambda \mid Y_i) \propto P(Y_i \mid \lambda)P(\lambda)$ which yields,

$$P(\lambda \mid Y_i) = \lambda^{N\bar{y}} e^{-N\lambda} \lambda^{\alpha-1} e^{-\beta\lambda} = \lambda^{N\bar{y}+\alpha-1} e^{-(\beta+N)\lambda} \tag{5-19}$$

Equation (5-19) excludes the term $\frac{\beta^\alpha}{\Gamma(\alpha)}$ because it is independent of λ. It is worthy of note that this equation is a form of gamma distribution with parameters $\lambda \sim gamma(N\bar{y} + \alpha, \beta + N)$. Therefore, it can be inferred that the posterior probability distribution of a gamma prior is a conjugate pair of Poisson (or Binomial) likelihood function.

5.4 Application of Methodology

The Elgin oil well platform represents a suitable real life plugging and abandonment accident wherein personnel struggled to understand the failure mechanisms and dynamics. The absence of an ignition source invariably helped to contain what could have been a life-threatening catastrophe. By and large, the blowout and uncontrollable spill dragged on for over seven (7) weeks before the well was eventually killed (Total, 2013). The plugging and abandonment operations are typically experienced-driven and as a result flawed by subjective expert judgement of incidence possibilities. Therefore, it is necessary to reduce the uncertainties associated with this rigorous activity to the barest minimum. It is a common encounter that different experts in a group would rank a single event occurrence differently. This observation is exacerbated as the expert group widens and events become larger. The notable challenges surrounding the well attributes are the knowledge of the platform, nature of the reservoir and the wellbore design as indicated in Table 5-1. In accident scenarios analyses, the probability of occurrence and the resulting consequence(s) are important metrics for establishing the risks of any system. These two properties are not directly obtainable in the decommissioning and abandonment of oil and gas wells. This is especially the case due to the uncertainty in the well attributes condition and limited data readily available for the risk estimation.

As shown in Table 5-1, a hydrocarbon-containing and flowing or non-flowing reservoir have a high impact on the end consequence. However, the fluid severity can both be influenced by a high probability of occurrence and equally high influence on the end consequence. In terms of the wellbore, the probability of failure is driven by ageing and service life of components. Where the integrity of the wellbore is intact, the failure of the system is not imminent and as such, not influenced by the end consequence. For the platform, both environmental zone, facility complexity and its monitoring and control type have a strong influence on the end consequence rather than the probability of occurrence of these attributes. Based on this definition, the data collection process takes input from the attribute assignments against the strength of influence defined by the probability and consequence of occurrence.

Table 5-1. Well plugging and abandonment attributes in risk analysis

		Influences	
Systems	**Attributes**	Probability	Consequence
Reservoir	Flowing/Non-flowing	×	✓
	Fluid type (oil or gas)	×	✓
	Fluid severity (sour or non-sour)	✓	✓
Wellbore	Age	✓	×
	Component type	✓	×
Platform	Environmental zone	×	✓
	Major/minor facility	×	✓
	Manned/unmanned facility	×	✓

× = Not attributed to influence
✓ = Attributed to influence

As this study is motivated by the paucity of data and the need to rely on source-to-source variability, it is necessary to replicate the data collection process in a way that represents practical experience in the decommissioning and abandonment industry. Therefore, the dataset presented in this case study describes the ranking from 10 engineers and academics with considerable field experience. The data is obtained via a Design for Decommissioning (DfD) workshop conducted at the University of Strathclyde in the Summer of 2017. It represents equivalent failure data collected from different sources, a scenario similar to expert judgements at an individual-level from a sample of respondents believed to have equal but varying knowledge and experience – subject matter experts. It is worth mentioning that these data are guestimates and possibilities due to the unfamiliar nature of some specific causal events, making it pertinent to adopt the HBA presented herein. The data were collected for pre-defined failures of the basic events identified by the Mineral Management Service, MMS (Nichol et al., 2000) report on the risk assessment of temporarily abandoned or shut-in wells as shown in Table 5-2. The work established that the top-level hazard is the leakage of hydrocarbon to the mudline and this PhD thesis has been built on that as it is a globally accepted well integrity failure.

In a top-down deduction manner, the zone isolating barrier is dependent on the occurrence of excessive pressure differentials and/or injection into nearby wells such as, sidetracking for the purpose of Enhanced Oil Recovery (EOR). Also, the actualisation of hydrocarbon leak through the primary plug is sufficient to compromise the plugged and abandoned well. Yielding of casing strings is also a potential cause of compromised wellbore integrity and unbalanced load of the formation fluid or geological forces can yield the casing strings. An unhindered hydrocarbon leak from downhole through the production plug can also compromise the well integrity independently. The annulus barrier degradation is a common cause failure which when combined with debonding of plug s and casing strings can lead to hydrocarbon leak through the casing hangar/assembly, and when insufficient barrier length can compromise the overall well integrity. The insufficient barrier length occurs due to a loss of barrier during cementing or inadequate barrier density. The annulus barrier can also be contaminated if the mood removal process is poor, or the barrier shrinks. The combination of such contamination and a degradation in the annulus barrier can also lead to the top-level failure, and it is on the basis of this system description that Table 5-2 is formulated.

Table 5-2. Causal events and description

Causal events	Description	Dependency	
		Intermediate Events	Description
$B_{1.1}$	Pressure differentials	B_1	zone isolating barrier
$B_{1.2}$	Injection into nearby wells		
B_2	Leak through lower/primary plug		
$B_{3.1}$	Prolong exposure to migrating fluid		
$B_{3.2.1}$	Formation fluids load effect	$B_{3.2}$	Yielding of casing
$B_{3.2.2}$	Geological forces	B_3	Secondary well barrier failure
B_4	Leak through production plug		
$B_{5.1}$	De-bonding of plug & casing	B_5	Leak through casing hangar/assembly
$B_{5.2}$, $B_{6.2}$, $B_{7.2}$	Annulus barrier degradation		
$B_{6.1.1}$	Inadequate barrier density	$B_{6.1}$	Insufficient barrier length
$B_{6.1.2}$	Loss of barrier		
$B_{7.1.1}$	Poor mud removal	$B_{7.1}$	Contamination of annulus barrier
$B_{7.1.2}$	Barrier shrinkage		

The collected data for the identified causations is as shown in Table 5-3. The source column represents the guestimates and possibilities obtained and recorded by the 10 participants, assuming a similitude characteristic with data coming from related but dissimilar activities such as drilling, intervention, workover, or completion operations. The duration of leak column represents the number of trials or demands for which the well plugging and abandonment operation failure is active before the well was successfully killed. Furthermore, the causal events can only be aggregated due to the small sample size to conduct probabilistic risk analysis. The process of aggregating such data can then be performed using the two-parameter Weibull distribution and the gamma distribution, as shall be seen in the succeeding Sections.

Table 5-3. Accident Precursor Data (APD) obtained as guestimates and possibilities of occurrence.

Source	Duration of the leak (N_i)	B_2	$B_{1.1}$	$B_{1.2}$	$B_{3.1}$	$B_{3.2.1}$	$B_{3.2.2}$	B_4	$B_{5.1}$	$B_{5.2}$	$B_{6.1.1}$	$B_{6.1.2}$	$B_{6.2}$	$B_{7.1.1}$	$B_{7.1.2}$	$B_{7.2}$
1	1	-	2	2	1	1	-	1	-	3	3	1	3	-	8	3
2	3	1	-	-	-	-	1	1	-	1	3	2	1	-	1	1
3	3	-	-	1	3	-	1	2	2	-	1	2	-	-	-	-
4	1	1	1	-	1	1	-	3	-	5	-	1	5	1	1	5
5	1	2	-	-	-	-	2	3	5	-	1	-	-	2	10	-
6	2	3	3	4	-	3	5	-	5	-	1	-	-	3	3	-
7	5	3	1	1	1	-	3	4	4	2	-	-	2	3	3	2
8	1	4	-	-	-	-	2	-	-	-	-	3	-	4	-	-
9	1	5	1	1	-	2	-	5	6	1	-	-	1	5	-	1
10	2	1	1	1	7	-	1	7	6	1	1	-	1	1	1	1

5.4.1 Weibull Distribution Approach

The shape and scale parameters can be empirically estimated using the linearization technique discussed in Section 5.2.1.2, as expressed by Equation (5-8). Taking causation event $B_{1.1}$ for example, the Accident Precursor Data (APD) observed can be reorganized ascendingly as seen in Table 5-5 below through ranking.

Table 5-4. Weibull estimation for causation event $B_{1.1}$

Rank (k)	Source	Duration of the leak (N_i)	$B_{1.1}$	$y = B_{1.1}N_i$	$P(y)$	$\ln\left(-\ln\left(1 - P(y)\right)\right)$	lny
1	1	1	2	2	0.06731	-2.66384	0.69315
2	4	1	-	-	0.16346	-1.72326	-
3	5	1	-	-	0.25962	-1.20202	-
4	8	1	-	-	0.35577	-0.82167	-
5	9	1	1	1	0.45192	-0.50860	0
6	6	2	3	6	0.54808	-0.23007	1.79176
7	10	2	1	2	0.64423	0.03292	0.69315
8	2	3	1	3	0.74038	0.29903	1.09861
9	3	3	-	-	0.83654	0.59398	-
10	7	5	1	5	0.93269	0.99269	1.60944

Column 6 of Table 5-5 is the median rank used to estimate the proportion of the dataset that would fail by the end of the leak duration. Polyfitting the last two column on a straight-line graph as a polynomial function of order one using the MATLAB command polyfit($\ln\left(-\ln\left(1-P(y)\right)\right)$, lny, 1) yields a best fit of [0.24748, 0.71806]. Therefore, a best fit line of the form $y = 0.24748x + 0.71806$ indicates that the slope is 0.24748 with a vertical intercept of 0.71806 (Appendix A). Equating these values with the right-hand side term of Equation (5-8) gives the approximate values of the shape and scale parameters to be $\alpha = 0.24748$, and $-\alpha \ln \beta = 0.71806$, from which, $\beta = 0.05494$. With α and β values known, the failure probability of causal event $B_{1.1}$ can be aggregated using the Weibull MATLAB algorithm wblpdf(1.9, 0.24748, 0.05494) to obtain $p(y) = 0.0106$.

5.4.2 Gamma Distribution Approach

Gamma distribution is especially suitable for predicting the parameter of interest until a future event occurs. Given that the dataset available for such prediction is sparse, it is not accurate to linearize the shape and scale parameters. In addition, the result of a linearised α and β values would yield a much larger value for Gamma distribution than it did for Weibull distribution, making it necessary to systematically estimate these parameters. For example, a MATLAB script for the estimated parameters from previous Section – gampdf(0.24748, 0.05494, 1.9) – would yield $p(y) = 0.1794$ which is approximately 17 times larger. To that end, aggregating the dataset to follow a gamma distribution would require the hyper prior parameters to also follow a gamma distribution through Hierarchical Bayesian Analysis (HBA) method. The main advantage is that the Gamma distribution allows data to be examined at a multi-stage level.

The HBA method has been comprehensively discussed in Section 3.5.5 and its formalism is such that the Probability Density Function (PDF) can be analysed using Binomial properties where occurrence probability is the parameter of interest needed (or available) to represent the data, thus

$$P_f(y_i|P) = \binom{N_i}{y_i} P^{y_i}(1-P)^{(N_i - y_i)}, \qquad 0 \le y_i \le N_i \qquad \text{(5-20)}$$

The first stage prior distribution for the data set obtained from Equation (5-20) gives

$$f_0(P|\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} P^{(\alpha-1)}(1-P)^{\beta-1} \qquad \text{(5-21)}$$

In the case where discrete data representing the failure y is presented in the form of failure rate, λ and exposure time, t, then the likelihood function follows a Poisson distribution given by Equation (5-22).

$$P_f(y_i|\lambda_i) = \frac{(\lambda_i t)^{y_i} e^{-\lambda_i t}}{y_i!}, \quad i = 0,1, \dots. \tag{5-22}$$

The corresponding first stage prior distribution for the data set yields Equation (5-23).

$$f_0(\lambda|\alpha, \beta) = \frac{\beta^\alpha \lambda^{\alpha-1} e^{\beta\lambda}}{\Gamma(\alpha)} \tag{5-23}$$

It is evident from Equations (5-20) through (5-23) that prior knowledge of the occurrence probability or failure rate is required to assess the parameter of interest. In practice, this information is lacking, and approximate estimation relies heavily on experience. Therefore, it is necessary to predict a mean and variance value small enough to model the distribution. The distributions of the hyper-prior parameters α and β are assumed to have a gamma distribution with mean and variance $\left(\mu_y = \alpha\beta, \sigma_y^2 = \alpha\beta^2\right)$ equal to 1.00e-4 in this analysis. From the foregoing, the posterior predictive distribution emanating from the first stage prior distribution and (α, β) - estimation follows

$$\begin{gathered} y_i \sim bin(P_i, N_i) \\ P_i \sim beta(\alpha, \beta) \\ \alpha \sim gamma\left(\mu_y, \sigma_y^2\right) \\ \beta \sim gamma\left(\mu_y, \sigma_y^2\right) \end{gathered}$$

The gamma distribution model is coded in MATLAB (R2018a), taking advantage of its in-built gamma pdf tools as shown in Figure 5-1 and APPENDIX H. The aggregation procedure within HBA enables the failure probabilities to be obtained as a mean value with 95% confidence interval.

```
f(y), y = (y_1, ..., y_k)^T     % Objective function
y_i(i = 1, 2, ..., n)       % Initialize a population of causations from source-to-source
for i = 1:n          % All n source-to-source data points
  for j = 1:k        % All k causation events
  N_{j,k}(k = 1, 2, ..., N)     % List the number of P&A operations N_{j,k} recorded
  μ = mean(y_i.N_{j,k}/sum(N_{j,k})) % Estimate the mean parametrically
  σ = std(y_i.N_{j,k}/sum(N_{j,k}))  % Estimate the standard parametrically
  (α, β) = gampdf(μ, σ)    % Estimate the shape and scale parameters
end
p(y_i) = p(α_i, β_i)       % Obtain the mean probability from the distribution
end
Post-process results and visualization
```

Figure 5-1. MATLAB code for probability estimation

5.5 Result and Discussion

The results obtained from the methods discussed in Section 5.3.1 and Section 5.3.2 are as shown in Table 5-6. The aggregated failure probabilities for all causal events leading to the top-level failure, characterised by the leakage of hydrocarbon to the mudline, using both methods have been reported and compared. The results summary illustrates the probability modelling capabilities of both methods and further demonstrates the variability in their estimation accuracies. As the Gamma distribution relies heavily on the strength of the Hierarchical Bayesian Analysis (HBA) where the reported failure probabilities are obtained from a multi-level solution process, the aggregated values are the mean distribution from the posterior predictive distribution.

Table 5-5. Failure probability of causal events using Weibull and Gamma Distribution.

Events	Description	$p_{weibull}(y)$	$p_{Gamma}(y)$	Relative Difference
$B_{1.1}$	Pressure differentials	0.0106	0.0850	8.02
$B_{1.2}$	Injection into nearby walls	0.0256	0.1050	4.10
B_{2}	Leak through lower/primary plug	0.0079	0.1900	24.05
$B_{3.1}$	Prolong exposure to migrating fluid	0.0221	0.1470	6.65
$B_{3.2.1}$	Formation fluids load effect	0.0372	0.0500	1.34
$B_{3.2.2}$	Geological forces effect	0.0143	0.1860	13.01
B_{4}	Leak through production plug	0.0067	0.2750	41.04
$B_{5.1}$	De-bonding between plugs and casing	0.0061	0.2950	48.36
$B_{5.2}$	Annulus barrier degradation	0.0163	0.1200	7.36
$B_{6.1.1}$	Inadequate barrier density	0.0209	0.0595	2.85
$B_{6.1.2}$	Loss of barrier	0.0278	0.0850	3.06
$B_{6.2}$	Annulus barrier degradation	0.0033	0.1200	36.36
$B_{7.1.1}$	Poor mud removal	0.0066	0.1750	26.51
$B_{7.1.2}$	Barrier shrinkage	0.0064	0.2250	35.16
$B_{7.2}$	Annulus barrier degradation	0.0182	0.1200	6.59

The relative difference was used as a form of importance measure to compare the two methods. The results in Table 5-5 revealed that the occurrence probability obtained using the Gamma distribution is significantly higher than those obtained through Weibull approximation method. It can be inferred that Weibull distribution, albeit able to estimate approximate occurrence probabilities through linearisation, underestimates the values making it less than suitable in decommissioning risk analysis where uncertainties are desired to be minimised. For instance, $p_{Gamma}(y) = 134\% \times p_{Weibull}(y)$ for the formation fluids load effects probability and much larger in other events. Furthermore, the relative difference between these methods showed a progressive increase and would continue to do so in the presence of new evidence, making the HBA method flexible. This trend is especially desirable where data uncertainty tends to null as the knowledge of equipment and reservoir condition become evident.

In scenarios where the causal event's prior failure probability approaches the mean distribution value of the probability, the relative difference will converge, that is, tend to unity. This special scenario is observed in event $B_{3.2.1}$ with a relative difference of ~34%. Therefore, it is noteworthy that the HBA method is flexible and well suited to the technical challenges posed by decommissioning and abandonment operational risks.

The mean values from the posterior predictive Gamma distributions representing the exact values of the causal events failure probability predicted with 95% confidence level are as shown in Table 5-6. A closer look at the Weibull distribution probability estimation method and its associated confidence levels revealed a noteworthy bias to be especially suitable for estimating the failure probability of new components, making this method unreliable for the accuracy of estimation desirable in the context of decommissioning and abandonment. It is also observed that causal events $B_{5.2}$, $B_{6.2}$ and $B_{7.2}$ are repeated events modelled within the fault tree using the common cause failure formalism, yet the Weibull distribution method returned different values for each event due to the median rank techniques adopted. This discrepancy further limits the application area of the Weibull distribution in the cessation of production phase failure analysis.

Table 5-6. Causal events failure probability with 95% confidence level.

Events	Gamma Distribution		Weibull Distribution	
	Probability	95% CI	Probability	95% CI
$B_{1.1}$	0.0850	(0.0778, 0.0923)	0.0106	(0.0032, 0.0180)
$B_{1.2}$	0.1050	(0.0942, 0.1159)	0.0256	(0.0182, 0.0330)
B_{2}	0.1900	(0.1598, 0.2203)	0.0079	(0.0005, 0.0153)
$B_{3.1}$	0.1470	(0.1102, 0.1838)	0.0221	(0.0147, 0.0296)
$B_{3.2.1}$	0.0500	(0.0445, 0.0555)	0.0372	(0.0298, 0.0446)
$B_{3.2.2}$	0.1860	(0.1484, 0.2236)	0.0143	(0.0069, 0.0217)
B_{4}	0.2750	(0.2091, 0.3410)	0.0067	(0.0005, 0.0129)
$B_{5.1}$	0.2950	(0.2274, 0.3262)	0.0061	(0.0058, 0.0064)
$B_{5.2}$	0.1200	(0.1044, 0.1356)	0.0163	(0.0132, 0.0194)
$B_{6.1.1}$	0.0595	(0.0478, 0.0712)	0.0209	(0.0135, 0.0283)
$B_{6.1.2}$	0.0850	(0.0757, 0.0943)	0.0278	(0.0204, 0.0352)
$B_{6.2}$	0.1200	(0.1044, 0.1356)	0.0033	(0.0024, 0.0042)
$B_{7.1.1}$	0.1750	(0.1425, 0.2075)	0.0066	(0.0057, 0.0075)
$B_{7.1.2}$	0.2250	(0.1843, 0.2657)	0.0064	(0.0056, 0.0072)
$B_{7.2}$	0.1200	(0.1044, 0.1356)	0.0182	(0.0106, 0.0258)

It has been shown that the Weibull distribution approach offers a linearisation technique to ease the computation of parameters of interest. However, due to the systematic approach of median ranking for each dataset and sequencing, the method fell short in benefiting from the multi-level estimation process which is within the HBA capability. In addition, the Weibull distribution does not capture the common cause failure which emanates from annulus barrier degradation repetition and is overly sensitive to paucity in the data. This resulted in the underestimation or overestimation of the mean probability distribution which is not a direct representative of the sparse data likelihood and may further introduce additional uncertainty.

5.6 Conclusion

The failure analysis of decommissioning and abandonment operations is experience-driven and does not often rely on sufficient or accurate data, making the analysis susceptible to high degrees of uncertainty. The uncertainties vary in form and can emanate from data paucity, model formulation and or assumptions of the inherent risks due to limited knowledge of the overall operational sequence. The knowledge of the hazards become evident only after the operation is in progress and it is desirable to develop a methodology capable of aggregating and updating the available data when new information become available. The approach developed in this research work is based on Hierarchical Bayesian Analysis (HBA) to tackle the uncertainty issue and is compared with a similar statistical tool – the Weibull distribution – in terms of strength and modelling capabilities. The HBA utilized the collected Accident Precursor Data (APD) from similar or analogous operation. The source-to-source variability are considered using the multi-stage hierarchy to estimate the posterior predictive distribution for each event's failure probability with aggregated mean and variance at 95% confidence level.

The Weibull distribution, on the other hand, is demonstrated to be capable of modelling data paucity but fall short in predicting the failure probability with similar level of accuracy and does not have the ability to incorporate temporal variability in the model. This is due to its empirical linearisation procedure where ranking of the dataset influences the convergence. The relative difference, measured in percentage, between both methods was used to substantiate the strength and superior modelling capability of the HBA technique. The relative differences for each event were seen to vary from 1.34 to ~50, in the de-bonding between mechanical plugs and casing, making the HBA a better estimator for the decommissioning and abandonment operational failure analysis.

5.7 Summary

This Chapter presented the statistical methods underpinning Hierarchical Bayesian Analysis to estimate the failure probabilities of accident contributory factors when such data is sparse and obtained from source-to-source. The variability inherent in the data collection process introduced additional uncertainty to the data and reliance on it for safety analysis means that sufficient confidence level was required. The methods investigated here were the two-parameter Weibull distribution and the Gamma distribution. The Weibull distribution thrives on analysing components' reliability where the interaction among parameters can be linearised, whereas the Gamma distribution is suited to parameter of interest prediction until a future event occurs and is capable of multi-level modelling. The results were presented for similar small-sized datasets and both methods were investigated for linearisation and numerical computation in MATLAB. The results obtained for Weibull distribution were reported to be lesser than those from the Gamma distribution, making the latter best suited to the failure analysis of decommissioning and abandonment operations that are prone to risks underestimation. Moreover, the variation between both methods, measured by their relative differences, ranged between 34% to ~5000% in favour of Gamma distribution through the Hierarchical Bayesian Analysis. The succeeding Chapters present the case studies and use the results of the HBA for further analysis.

Chapter 6: Case Study – Permanent Abandonment System

6.1 Outline

This Chapter demonstrates the application of the Dynamic Integrated Safety Analysis (DISA) model discussed in Chapter 4. The case study presents the accident evolution scenarios for the Elgin Platform with wellbore failure modes reported by The Minerals Management Service (MMS, 2000). The case study system description is presented in detail and the data obtained from Chapter 5 are presented in Section 6.2. The development of the FTA, ETA, BT tools, BN and DBN models are described analytically in Section 6.3. Section 6.4 presents the dynamic failure analysis outcomes followed by the Chapter summary to offer concluding remarks on the presented model formulation.

6.2 Introduction

The framework is applied on the 22/30c-G4 well of the Elgin Platform located in the middle of the North Sea between Scotland and Norway, approximately 240 km East of Aberdeen. Cessation of production is already in place and the well was undergoing plugging and abandonment operation when natural gas in enormous quantity began to leak into the wellbore due to an abrupt pressure differential that could not be bled off in good time. The principal particulars of the well are as shown in Table 6-1 below.

Table 6-1. Case study principal particulars.

Platform Particulars	Well conditions
Reservoir condition	HT/HP
Ocean depth	90 m
Reservoir depth	5500 m
Reservoir temperature	190 ℃
Reservoir pressure	1100 bar
Fluid type	Natural gas
Fluid severity	Sour

An uncertainty related to a zone within the wellbore at vertical depth between 5130 m and 5370 m further exacerbated due to the pore pressure gradient between 2150 kg/m^3 and 2200 kg/m^3 including the potential occurrence of a ballooning effect (Total, 2013).

To demonstrate the applicability of the framework, sufficient failure data and overall knowledge of the reservoir at the cessation of production is required. Unfortunately, this two information are often lacking due, in part, to the accessibility of decommissioning database and incomplete maintenance records of the well during service. In addition, there are fewer research papers focusing on present study due to data paucity. Therefore, the previous Chapter presented a unique approach to obtain and process relevant data which would then be relied upon in this Chapter.

In general, the wellbore casings schematic is examined in detail to identify the barrier and/or mechanical plugs at each strategic zones and potential hazards that could compromise their integrity. This exercise was achieved through a Design for Decommissioning (DfD) and abandonment workshop involving 10 engineers and academic participants with considerable field experience (Appendix B). Two types of data were collected for each causal (or basic) event – the failure guesstimates and the number of trials representing the duration of leak before the well was killed. The well was intended to be shut-in before it was deemed uneconomical and problematic and consequently, abandoned permanently. To that end, the overall Permanent Abandonment (PA) sequence would be investigated in the trained DBN model to validate its performance characteristics and potentially anticipate the inspection and/or maintenance regime.

It is worth mentioning that the exact nature of the fluid characteristics was not known except that the well is pressure depleted by ca. 800 bar and will continue to do so until completely plugged. Moreover, the reservoir was reported to be nonviable economically prior to cessation of production. In addition, the rate of gas leakage from the wellbore was recorded to be approximately 2 kg/s equivalent to 12 mmcf/day with a large sheen of condensate on the water surface. The natural gas is being released atop the G4-wellhead platform at a low pressure of

5 bar emanating from a non-producing reservoir above the Elgin formation. These accident evolution over time further necessitates dynamic safety modelling. As decommissioning, plugging and abandonment operations are not an investment and the cost of overseeing the activities are estimated to be close to those of capital projects, oil and gas operators adopt conventional quantitative risk analysis to mitigate the accident levels although these techniques are able to address events with known interactions, cannot accommodate the dynamic nature of a blowout, leakage or natural seepage commonly encountered during plugging and abandonment. For this reason, the static nature of conventional quantitative risk analysis undermines it credence to capture, assess and mitigate against dynamic failure.

The design for decommissioning workshop yielded a dataset, representing source-to-source variability as detailed and analysed in Chapter 5. The data is used as a dataset for the purpose of simulation to train the DBN models to substantiate their performance and permanence. The data was collected for both basic events and associated safety barriers implemented to reduce the likelihood of fire and explosion and are presented in Appendix C.

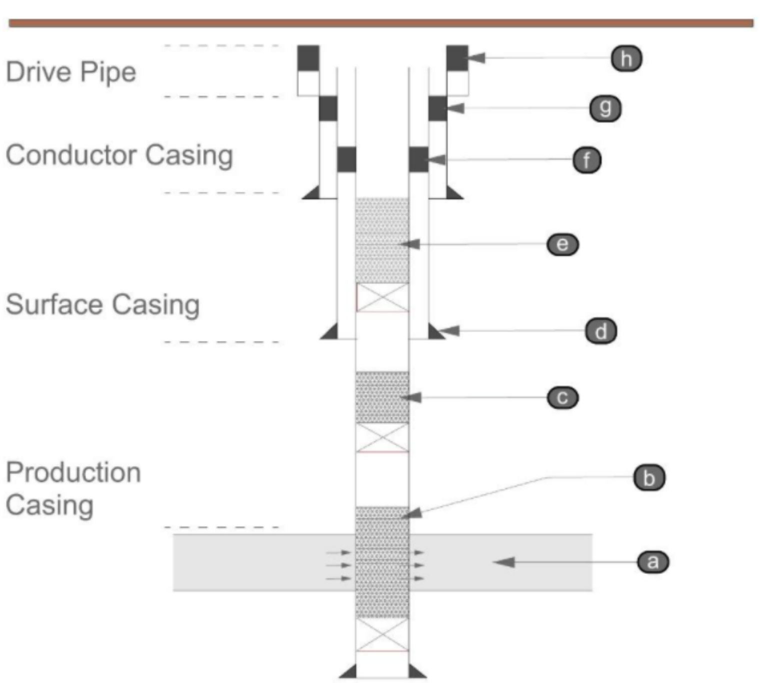
6.3 Accident model formulation

This Section presents the model formulation for the case studies with the fault tree, event tree and bowtie as the starting point through to the BNs with relevant relaxation strategies, and then BNs transformation into corresponding DBNs.

6.3.1 Reliability model for permanent abandonment system

6.3.1.1 FTA for Permanent Abandonment System

Following the accident evolution of the G4-well, a representative schematic is constructed for the wellbore plugging characteristics as depicted in Figure 6-1. The schematic for the PA is imminent as a reference for shut-in and temporary abandonment wells. The boundaries of the PA need to be clarified prior to formulating the FT model. The leakage of hydrocarbon to mudline is identified to be the top event of the FT. The top event is then subdivided into three subsystems, representing the system constraints as depicted Figure 6-2.



a- Production zone
b- Zonal isolation plug
c- Primary barrier plug
d- Casing shoe
e- Secondary barrier plug
f- Production seal to mudline
g- Surface seal to mudline
h- Conductor seal to mudline

Figure 6-1 Permanent Abandonment Well Schematic (adapted from Nichol et al, 2000)

It is worth mentioning that the well schematic and associated boundary conditions were a result of comprehensive hazard identification workshop by experts, on the barrier plugs at different layers. In addition, as FT analysis is static in nature with basic Boolean logic and the failure rate or mean time to failure (MTTF) are unavailable, the system Most Probable Cause (MPC) will be determined using the Minimum Cut-Set (MCS). The mean distribution values estimated in previous Chapter will be used as the prior failure probability for each basic event. In addition, the potential leak route is characterised by the casing containment, with primary focus on the surface casing and production casing. From the physical inspection of the well schematic, it was found that leak routes via other casings would yield no significant effect due to the longer paths the leaking fluid would have to overcome while migrating uphole.

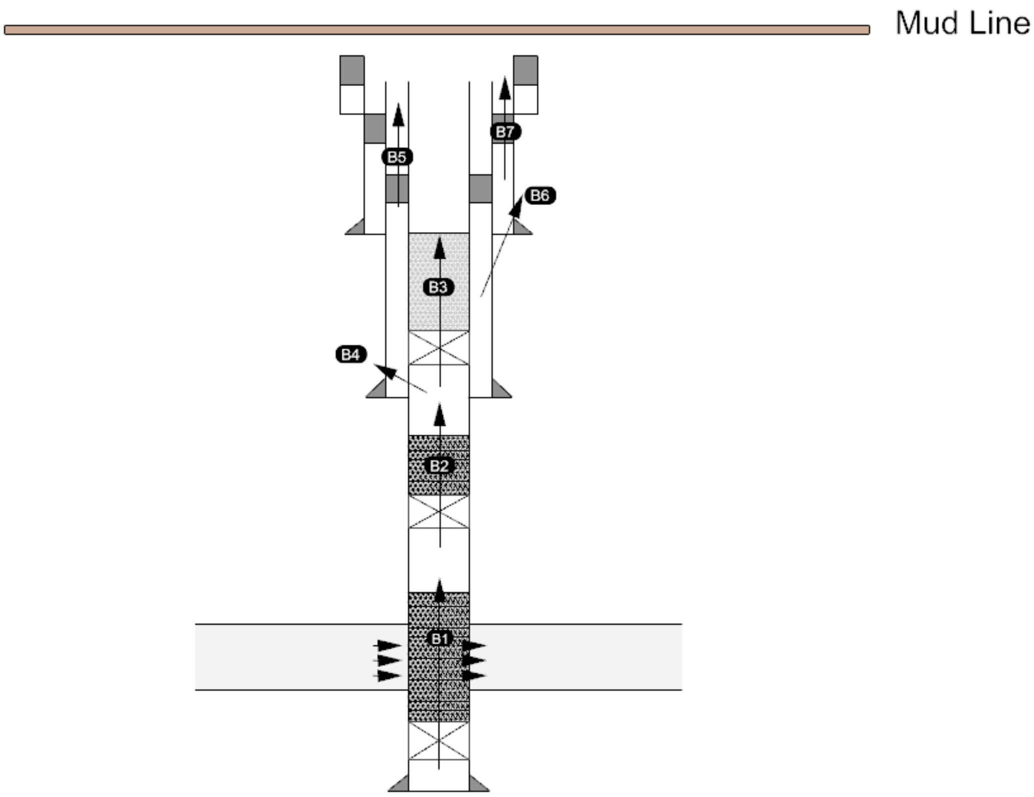


Figure 6-2 Well PA leak route

As seen in Figure 6-2, the leakage of hydrocarbon to mudline is divided into the leak through isolation plug (B1), leak through lower plug (B2) and leak through upper plug (B3-7) and associated barriers subsystems. The leak route is illustrated by Figure 6-3, where cross flow to other formation due to failure of the primary cement outside the production casing is negligible. For the leak through isolation plug, pore pressure build-up (B1.1) and injection into nearby well (B1.2) are enough to compromise the isolation plug. The leak through the primary or lower plug closest to the production casing caused by cascade of other events is modelled as a single point failure in the FT model. Lastly, the combined leak through the upper or secondary plug is divided into leak through the upper plug (B3) and a combined effect of leak caused by the annulus and production plugs (B4-7). The annular plug tends to keep the pressure slightly above the pore pressure to prevent the ingress of formation fluids into the wellbore.

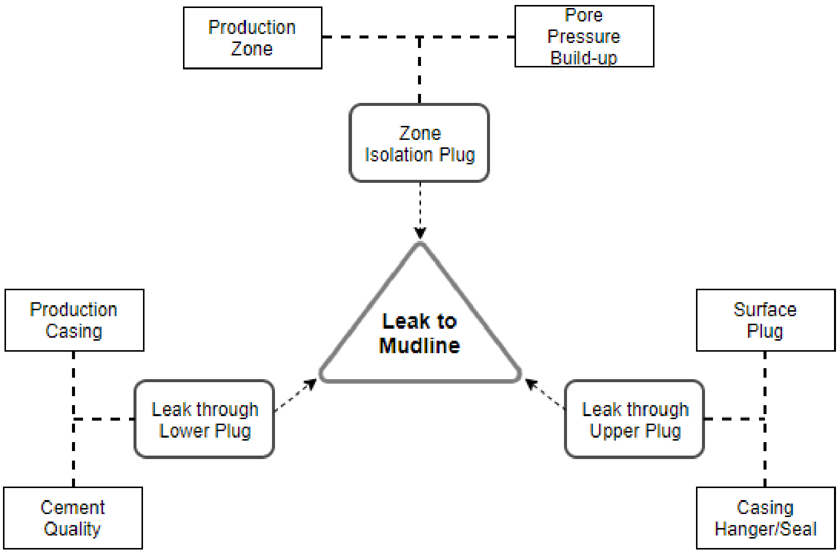


Figure 6-3 Limiting conditions for well PA systems failure

All the causal dependent subsystems are expanded and explained in detail as shall be seen in subsequent paragraphs. Overall, there are a total of 15 basic events in the FT model representing the failure of the abandonment operation as shown in Table 6-2.

Table 6-2. Basic Events for permanent abandonment FT

Events Identifier	Event Description
$B_{1.1}$	Pressure differentials
$B_{1.2}$	Injection into nearby walls
B_{2}	Leak through lower/primary plug
$B_{3.1}$	Prolong exposure to migrating fluid
$B_{3.2.1}$	Formation fluids load effect
$B_{3.2.2}$	Geological forces
B_{4}	Leak through lower/primary plug
$B_{5.1}$	De-bonding of plug & casing
$B_{5.2}$, $B_{6.2}$, $B_{7.2}$	Annulus barrier degradation
$B_{6.1.1}$	Inadequate barrier density
$B_{6.1.2}$	Loss of barrier
$B_{7.1.1}$	Poor mud removal
$B_{7.1.2}$	Barrier shrinkage

A seven stage FT is constructed for the case study permanent abandonment well consisting of 13 gates and 15 basic events including 3 repeated events. Figure 6-4 depicts the fault tree for the chain of events within the wellbore leading to the permanent abandonment well failure top event. The FT model was developed using PTC Windchill® FTA software tool. The formulation was limited to static gates, as the cost of implementing time-variant dynamic gates add to the cost of overall decommissioning not to mention the advanced modelling efforts required. The applicable gates are AND/OR for the sake of representing the interactions of the basic events in a precise, realistic, and practical sense. Moreover, the static logic gates are utilized to preserve the capability of the FT model, and this would be mapped into a dedicated dynamic model as shall be seen later in this Chapter.

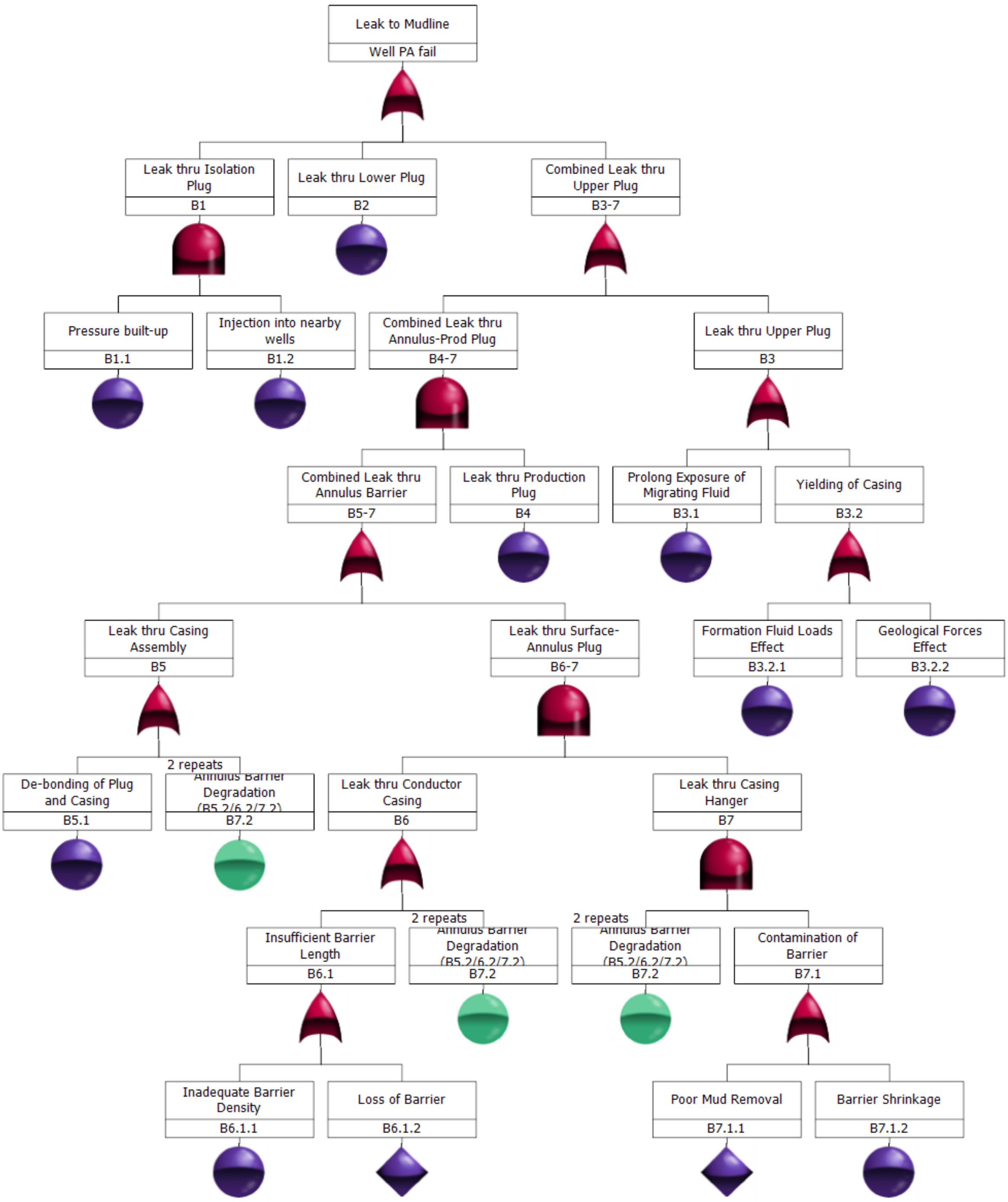


Figure 6-4 Fault tree for well plugging and abandonment failure.

As seen from Figure 6-4, the leak to mudline top event is connected to its subsystems by an *'OR'* gate, making the failure of the top event certain should any one of the three subsystems be true, because all the barrier plugs are crucial to maintain the integrity of the plugging and abandonment operation. In this model, all basic events are assumed to be statistically independent in order to capture all possible critical paths in the system. In the leak through upper plug subsystem (B_3), prolong exposure of migrating fluid ($B_{3.1}$) and yielding of the casing ($B_{3.2}$) are the identified components. These components are modelled using the *'OR'* gate assuming the any one of them must fail for the upper plug to fail. The casing can yield because of either formation fluid load or geological forces, modelled through an *'OR'* gate.

The FT model in the combined leak through annulus and production plugs system (B_{4-7}) is formulated using an *'AND'* gate assuming that both the combined leak through the annulus barrier (B_{5-7}) and the leak through production plug (B_4) must be compromised for the subsystem to fail in its entirety. The combined leak through annulus barrier is then separated into the leak through casing assembly (B_5) and the leak through the surface and annulus plugs (B_{6-7}), both of which have been modelled with an *'OR'* gate. The leak through the casing assembly is further separated into a type of failure caused by de-bonding between plug and casing ($B_{5.1}$) and the degradation of the annulus barrier ($B_{5.2}$). Both ($B_{5.1}$) and ($B_{5.2}$) are interacting via an *'OR'* gate, indicating that any one of them can trigger the leak through the casing assembly.

The leak through surface-annulus plug is then separated into the leak through conductor casing B_6 and leak through casing hangar (B_7). The leak through casing hangar is caused by annulus barrier degradation ($B_{7.2}$) and contamination of the barrier and is modelled using an *'AND'* gate assuming that both contamination and degradation of the annulus barrier must be true for the casing hangar to fail. The contamination of barrier is initiated by potential poor mud removal ($B_{7.1.1}$) or shrinkage of the barrier ($B_{7.1.2}$). Both basic events are interrelated by an *'OR'* gate assuming that any one of them must fail for the barrier to be contaminated.

The leak through conductor casing (B_6) is characterised by the failure due to insufficient barrier length ($B_{6.1}$) to provide a good seal job and degradation of annulus barrier ($B_{6.2}$). The subsystem is described by an *'OR'* gate indicating that the failure of any one of $B_{6.1}$ and $B_{6.2}$ must fail for the fluid to leak through the conductor casing. Insufficient barrier length is modelled using '*OR'* gate to represent the contributions from inadequate barrier density ($B_{6.1.1}$)

and loss of barrier ($B_{6.1.2}$) within the layer. This means that the failure of any one of its components is enough to render the barrier length insufficient.

6.3.1.2 ETA for Permanent Abandonment System

The ET for the case study was formulated based on the assumption that the well abandonment of interest is rig-based, making the potential of fire and explosion likely. The top event of the FT, characterised by the leak of hydrocarbon to mudline, becomes the initiating event (IE) of the ET. The ET consist of three level representation of the accident evolution – the initiating event, safety barriers and the end consequences. The presence of ignition source would escalate the extent of loss if proper mitigation were not implemented. Therefore, the *safety barrier* phase in the ET corresponds to the various strategies developed to deal with the accidental event. The safety barriers serve to respond to cascading of events by impeding the accident sequence or mitigating the end consequences.

Numerous technical meetings, research group discussions and peer-reviewed publications have taken place as part of this research study to validate the identified safety barriers. Notable contributions from professional engineers (P.Eng.) and offshore and maritime industry experts have confirmed the BT structure, and all were in agreement. Based on the information available in the peer-reviewed publications, this sequential and nonsequential accident has been modelled. The accident contributory factors are systematically structured into five safety barriers in way of the accident evolution route to prevent the end consequences. A brief description of these modelled safety barriers is given below.

Hydrocarbon detection sensor (HDS): The release of hydrocarbon within the wellbore at any of the barrier plug zone is primarily responsible for the loss of containment that initiates the accident process. The hydrocarbon detection sensor is a barrier designed to notify monitoring personnel if there has been polarity difference between water at mudline and leaked hydrocarbon. It prevents the occurrence of hydrocarbon release uphole to the surrounding water. It has been identified that operational error, inspection error, maintenance error and design error are the major factors that influence the failure of the hydrocarbon detection system as depicted in Figure 6-5.

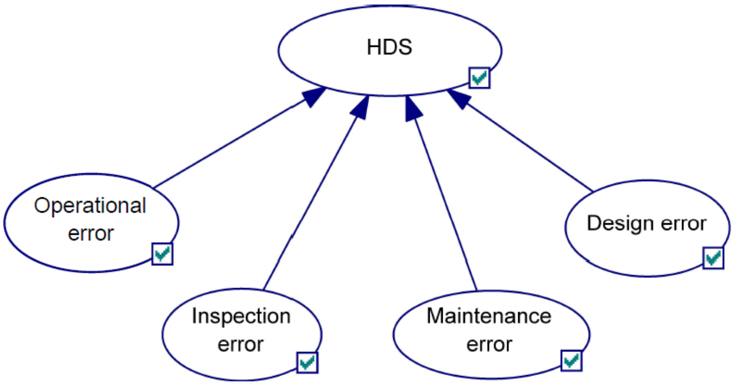


Figure 6-5 Hydrocarbon detection sensor network

Ignition prevention system (IPS): Ignition prevention system controls the escalation of vapor cloud into pool fire in the likely event of fire and explosion. The reliability of the ignition prevention system is an essential factor in the occurrence of catastrophe, as fire cannot ensue without the ignition barrier prior failure. To prevent fire and explosion during plugging and abandonment operation, an IPS safety barrier must be installed to focus on all potential ignition sources and consequently prevent the outburst of fire and explosion. The major factors that influence the failure of this barrier are the hot work failure and human error around noncompliance as shown in Figure 6-6.

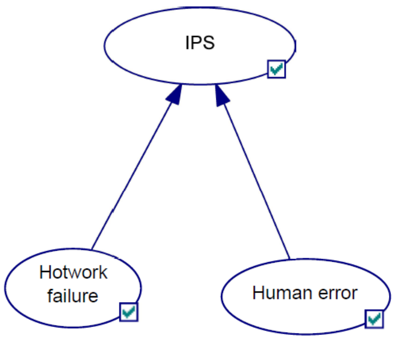


Figure 6-6 Ignition prevention system network

Flame Arrestor System (FAS): The primary function of this barrier is to isolate the flame pathway through the prevention of one or more mechanisms needed to propagate flamelets. For flame to propagate, an ignition source, fuel, and oxygen must be present. To avoid domino effect, the FAS is triggered to trap the flame while allowing gases an easy passage. It minimises the extent and duration of explosion by absorbing the dissipating heat. The FAS is immediately relied on to disconnect the combustion elements (temperature, oxygen, and hydrocarbon), soon as fire and explosion events occur. The failure of the FAS escalated fire, loss of the offshore asset and nearby properties including casualties, necessitating the installation of an alarm and sprinkler system (AaS). The major factors that are responsible for the failure of the FAS barrier are the fire detection system failure, human error (in the area of noncompliance), and emergency shutdown failure as illustrated in Figure 6-7.

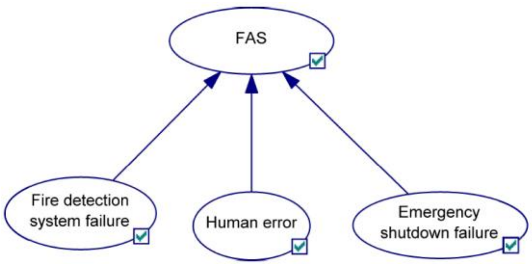


Figure 6-7 Flame arrester system network

Alarm and Sprinkler System (AaS): The function of the AaS is to extinguish, contain, or control the fire and explosion when the FAS barrier fails to isolate the fire escalating elements on demand. The activation of the AaS provides warning to offshore personnel on the severity level of the outburst, as well as notifies the emergency evacuation plan team to respond to the alarm. The only factor influencing the failure of this barrier is the reliability or unavailability of the FAS on demand.

Emergency Evacuation System (EES): The EES reduces the extent of damage caused by fire and explosion due to the consequent failure of preceding safety barriers. The primary function for the installation of this barrier is to prevent fatalities. The timing of the AaS to function on demand is hugely important in this scenario; otherwise, the emergency evacuation plan might be insignificant following a catastrophe. The failure of the emergency evacuation plan leads to significant damage to offshore assets and nearby properties including fatalities. Major factors influencing the failure of this barrier are the evacuation error, communication error and emergency preparedness failure as shown in Figure 6-8.

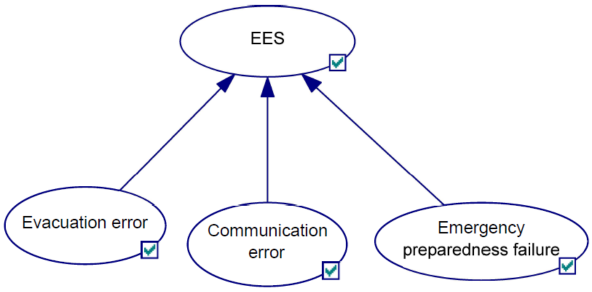


Figure 6-8 Emergency evacuation system network

Subsequently, for each identified safety barrier, a list of additional causal events or factors is developed, and relevant safety barriers emanated to address them until the end consequence is eliminated or mitigated against. The leak to mudline initiating event, associated safety barriers and potential consequences resulting from the worst-case scenarios is formulated as illustrated in the structure of Figure 6-9.

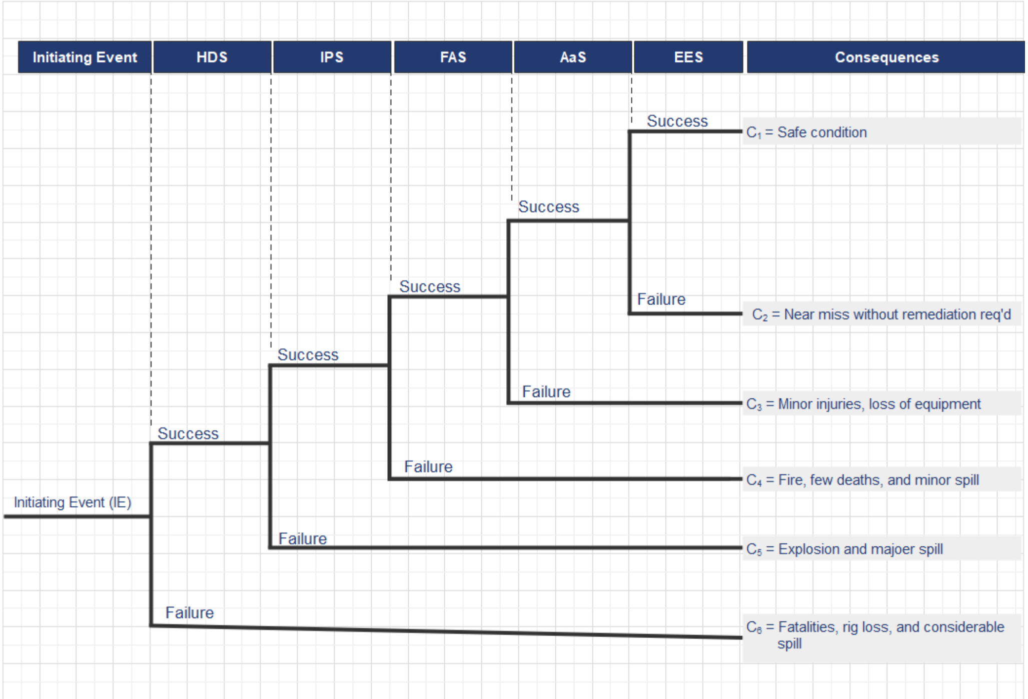


Figure 6-9 Well PA event tree structure

Figure 6-9 shows all the potential accident scenarios and sequence of events leading to the end consequences. In the *'Safety Barrier'* segment, characterised by HDS, IPS, FAS, AaS and EES, for each barrier all possible measures are identified, recorded, and implemented in the sequence they will be triggered. The functionality of the safety barriers is then categorized into binary functions depending on whether they perform their intended task or not, typically, as 'works' or 'fails'. In the *'Consequence'* column, all possible outcomes such as near miss, minor and/or major fire and explosion etc. that may incur huge cost of remediation are identified and recorded. Finally, the joint product of the frequency of the initiating event and the conditional probability of safety barriers in way of the end event sequence for each path is estimated and recorded to ease consequence occurrence probabilities estimation.

Information collected for the well abandonment event tree formulation is based on the work of Nichol et al. (2000), Lavasani et al. (2015), Abimbola et al (2016), Babaleye et al (2019a, 2019b), Fam et al. (2020), and experts' opinion and validation by way of feedbacks from experts. During the accident evolution development stage, several technical meetings among experts and research group were held to collect modellable information. To this end, information was collected from the Centre for Risk, Integrity and Safety Engineering (C-RISE) research group, two oil and gas operators and one consultancy company. Particularly, participating experts included researchers, academics, and engineers with considerable years of field experience.

6.3.1.3 BT for Permanent Abandonment System

Following the construction of the FT and ET, the BT is modelled with the FT on the left end representing the root causes of the top event. The top event then becomes the initiating event for the ET represented on the right end of the BT model and depicting the possible outcomes resulting from the failures of implemented safety barriers. As the BT is especially suited to visualise cause-consequence relationships among interacting events, all calculations would be conducted within the dedicated dynamic model.

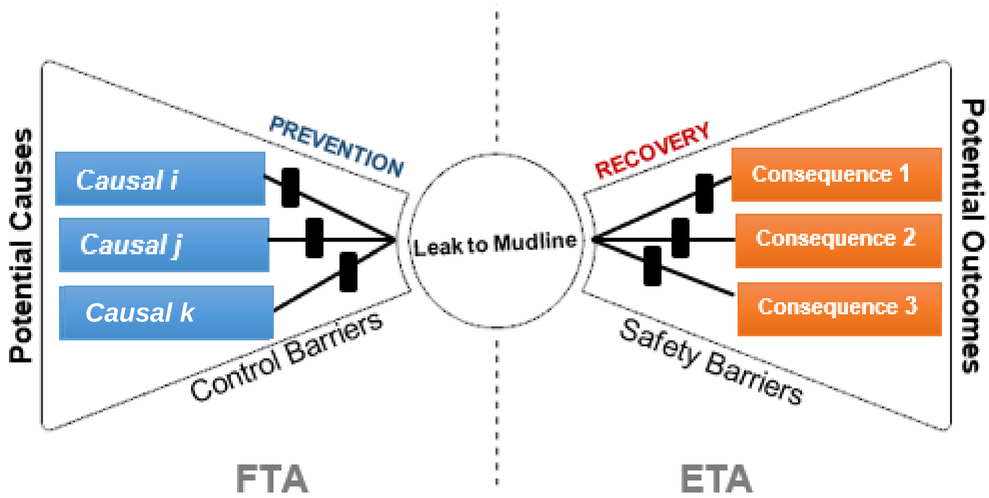


Figure 6-10 Bowtie structure

6.3.1.4 Consequence Modelling for Permanent Abandonment System

Decommissioning and abandonment accidents are characterized by the personnel safety, environmental safety, and the loss of asset due to fire and explosion. Personnel safety is accounted for by the loss of personnel's life during the plugging operation due to fire, explosion, and suffocation. The environmental risk is defined by the amount of hydrocarbon spill and its adverse effect on marine lives, nearby residents, potential property damage and the cost of remediation. The loss of asset is attributed to the potential loss of the rig used for the abandonment operation. Fire and explosion are the main threat given the scenario that hydrocarbon has leaked uphole to mudline. The evolution of a catastrophe is assumed to emanate from the point where a leak exists, and this study assumes the well contained non-sour formation fluids. The leak propagates to the formation of fire or hazardous cloud until it is escalated through an ignition source. For a gas well, a jet fire (or pool fire for a liquid well) propagates. A vapour cloud is formed in the absence of an ignition source and may be escalated by the wind. The consequence of such leak from C_2 to C_6 and their occurrence sequence represented on the event tree constituents of Figure 6-9 above. To preserve the practicality of the consequence model, a safe state C_1 is added to represent the non-occurrence of the accident.

6.3.2 Development of uncertainty models

6.3.2.1 Data Processing

The first step after the collection of data during the design for decommissioning workshop was to clean the dataset for analysis. The data cleaning function has been written to file using MATLAB (Appendix E). Prior to the analysis, the unrefined dataset is backed-up and stored on two trusted repositories in '*StrathCloud'* and *'Mendeley'*, partly because of accessibility for future reference, and partly due to journal peer-review requirement. Data for leak to mudline representing basic events considered to have insignificant effect on the permanent abandonment, or risk factors identified for the primary cement outside the production casing are removed from the dataset, as in both cases the accident model has overly long chains of event with very low probability contributions. Where there are void cells within the dataset, these have been substituted with zero values for the sake of computation. In addition, datasets recorded as zeros are treated like the void cells cleaning approach. A .*txt file corresponding to void cells and zero values occurrences is also stored, making it possible to identify fluctuations between source-to-source variability. Consequently, the processed data is then obtained and used for analysis and training in the developed relaxation strategies and the dynamic failure models such as the BN and DBN.

6.3.2.2 Noisy-OR gate formalism

The N-OR gate developed for relaxing the conditional probability table to express conditional dependency among interacting events consists of a $i - by - j$ events represented by 2^n conditional dependencies. Elicitations were specified for each contributory factor to accommodate the effect of data paucity and thus, reduce the model uncertainties. Several relaxation strategies were studied and analysed, however, this formalism and that which follows next were adopted as the practically suitable for conditioning the data based on the training input dataset of Chapter 5. The conditional probability for conventional *'AND'* and *'OR'* gate prior to implementing the N-OR to train the data is shown in Figure 6-11.

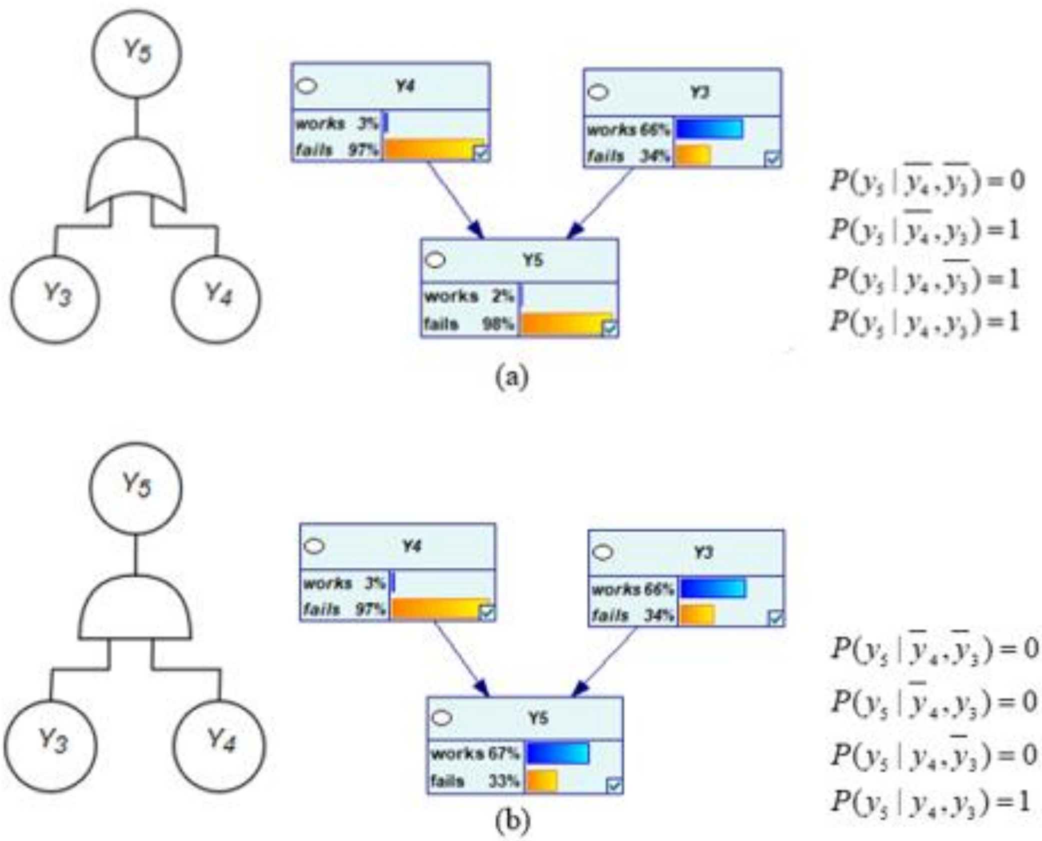


Figure 6-11 Node CPT outputs (a) OR gate (b) And gate

In this formalism, the underlying principle of this type of gate is based on the assumption that any accident causal element is independently capable to influence the common outcome, commonly referred to as *'child'*, even if other causes are absent. In other words, the common child can only be initiated given that at least one of the causal elements is true and unhindered (Neapolitan, 2009). As the failure probabilities are obtained as mean distributions for all input data, the refined data are conditioned according to Equation 6-1 to standardize the range of dependent child variables in the range [0,1].

$$p(a \mid \bar{b}_1, \bar{b}_2, \dots, b_f, \dots, \bar{b}_{n-1}, \bar{b}_n) = p_f \tag{6-1}$$

where n is a causal binary variable $B_1, B_2, \dots, B_{n-1}, B_n$ with a common outcome (child) A.

The objective of the N-OR gate process is to address the uncertainty related to parametric modelling within the conditional probability table due to uncaptured hazards. Captured hazards represents performance parameter measurements within the expert opinion, historical data, or literature limits for the well permanent abandonment failure. In the case of uncaptured data, these usually represents noise or faulty data. To satisfactorily model the single failure capable of independently initiating the outcome, the conditional probability table for the leak through casing assembly as shown in Figure 6-12 will be computed as illustrated in Table 6-3 and numerically expressed as

$$P(B5 = b5|B5.1 = b5.1, B7.2 = b7.2) = P_{b5.1}P_{b7.2}$$

$$P\big(B5 = b5\big|B5.1 = \bar{b}5.1, B7.2 = \bar{b}7.2\big) = 0$$

$$P\big(B5 = b5\big|B5.1 = b5.1, B7.2 = \bar{b}7.2\big) = P_{b5.1}$$

$$P\big(B5 = b5\big|B5.1 = \bar{b}5.1, B7.2 = b7.2\big) = P_{b7.2}$$

$$P\big(B5 = \bar{b}5\big|B5.1 = b5.1, B7.2 = b7.2\big) = (1 - P_{b5.1})(1 - P_{b7.2})$$

$$P\big(B5 = \bar{b}5\big|B5.1 = \bar{b}5.1, B7.2 = \bar{b}7.2\big) = 1$$

$$P\big(B5 = \bar{b}5\big|B5.1 = b5.1, B7.2 = \bar{b}7.2\big) = (1 - P_{b5.1})$$

$$P(B5 = \bar{b}5 | B5.1 = \bar{b}5.1, B7.2 = b7.2) = (1 - P_{b7.2})$$

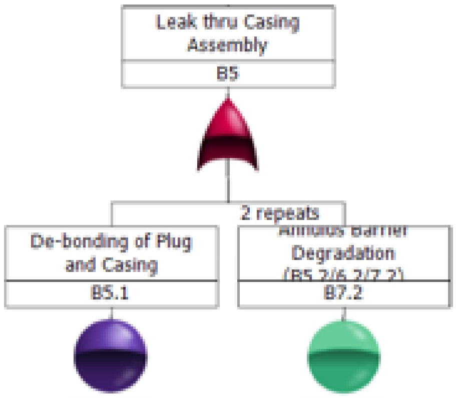


Figure 6-12 Leak through casing assembly fault tree

Since the N-OR formalism is a generalization of the logical OR-gate, a link probability connecting each conditional probability to the failure probability of each unique combination of causes B_i given by l_α is estimated as follow.

Table 6-3. N-OR CPT for leak through casing assembly.

Outcomes	$\mathbf{B_{5.1}}$	$\mathbf{B_{7.2}}$	$\boldsymbol{l_\alpha}$	$\boldsymbol{\bar{l}_\alpha}$	$\mathbf{B_5}$
1	F	F	0	1	$l_{\alpha 1} \times (1 - P_{b5.1}) \times (1 - P_{b7.2})$
2	F	T	0.9	0.1	$l_{\alpha 2} \times (1 - P_{b5.1}) \times P_{b7.2}$
3	T	F	0.8	0.2	$l_{\alpha 3} \times P_{b5.1} \times (1 - P_{b7.2})$
4	T	T	0.98	$0.02 = 0.2 \times 0.1$	$l_{\alpha 4} \times P_{b5.1} \times P_{b7.2}$

The link probability corresponds to uncaptured data for each causation, as the event or series of events leading to their occurrence are not completely known. Thus, the contribution of this added uncertainty is incorporated into the conditional probability table to fully define the dependence amongst interacting causations and are used to strengthen the degree of belief through experiential learning. The CPT computation to condition the dynamic model is intensive due to the 2^n parameters required and therefore, MATLAB code is developed for the sake of simplicity as presented in APPENDIX D.

The noisy-OR model relies on the failure of at least one causation acting independently to cause the common outcome (child variable) to fail and uses a link probability to establish the dependence among possible outcomes. However, it is not capable of representing uncertainties associated with the uncaptured data, which can remotely influence the occurrence of the common outcome and the uncertainty introduced into the model due to parameterisation error. To achieve this, a form of the noisy-OR, called leaky N-OR is developed.

6.3.2.3 Leaky Noisy-OR gate formalism

The leaky noisy-OR (LN-OR) gate is developed to account for a practical scenario where the common outcome occurs even though there is no contribution from any of the identified causations. The LN-OR is especially suited to account for the likelihood of an uncaptured data in the probable causes of the accident. It is modelled to establish dependency for the leak of hydrocarbon to mudline subsystems and components level. Invariably, the LN-OR utilizes a leak probability to accommodate the contribution from an uncaptured cause or causes of failure. The conditional probability for each cause is elicited to condition the failure data related to each barrier plug of the permanent abandonment upper cap. The only notable parameters corresponding independently to the leak to mudline are the isolation plug, lower (primary) plug and the combined leak through upper (secondary) plug. This narrows the total number of input parameters for effective conditioning to eight i.e., 2^3 and the leak probability can be expended primarily on the outliers and thus, the model would have accounted for both captured and uncaptured contributory factors without superfluously increasing the dimensions in the elicitation that would compromise the robustness of the dynamic computation engine, reliability of the data analysis and interpretation process.

The uncaptured event with a leak probability p_o is specified as shown in Equation 6-2, such that

$$p(a \mid \bar{b}_1, \bar{b}_2, \ldots, \bar{b}_{n-1}, \bar{b}_n) = l_o \tag{6-2}$$

where n is a causal binary variable of events $B_1, B_2, \ldots, B_{n-1}, B_n$ with a common outcome (child) A. Typically, the value specified for l_o depends largely on the degree of belief to which the contributory factors influence the outcome and is defined to be 5% in this study.

During CPT elicitation, the LN-OR is defined for all combinations of events and the leak probability incorporated based on the input failure data prior to instantiating the overall probability of leak to mudline. The CPT elicitation for Figure 6-12 is highlighted in Table 6-4.

Table 6-4. LN-OR CPT for leak through casing assembly.

Outcomes	$\mathbf{B_{5.1}}$	$\mathbf{B_{7.2}}$	$\boldsymbol{l_o}$	$\boldsymbol{\bar{l}_o}$	$\mathbf{B_5}$
1	F	F	0.05	0.95	$l_{o,1} \times (1 - P_{b5.1})(1 - P_{b7.2})$
2	F	T	0.9	0.1	$l_{o,2} \times (1 - P_{b5.1}) \times P_{b7.2}$
3	T	F	0.8	0.2	$l_{o,3} \times P_{b5.1} \times (1 - P_{b7.2})$
4	T	T	0.98	$0.02 = 0.2 \times 0.1$	$l_{o,4} \times P_{b5.1} \times P_{b7.2}$

6.3.3 Development of BN and DBN models

6.3.3.1 BN Model

In this Section, the modelled conventional bowtie structure and associated learning parameters are illustrated for N-OR and LN-OR formalisms for the input failure dataset. A BN with sufficient and well-defined nodes can model complex and dynamic systems with considerable accuracy and are suitable for handling nonsequential and non-linear dynamic problems such as the kind posed by decommissioning and abandonment systems. The network for the case study was formulated by using the causal events of the leak to mudline FT as input in the root nodes as shown in the BN generic structure. The causal or basic events of the FT correspond to the basic failure events of the well PA failure. The interrelationship among the root nodes, characterised by various logic gates and relaxation strategies, is represented by an arc. The faulty or intermediate events of the FT correspond to the intermediate nodes on the BN from where the arcs emanating from the root nodes terminate. In addition, the top event corresponds to the pivot node connecting the FT to the ET side of the BT. The end consequences of the BT correspond to the leaf node in the BN, which is essentially dependent on the occurrence and nonoccurrence of the failure of safety barriers in place.

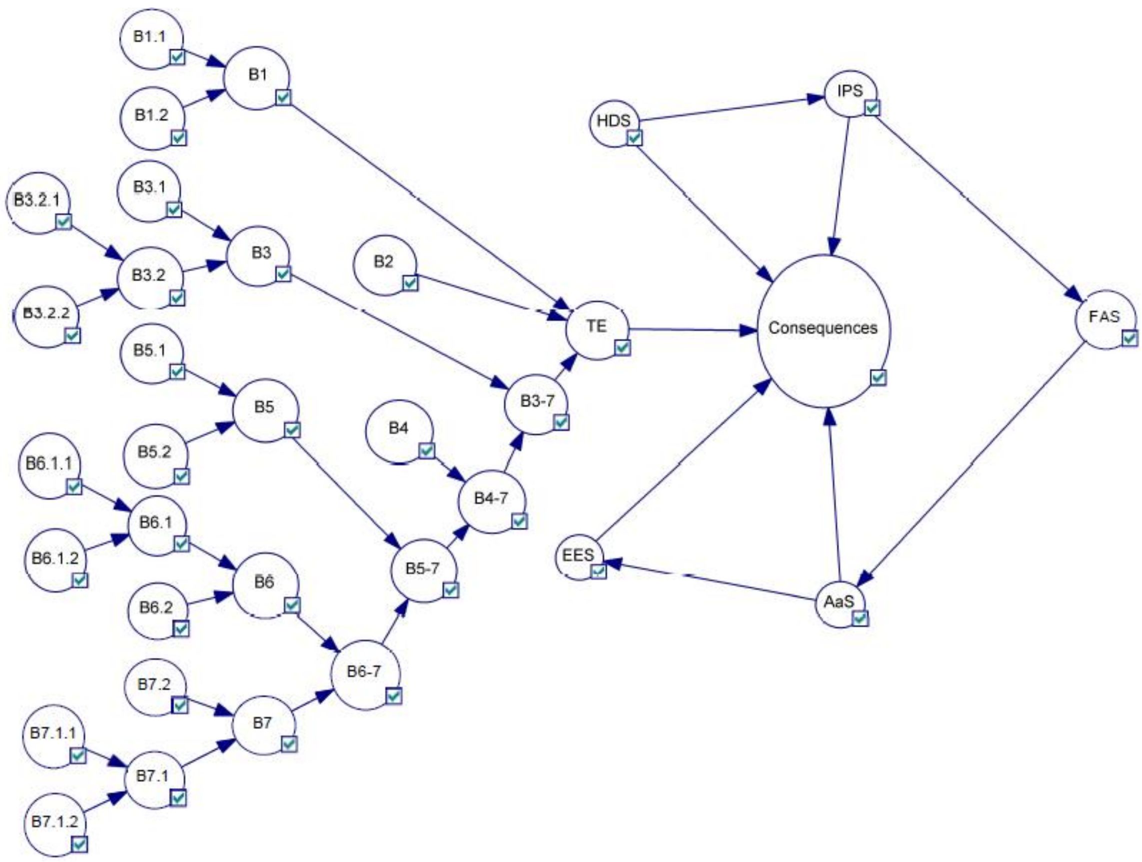


Figure 6-13 Bayesian network for permanent abandonment operation

Furthermore, the failure probabilities of the basic events are used as input for the root nodes in the form of prior marginal probability. The intermediate, pivot and leaf nodes probabilities are assigned through the conditional probability table. When dependencies among interacting events are not considered, the FTA yields similar results for the top event; and where the safety barriers are assumed to be activated sequentially, the end consequences occurrence probability is the same for the ETA. These outcomes are rational and reasonable because each event is statistically independent and the failure datasets have not been normalized to condition the dataset, making FTA and ETA impractical for the present case study.

To model dependencies that exist amongst accident causations, N-OR and LN-OR relaxation strategies have been developed to quantify the interactions within the child node's conditional probability tables. The following four (4) steps typifies the procedure leading to BN or DBN elicitation of failure probability of interest.

Step (1): Estimate the failure probability for all parent nodes within the BN, and their corresponding safe state probabilities.

Step (2): Assign non-zero leak probability l_α to represent dependency of all causations in the case of LN-OR formalism; N-OR leak probability may be assigned prior to succeeding step.

Step (3): Elicit the conditional probability table based on N-OR and LN-OR algorithms, separately.

Step (4): Estimate the top event probability by assigning the appropriate parent nodes state conditional probabilities i.e., safe/unsafe, yes/no, true/false, or works/fails etc.

Based on these steps, the leak to mudline characterised by the failure of barrier plugs B1, B2 and/or B3-7 depicted earlier in Figure 6-13 is calculated. The probability of TE, using N-OR logic within the BN with step (1) is as shown in Table 6-5.

Table 6-5. Failure and safe state probabilities of top event.

Identifier	Causal description	Failure probability	Safe state probability
B1	Leak through isolation plug	0.0089	0.9911
B2	Leak through primary plug	0.1900	0.8100
B3-7	Combined leak thru upper plug	0.1074	0.8926

Step (2) yields column 5 & 6 of Table 6-6 and steps (3) and (4) are as highlighted in the same Table 6-4.

Table 6-6. N-OR CPT for leak through mudline (TE).

States	B_1	B_2	B_{3-7}	l_o	$\bar{l}_o$	$CPT(TE)$
1	F	F	F	0.00	1.00	0.00•0.9911•0.8100•0.9996=0
2	F	F	T	0.90	0.10	0.90•0.9911•0.8100•0.1074=7.560E-02
3	F	T	F	0.80	0.20	0.80•0.9911•0.1900•0.9996=1.506E-01
4	F	T	T	0.98	0.02=0.2x0.1	0.98•0.9911•0.1900•0.1074=1.982E-02
5	T	F	F	0.40	0.60	0.40•0.0089•0.8100•0.9996=2.882E-03
6	T	F	T	0.94	0.6x0.1=0.06	0.94•0.0089•0.8100•0.1074=7.278E-04
7	T	T	F	0.88	0.6x0.2=0.12	0.88•0.0089•0.1900•0.9996=1.487E-03
8	T	T	T	0.988	0.6x0.2x0.1=0.012	0.988•0.0089•0.1900•0.1074=1.794E-04
						P(TE) = ΣCPT(TE) = 0.2533

In the same manner, following the steps (1) to (4) above and assuming a leak probability of 5% which is selected arbitrarily due to insufficient model data, the LN-OR influence on the top event probability can be estimated, thus

Table 6-7. LN-OR CPT for leak through mudline (TE).

States	B_1	B_2	B_{3-7}	l_o	$\bar{l}_o$	$CPT(TE)$
1	F	F	F	0.05	0.95	0.05•0.9911•0.8100•0.9996=4.012E-02
2	F	F	T	0.905	0.1x0.95=0.095	0.905•0.9911•0.8100•0.1074=7.803E-02
3	F	T	F	0.810	0.2x0.95=0.19	0.810•0.9911•0.1900•0.9996=1.525E-01
4	F	T	T	0.981	0.2x0.1x0.95=0.019	0.981•0.9911•0.1900•0.1074=1.984E-02
5	T	F	F	0.430	0.6x0.95=0.57	0.430•0.0089•0.8100•0.9996=3.099E-03
6	T	F	T	0.943	0.6x0.1x0.95=0.057	0.943•0.0089•0.8100•0.1074=7.301E-04
7	T	T	F	0.886	0.6x0.2x0.95=0.114	0.886•0.0089•0.1900•0.9996=1.498E-03
8	T	T	T	0.9886	0.6x0.2x0.1x0.95=0.0114	0.9886•0.0089•0.1900•0.1074=1.795E-04
						P(TE) = ΣCPT(TE) = 0.2960

The ILN-OR approach is computed using the equations (14)-(16) with a lower and upper-bound leak probabilities given by $l_{min} \leq l \leq l_{max}$ with $l_{min} = 0$ and $l_{max} = 0.05$. Furthermore, a modality of 1.0 is assigned to the ignorance (T,F) model. The leaky probability boundaries offer the advantage of producing two sets of failure probabilities, which is in practice, realistic in a non-absolute and uncertain analysis. It is to be noted that each of the three causal nodes will be assigned three states, leading to 27 outcomes for each state of the leak through mudline event (top event node). In addition, the top event will be assigned three states to represent its occurrence (*t*), nonoccurrence (*f*), and associated ignorance (*t, f*).

Table 6-8. ILN-OR CPT for leak through mudline (TE).

States	$\mathbf{B_1}$	$\mathbf{B_2}$	$\mathbf{B_{3-7}}$	TE		
				t	f	t, f
1	F	F	F	(0, 0.05)	(0.8,0.9)	(0.2, 0.05)
2	F	F	T	0.905	0.064	0.031
3	F	F	T,F	0.800	0.200	0.000
4	F	T	F	0.810	0.090	0.100
5	F	T	T	0.800	0.100	0.100
6	F	T	T,F	0.980	0.019	0.001
7	F	T,F	F	0.400	0.400	0.200
8	F	T,F	T	0.940	0.040	0.020
9	F	T,F	T,F	0.88	0.060	0.060
10	T	T	T	0.9880	0.006	0.006
11	T	T	F	0.88	0.10	0.12
12	T	T	T,F	0.800	0.200	0.000
13	T	F	T	0.810	0.090	0.100
14	T	F	F	0.800	0.100	0.100
15	T	F	T,F	0.980	0.019	0.001
16	T	T,F	T	0.400	0.400	0.200
17	T	T,F	F	0.940	0.04	0.02
18	T	T,F	T,F	0.88	0.06	0.06
19	T,F	T	T	0.800	0.100	0.100
20	T,F	T	F	0.990	0.010	0.000
21	T,F	T	T,F	0.400	0.200	0.400
22	T,F	F	T	0.810	0.090	0.100
23	T,F	F	F	0.988	0.006	0.006
24	T,F	F	T,F	0.400	0.200	0.400
25	T,F	T,F	T	0.480	0.480	0.040
26	T,F	T,F	F	0.495	0.495	0.010
27	T,F	T,F	T,F	0.000	0.010	0.990

The N-OR returned a failure probability value higher than an AND-gate but lower than an OR-gate, making it a reasonable estimate with considerable confidence in rare accident scenarios where cost-saving is of crucial concern. The LN-OR, on the other hand, returned a failure probability value higher than the N-OR taking into account the effect of uncaptured hazards in the accident model.

In total, 13 N-OR, LN-OR, and ILN-OR models are developed for the failure parameters of the conditional probability tables of the dataset to train the BN model. The BN, DBN, and the three relaxation strategies were selected as they provided practically accurate network learning capability compared to training more generalized network models with learning algorithms such as the artificial neural network (ANN), fuzzy cognitive maps, and fuzzy set theory algorithm.

Furthermore, the computation engine within the developed algorithm for the BN includes the validation of dataset dependency, thus, the dataset is utilised to learn or train the network using experiential learning by splitting 80% dataset for learning and 20% for diagnosis.

6.3.3.2 DBN Model

The DBN is constructed from the BN to accommodate the cascade of failure of the overall system emanating from component- and subsystem-level failures over time. This is especially required because BN is static in nature as its joint probability distribution is generally represented by an instantaneous occurrence at a specific point in time or at a time interval (McNaught and Zagorecki, 2010). The BN depicts a discrete time model, and it represents a time slice which is then linked to the succeeding time slice by a temporal dependence arc. In order to develop a model for time-variant analysis and forecasting, the data is divided into clusters in the learning and validation set i.e., the event leading to the overall failure of the permanent abandonment is divided into quarterly accident evolution where the datasets are multiplied by fractional increments – 25%, 50%, 75% and 100% time slices. The quarterly increment is systematically chosen to preserve the correlation relationships of the time-variant data.

As previously mentioned in Section 4.8, the DBN model uses robust time slices in its computation engine to dynamically predict one- or multi-step forward or backward propagations of the time-variant data. The number of propagations is conditioned experientially by instantiating the network as a multiple of the observed evidence. Experiential learning with different numbers of evidence characterised by new observations were performed to obtain a realistic prediction model that accurately describe practical scenarios of well P&A integrity failure.

The elicitation of the conditional probability table for the two relaxation strategies remained unaltered for the dynamic model. However, the network is configured such that the time slice at state $t_{n-1} = t - 1$ feeds into the succeeding time-slice $t_n = t$ and so on. This means, for example, that the child nodes are connected to the parent nodes in the same time slice $t,$ and on the parent nodes and itself at preceding time slice $t - 1$ as shown in Figure 6-14.

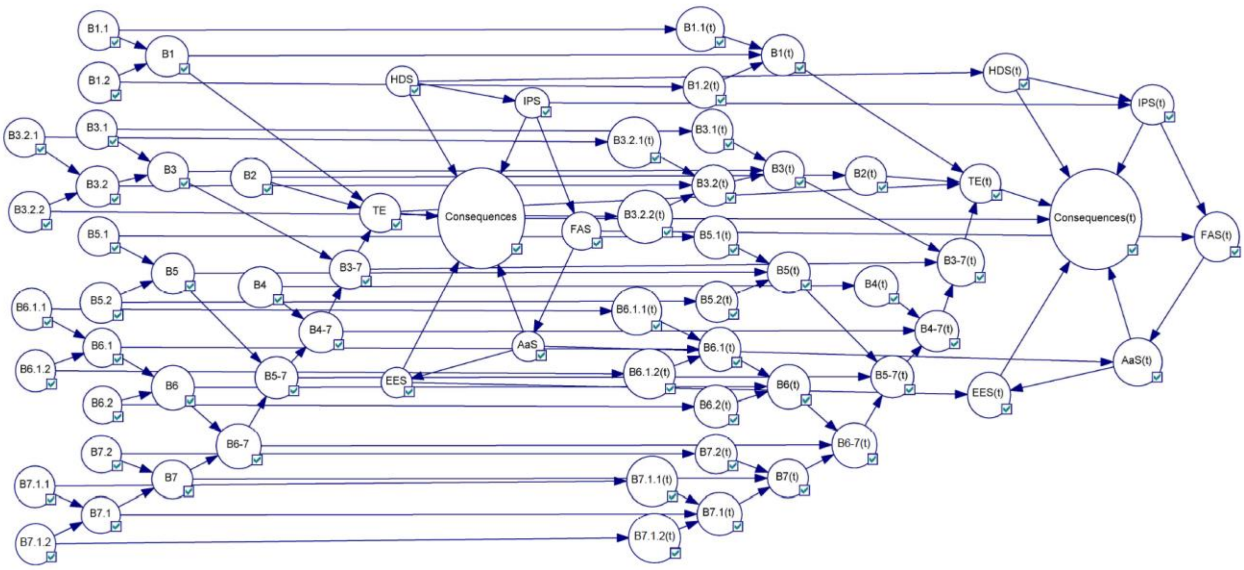


Figure 6-14 Dynamic Bayesian network for permanent abandonment

6.4 Discussion

The steps involved in conducting the proposed dynamic safety model are presented and the issue of underestimation of ‘AND’ gate and the overestimation of ‘OR’ gate were addressed by introducing advanced logic formalisms within the conditional probability table of the Bayesian networks to account for uncaptured hazards, dependencies among interacting events and the nonlinearity that may exist amongst these causations. Three models were developed to that end, namely, noisy-OR, leaky noisy-OR, and imprecise leaky noisy-OR. First, the N-OR formalism was utilised to account for the potential for the top event single undesired accident to occur in the presence of a single causal among many, which represents an event in its unhindered state. Compared to the AND/OR gates, the N-OR returned a failure probability value that is greater than ‘AND’ but lesser than ‘OR’ formalism, making N-OR a middle course representation of accident causals interaction. Secondly, the leaky N-OR thrived on the premise that the top event may still fail even when all its causations (parent nodes) do not fail. This is especially the case of a rare accident event modelling and is a commonplace occurrence in the offshore decommissioning industry. The leak probability takes a non-zero value as input and returned a value relatively higher than N-OR, AND, and OR models. Finally, the imprecise leaky N-OR addressed the influence of ‘ignorance’ incorporated into the accident scenario analysis. It thrives on the idea that the data used in the analysis sparse and analogous, the assumptions made by experts during hazard identification analysis may be flawed, and the mathematical model contained an assumed ‘leak’ and ‘link’ probabilities that do not reflect sufficient data. It returned two failure dataset representing upper and lower limits that can support decision makers remarkably.

Overall, the advanced logics demonstrated reliable performance of the BN model output and established that the dependency modelling would have reduced one of the many uncertainties associated with a rare accident of such a magnitude. The formalisms have been presented in their orders of superiority to address hazard identification analysis and overall risk assessment issues. Therefore, the result of the imprecise leaky N-OR is robust to support decommissioning and abandonment decision making process at every phase since it combines the benefits of both N-OR and leaky N-OR. Although, its elicitation is computationally challenging, but its implementation has unparalleled benefit and will be utilised as a control limit for monitoring the decommissioning and abandonment safety analysis in the subsequent Chapters.

6.5 Summary

This Chapter introduced the model formulation using advanced logics to relax the drawbacks of traditional quantitative risk analysis such as the FTA, ETA and bowtie, and was applied to the permanent abandonment system of oil and gas wells. The reliability models were presented systematically following the evolution of uncertainties in accident causal parameters and data paucity with the underlying assumption that the reservoir condition was not completely known at the cessation of production. The relaxation strategies within the Conditional Probability Tables (CPT) were required to differentiate the accident model behaviour from conventional logic gates and were applied to the case study of permanent well plugging and abandonment operation. It was demonstrated that the proposed dependency modelling through the relaxation strategies can provide a realistic estimate of the top event occurrence probabilities better than AND/OR gates. The ability to incorporate the dependency models was also verified by manual calculus since the script and book-keeping are often not transparent within the graphical interface of software tools. However, the accident model formulations still need to be improved to increase precision by considering predictive and diagnostic tools as shall be seen in succeeding Chapters.

Chapter 7: Well PA Results and Discussion

7.1 Outline

This Section seeks to sum up and present the main findings of the dynamic failure analysis from the developed data and model in its entirety. The results are presented on overall system level such that the accident scenarios represented by the FT and the accident evolution represented by the ET are considered with the weakest link leading to the end consequence as the component (s) of interest, otherwise known as the Most Probable Cause (MPC) of failure.

7.2 Static Failure Analysis outcomes for case study

7.2.1 FTA Results

The results summarised each of the main system characterised by barrier plug failures, safety barriers failure to respond on demand, and consequent catastrophe or the lack of it thereof. The severity of these failure modes, characterised by importance measure in the sensitivity analysis Section, are provided and presented in their significant order quantified by MPCs. For instance, as can be seen in Table 7-1, the combination of basic events leading to the top event estimation revealed the weakest links in the form of Minimal Cut Sets (MCS). The MCS provides practical intuition into the contribution of the basic events within the permanent abandonment accident evolution in its entirety.

Table 7-1 Failure probabilities of MCs for non-sour permanently abandoned well.

MC_j	Estimation Parameters	Cut Set Order	Event Description	MC_j probability
MC_1	B_2	1	Leak through the lower plug	1.90E-01
MC_2	$B_{3.2.2}$	1	Geological forces effect	1.86E-01
MC_3	$B_{3.1}$	1	Prolong exposure of migration fluid	1.47E-01
MC_4	B_4 $B_{5.1}$	2	Leak through the production plug; De-bonding of plug and casing	8.11E-02
MC_5	$B_{3.2.1}$	1	Formation of fluid loads effect	5.00E-02
MC_6	B_4 $B_{5.2}$	2	Leak through the production plug; Annulus barrier degradation	3.30E-02
MC_7	$B_{1.1}B_{1.2}$	2	Pressure build-up; Injection into nearby wells	8.93E-03
MC_8	B_4 $B_{6.2}$ $B_{7.2}$ $B_{7.1.2}$	4	Leak through the production plug; **Annulus barrier degradation;** **Annulus barrier degradation;** Barrier shrinkage	8.91E-04
MC_9	B_4 $B_{6.2}$ $B_{7.2}$ $B_{7.1.1}$	4	Leak through the production plug; **Annulus barrier degradation;** **Annulus barrier degradation;** Poor mud removal	6.93E-04
MC_{10}	B_4 $B_{6.1.2}$ $B_{7.2}$ $B_{7.1.2}$	4	Leak through the production plug; Loss of barrier; Annulus barrier degradation; Barrier shrinkage	6.31E-04
MC_{11}	B_4 $B_{6.1.2}$ $B_{7.2}$ $B_{7.1.1}$	4	Leak through the production plug; Loss of barrier; Annulus barrier degradation; Poor mud removal	4.91E-04
MC_{12}	B_4 $B_{6.1.1}$ $B_{7.2}$ $B_{7.1.2}$	4	Leak through the production plug; Inadequate barrier density; Annulus barrier degradation; Barrier shrinkage	4.38E-04
MC_{13}	B_4 $B_{6.1.1}$ $B_{7.2}$ $B_{7.1.1}$	4	Leak through the production plug; Inadequate barrier density; Annulus barrier degradation; Poor mud removal	3.41E-04

A closer look at Table 7-1 showed that there exist thirteen (13) minimal cut sets within the accident model. Of these, there are four first-order, three second order, and six fourth order MCS. The leak through lower plug appeared to be the Most Probable Cause (MPC) of failure capable of triggering the single failure characterised by top event occurrence. Similarly, the effect of geological forces is more probable to cause the overall system failure compared to the prolong exposure of migrating fluid and so on. The leak through production plug and the de-bonding of plug and casing must fail simultaneously to cause equivalent damage.

The relevance of the identified minimal cut sets of the FT analysis can be described from practical and realistic standpoint. For instance, the most of influential conditions of the basic events within a subsea or topside oil/gas well are temperature, pressure, and are associated with the leak through the lower or primary plug subsystem of the single failure system. Barrier shrinkage, loss of barrier and annulus barrier degradation are seen to be critical to the single failure occurrence. The integrity of these components must be ensured, otherwise, leakage pathways would manifest and can initiate a domino effect within the wellbore. The major strength compromise emanating from the identified barriers failure is the sensitivity of contact stress between interacting well casings (Saeed et al., 2018; Ahmed et al., 2015). The contact stress is further impacted by the micro-annuli created by the barrier shrinkage. The shrinkage of barrier is attributed to the quality of the plugging or cement job as this would provide structural adequacy and impede corrosive formation fluids migrating into the subsea casing systems annuli. Although, the downhole condition is often uncertain during plugging, the wellbore pressure and the sourness of the formation fluids can compromise the cement strength and consequently degraded. Due to this observation and noting that basic events $B_{5.2}$, $B_{6.2}$, and $B_{7.2}$ are common cause failures. Furthermore, the order 2^{nd}-order minimal cut sets include plugging failure influencers such as the leak through the production casing, pressure build-up, injection into nearby well, and annulus barrier degradation. The pressure build-up is especially critical as it can spontaneously escalate the equilibrium of the wellbore if not properly monitored and controlled. Lastly, the 4^{th}-order cut sets are related to the plug integrity within the wellbore that are crucial to the non-occurrence of the leak to mudline as a failure such as the poor mud removal, annulus barrier degradation, and inadequate barrier density can trigger a cascade of failure between casings in-contact stresses.

The results from the FTA helped in identifying critical components that require further analyses in a dynamic scenario to provide insight into when the plugged and abandoned well would have been compromised in order that sufficient control and inspection regime can be implemented to avert site remediation. The analysis of the FT result assumed that each contributory factor is statistically independent, but this need not be true as decommissioning and abandonment operations are a family of rare accidents with dependencies existing among interacting events, among events and their common causes, and also between the model formulation assumptions due to uncertainty. The dependencies will be the focus of the dynamic safety analysis herein. Prior to dynamic analysis, the FTA results would be used to initiate the consequence analysis within the ETA presented in the next Section to obtain the accident evolution results in its entirety. This further step will assist in the identification of weak links among the safety barriers in place and how the end consequences advances.

7.2.2 ETA Results

The single failure identified as the top event of the FT was used as the initiating event in the event tree analysis development to investigate the accident evolution scenario during decommissioning and abandonment phase. The ETA is based on the assumption that the safety barriers in place are sequential and would be triggered on-demand when the preceding safety barrier has failed. The occurrence probabilities of the end consequences are estimated through the propagation of initiating event and safety barrier failure probabilities in their states of interest. As noted from Figure 6-3 to 6-6, FTA is used to quantify the failure probabilities of all the safety barriers from the knowledge of their influencing factors discussed in Section 6.3.1.2. It is important to note that accident evolution analysis (ETA) is not needed post-decommissioning as the reservoir pressure would not have been sufficient to compromise the well integrity after plugging and abandonment.

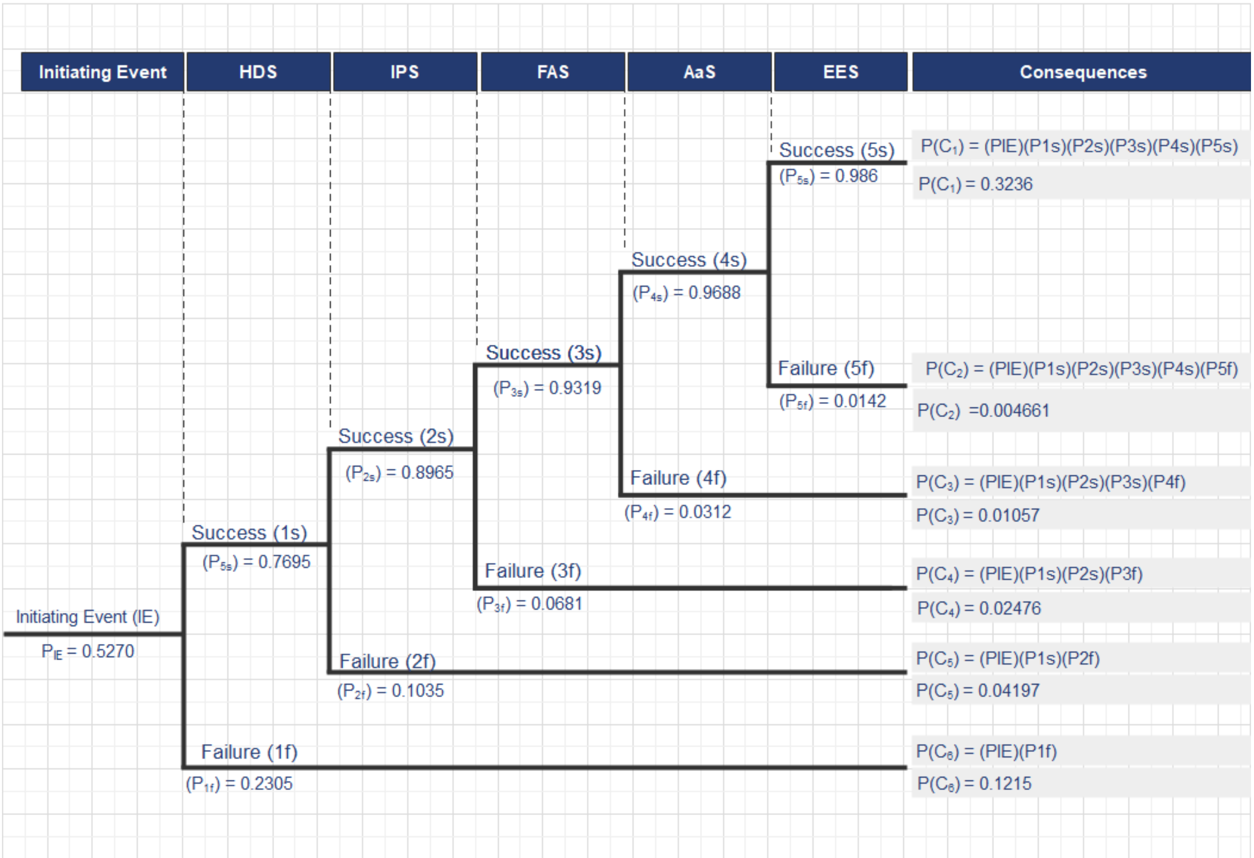


Figure 7-1 Accident evolution results

As can be deduced from Figure 7-1 above, when a hydrocarbon leak is spotted at the mudline or seabed (IE), the Hydrocarbon Detection Sensor (HDS) is triggered. The trigger can notify the Ignition Prevention System (IPS) and the subsequent safety barriers leading to a safe state end consequence with an occurrence probability of 32.36% (consequence C_1). If the Emergency Evacuation System (EES), in the form of a dedicated crew with adequate training to rescue-and-evacuate, fails to successfully perform its intended function, the first failure scenario – near miss without remediation required – with an occurrence probability of 0.47% (consequence C_2) is reported. If the Alarm and Sprinkler System (AaS) is faulty and refuses to initiate on-demand, then the decommissioning and abandonment crew would be unaware of the imminent danger leading to potential minor injuries and loss of equipment with an occurrence probability of 1.06% (consequence C_3). The failure of the Flame Arrestor System (FAS) will lead to a hazardous scenario characterised by fire, few deaths, and minor sill with occurrence probability of 2.48% (consequence C_4). If the IPS fails to trigger due to fault or damage, explosion and a major hydrocarbon spill is imminent with an occurrence probability of 4.20% (consequence C_5). If the first safety barrier (HDS) malfunctions, then all other safety barriers sequentially positioned to receive signals from it will be redundant and the personnel would have been unaware of the potential fatalities, rig loss, and considerable hydrocarbon spill waiting to happen with an occurrence probability of 12.15% (consequence C_6). Since the safety barriers are propagated as though they were linear and sequential without consideration for dependency, the FTA and the ETA will be combined into a bowtie and mapped into a BN to conduct probabilistic failure analysis in the subsequent Sections.

7.2.3 Bowtie mapping into BN Results

The combined accident scenarios modelling within the BT is as shown in Figure 7-2, where each basic, intermediate, and top event becomes the root, intermediate, and leaf node of the BN, respectively. Three (3) advanced logic gates (Noisy-OR, Leaky Noisy-OR, and Imprecise Leaky Noisy-OR) are used in the BN to factor in the dependence and uncertainty associated with the accident model, parameter shortcomings, and model formulation assumptions. First on the FTA side, the failure probability of each event estimated in Chapter 5, are transformed to become the marginal probabilities in the BN. Furthermore, on the ETA side, each safety barrier is modelled to be dependent on the one preceding it and the dependency is elicited within its CPT as described in Section 4.

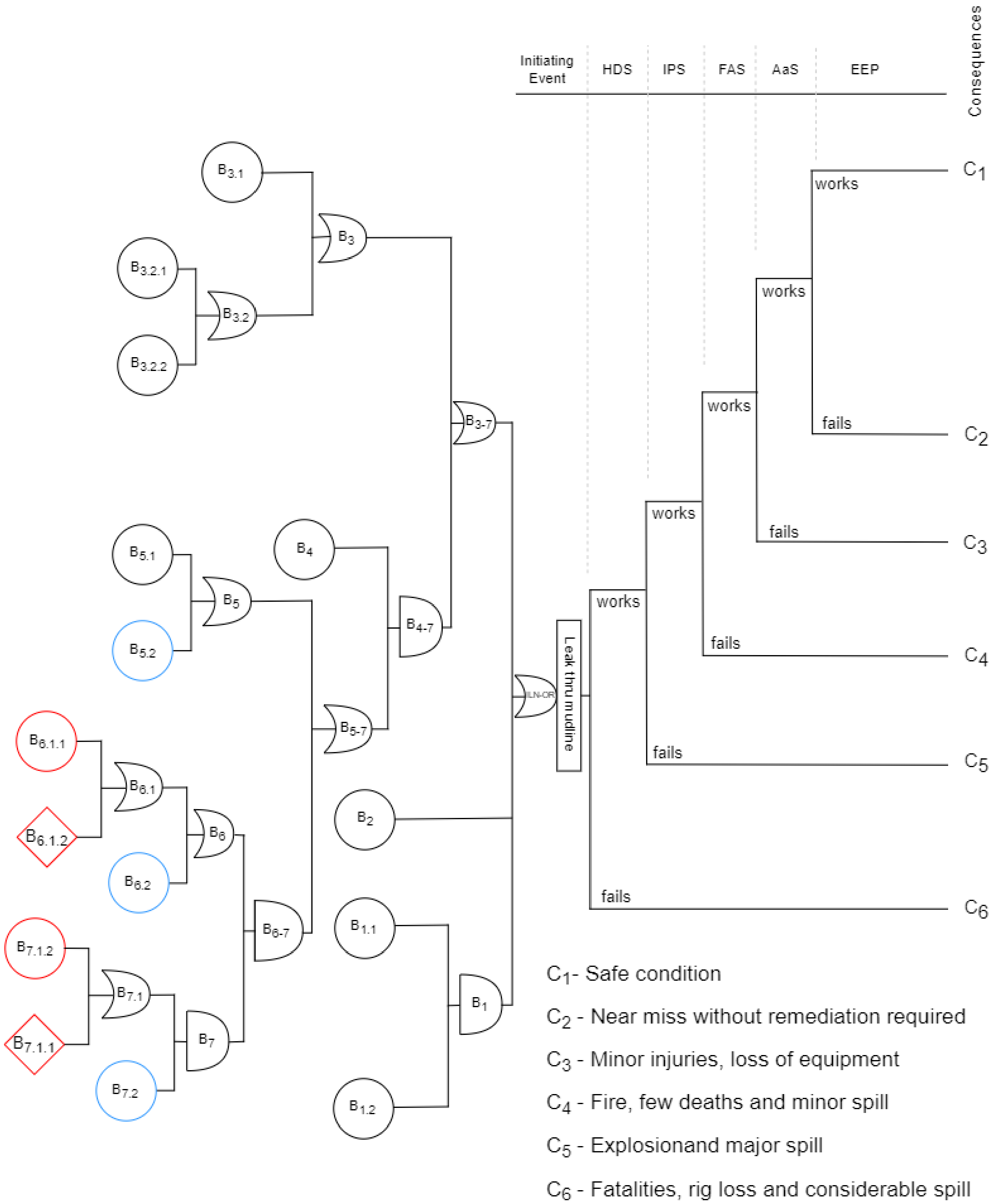


Figure 7-2 Bowtie model for permanent abandonment operation

The permanent abandonment bowtie shows how the faulty events B_1, B_2, and B_{3-7} could evolve to cause the leak of hydrocarbon to the mudline. The leak of hydrocarbon to the mudline can propagate into loss of assets and personnel including environmental loss which may lead to huge economic loss as a result of site remediation if safety barriers are not adequately implemented. The bowtie does not only provide an insight into the key performance parameters needing to be monitored and controlled during the permanent abandonment operation.

7.2.4 Selection of permanent abandonment-controlled parameters

Through the Design for Decommissioning (DfD) workshop on permanent well abandonment assessment methodologies, plugging and abandonment options were conducted, and technical solutions were discussed based upon the limited knowledge of the reservoir conditions. The two (2) notable concerns were the quality of cement job during plugging and the casing integrity characterised by yielding. These potential failure modes were further fleshed out to obtain the parameters used in the case study accident model depicted by the bowtie above. These parameters of interest are used to learn, monitor, and control the accident scenarios. Therefore, the parameters describing the well integrity related to the cement quality are the barrier shrinkage, loss of barrier, inadequate barrier, and annulus barrier degradation. In addition, the parameters related to the casing integrity failure are the pore pressure build-up, injection into nearby well, geological loads effect, and formation fluids load effect. For dynamic failure analysis, the parameters capable of deteriorating over time would be selected as inputs to instantiate the DBN. These parameters are the annulus barrier degradation, pressure build-up over time and loss of barrier as represented in Table 7-2 where ✓ and × refer to key performance parameters of interest and those not of interest, respectively.

Table 7-2 Well PA-controlled parameters for inspection modelling

Performance Data	BN Analysis	DBN Analysis
Barrier shrinkage	✓	×
Loss of barrier	✓	✓
Inadequate barrier	✓	×
Annulus barrier degradation	✓	✓
Pressure build-up	✓	✓
Injection into nearby well	✓	×
Geological loads effect	✓	×
Formation fluids load effect	✓	×

7.2.5 Probabilistic risk analysis results

7.2.5.1 Post-decommissioning with rigless scenario

By way of system reliability analysis, the well plugging and abandonment schematic system description offers insight into the leakage routes and how it propagates into a single failure defined by the leak of hydrocarbon through the mudline. The prior marginal probabilities of all basic events are identified (as presented in Chapter 5 with mean distribution as shown in APPENDIX G) and assigned to the nodes. The interactions between these causations – between the parent nodes and their corresponding child nodes – are represented by the AND/OR gates in a similitude transformation from FTA and ETA into BNs. That is, the Conditional Probability Tables (CPT) for all basic events and their intermediates are described in binary 0's and 1's. However, the advanced logic gates Noisy-OR, Leaky Noisy-OR, and Imprecise Leaky Noisy-OR are separately utilised to describe the dependencies between the three (3) faulty events – leak through zonal isolation plug (B_1), leak through lower plug (B_2), and combined leak through upper plug (B_{3-7}) – leading to the top event occurrence. The conditional probability tables specified for the faulty events as described in Section 6.3.3.1 is used to estimate the top event failure by considering the different plugging and abandonment reliability issues. The reliability issues combined with the uncertainty associated with data sparsity, modelling assumptions and parameter knowledge were incorporated within the relaxation strategies built into the advanced logic gates. Similar approach is used to estimate the end consequences during a rig-based abandonment operation.

Due to the implementation of dependency and uncertainty models within the BNs, the top event estimated occurrence probability is different considerably when compared to that obtained from the FTA, making the BN a flexible and more practical representative of the accident scenarios analysis. For example, the failure probability of the top event yields 0.2835 using the FTA, and 0.2533, 0.2960 and [0.2377, 0.7226] using N-OR, LN-OR and ILN-OR respectively as shown in Table 7-3. This notable difference indicates that the FTA overestimated the failure probabilities because it treated each contributory factor as though it were statistically independent. Furthermore, instantiation of the BNs model at the instance when the first leak of hydrocarbon to the mudline is spotted (i.e., $P(B_i = true|TE = true)$) revealed that the leak through the upper plug between the production and surface casings is more probable to fail in comparison with the other accident contributory factors.

Table 7-3 Top event failure probability comparison

Sample size	FT Analysis	BN Analysis		
		Noisy-OR	Leaky Noisy-OR	Imprecise Noisy-OR
10	0.2835	0.2533	0.2960	[0.2377, 0.7226]

7.2.5.2 Pre-decommissioning with rig-based scenario

During the decommissioning operation, especially, using a rig-based approach it is not uncommon to encounter the end consequences described in Section 6.3.1.4 and the consequence model is analysed and reported herein.

The Noisy-OR formalism within the BNs showed that the safe condition occurrence probability is 62.66%, indicating that the performance reliability of the overall accident model is high given that all safety barriers in place are all operational on demand. Hydrocarbon release occurrence probability is estimated to be 20.74% and appeared to be the first and most probable incident, albeit the absence of an ignition source would be sufficient to interrupt the accident propagation medium. The absence of an ignition source is a planning issue rather than operational and is expected to have been factored into the risk contributors prior to commencement of decommissioning and abandonment operation. Vapour cloud has an occurrence probability of 8.75%, making its actualisation dependent on external failure due to planning, since a vapour cloud cannot propagate unless it is escalated by wind. To a lesser degree, the occurrence probability of pool fire (similar to jet fire if wellbore contains gas) is 3.67%. Furthermore, the occurrence probability of casualties, characterised by explosion and major spill is found to be 3.30%. For this to happen, all safety barriers except emergency evacuation plan (EEP) must have failed on demand and leak of hydrocarbon spotted. The least consequence defined by fatalities, rig loss and considerable spill, is found to have an occurrence probability of 0.88% which further confirms the classification of decommissioning and abandonment operation as a family of rare accident events evidenced by the low probability-high consequence trend.

On the other hand, the leaky Noisy-OR formalism showed a similar trend in the decreasing level of occurrence probabilities from safe condition to fatalities i.e., $C_1 - C_6$. However, the safe condition probability is found to be 63.52%. Hydrocarbon release accounted for 20.20% occurrence probability with a failure likelihood of vapour cloud up to 8.42%. Pool fire occurrence probability is estimated to be 3.49% when the casualty's occurrence probability is 3.54%, and the chances of fatalities occurring is 0.84%. The accident contributory factors for all the occurrences leading to the leak of hydrocarbon to mudline and end consequences are the same, validating the BN formulation from the bowtie.

In the ILN-OR approach, the calculations were performed in MATLAB & Simulink programming environment using the developed conditional probability table and the mathematical equations (14), (15), and (16) presented in Section 4.4.7. The results provided a lower bound and upper bound solutions for the occurrence probabilities. The lower-bound values representing an optimistic failure probability and the upper-bound, pessimistic. These lower- and upper-bound values also provided insight into the first sensitivity analysis for the investigated events as presented in Table 7-4.

Table 7-4 Consequence modelling results

Consequences	**ETA Results**	**BN Results**		
		N-OR	**LN-OR**	**ILN-OR**
C_1	0.3236	0.6266	0.6352	(0.5664, 0.7566)
C_2	0.0047	0.2074	0.2020	(0.1135, 0.1962)
C_3	0.0106	0.0875	0.0842	(0.0328, 0.0961)
C_4	0.0248	0.0367	0.0349	(0.0105, 0.0543)
C_5	0.0420	0.0330	0.0354	(0.0551, 0.0789)
C_6	0.1215	0.0088	0.0084	(0.0078, 0.0319)

7.2.6 Development of failure prediction models

The failure of a plugged and abandoned oil and or gas well is safety critical and complex, making it susceptible planned and unplanned hazardous scenarios that can compromise safety. To predict the failure model, one of two information is required – i.e. (1) the knowledge about any of or both the top event and the end consequences (2) new observation about one or more of the causations. The analysis that takes input from the first is termed "*diagnosis or backward propagation"* , and that relying on the latter is termed *"predictive of forward propagation"*. It is worthy of mention that during decommissioning and abandonment in a rig-based operation, BT is valid because the reservoir may still contain hydrocarbon that may migrate uphole to cause disruption of the Elgin Platform type and as a result, would be used for diagnoses i.e., backward propagation. On the other hand, during post-decommissioning, only the FTA end is valid because the reservoir would have been rendered non-producing and any traces of hydrocarbon migration would have been killed by the barrier or mechanical plugs in place. As a result, the FTA would be used for predicting top event occurrence.

7.2.6.1 Predictive Analysis

The forward propagation analysis takes input from the key performance parameters identified in Table 7-2 of Section 7.2.4 to predict the uncertainty associated with the failure model within the BN. The identification is based on the first static preliminary results obtained from traditional QRA and will represent Accident Precursor Data (APD) that would be collected in real-time during decommissioning and abandonment operation to forecast monitoring intervals. This forecast is performed to obtain posterior failure probabilities for the top event and associated end consequences.

From the list of performance parameters identified, it can be observed that the annulus degradation barrier is a common cause failure (CCF) capable of triggering the leak through casing assembly, the leak through conductor casing, and in combination with barrier contamination to cause the leak through casing hangar. Therefore, the CCF influence on the overall system failure can be critical. In total, 8 accident contributory factors are identified as performance parameters needed to investigate the leak or blowout scenario for this case study. The forward analysis is assessed such that the probability of leaf node (top event) will be updated by instantiating all the 8 causal factors to their true state representing the availability of evidence or new knowledge about their occurrence or non-occurrence. i.e., $P(\text{accident} = \{\text{true}\}|\text{root nodes} = \{\text{fail}\})$.

Table 7-5 Top event updated failure probability

Interval	FT Analysis	BN Analysis		
		Noisy-OR	Leaky Noisy-OR	Imprecise Noisy-OR
Prior	0.2835	0.2533	0.2960	[0.2377, 0.7226]
Posterior	0.5517	0.4666	0.4043	[0.4742, 0.7788]
$\|\%\Delta_{TE}\|$	48.6%	45.7%	26.8%	[49.9, 7.2%]

Table 7-5 show that there is a progressive increment in the posterior failure probabilities of the top event estimated through all the proposed methods. However, the upper bound posterior probability in the ILN-OR model is unresponsive to the influence of the performance data incorporated as new knowledge or evidence to update the degrees of belief associated with the source-to-source variability in the failure data used to generate the prior failure probabilities of accident causal factors. In addition, the implementation of forward propagation on the performance data to forecast the leak to mudline failure when real-time Accident Precursor Data are not readily available, leads to an overall significant increase in the top event occurrence probability. It is worth mentioning that the order in which the performance data are to be instantiated is beyond the scope of this research. To that end, experiential learning is adopted to investigate the trend and the strength of influence as shall be seen in the succeeding Section.

The corresponding end consequences posterior probabilities with the relative differences computed as an absolute percentage change are as given in the Table 7-6 below. In the consequence modelling, the highest percentage change in prior and posterior probabilities are observed within the conventional ETA results, indicating that static analysis used to calculate the priors were overestimated. This overestimation is not acceptable in decommissioning and abandonment operations because a noninvestment capital project is expected to drive minimum economic risk in order to motivate decision makers and attract rebates from the government. To that end, the advanced relaxation strategies implemented within the BN analysis provided a better representation of uncertainties associated with the modelling parameters, uncaptured hazards, and link probability.

A closer look at the consequence events outcome revealed a similar trend as those observed for the top event scenarios. There is a progressive increment across all methods for C_1 and C_5, and variable percentage reduction in C_2, C_3, C_4, and C_6. In the upper-bound of the imprecise leaky Noisy-OR logic, the degree of responsiveness ranges between 0.3% to 9.3%, making these consequences less sensitive to the monitoring performance data.

Table 7-6 Consequence modelling updated failure probability

End consequences		ETA Results	BN Results		
			N-OR	LN-OR	ILN-OR
C_1	$C_{1_{prior}}$	0.3236	0.6266	0.6352	(0.5664, 0.7566)
	$C_{1_{posterior}}$	0.6981	0.6788	0.6646	(0.6344, 0.7534)
	$\|\%\Delta_1\|$	53.6%	7.7%	4.4%	(10.7%, 0.4%)
C_2	$C_{2_{prior}}$	0.0047	0.2074	0.2020	(0.1962, 0.1135)
	$C_{2_{posterior}}$	0.1631	0.1750	0.1840	(0.1656, 0.1138)
	$\|\%\Delta_2\|$	97.1%	18.5%	9.8%	(18.5%, 0.3%)
C_3	$C_{3_{prior}}$	0.0106	0.0875	0.0842	(0.0961, 0.0328)
	$C_{3_{posterior}}$	0.0597	0.0672	0.0727	(0.0731, 0.0335)
	$\|\%\Delta_3\|$	98.2%	30.2%	15.8%	(31.5%, 2.1%)
C_4	$C_{4_{prior}}$	0.0248	0.0367	0.0349	(0.0543, 0.0105)
	$C_{4_{posterior}}$	0.0216	0.0257	0.0286	(0.0387, 0.0114)
	$\|\%\Delta_4\|$	14.8%	42.8%	22.0%	(40.3%, 7.9%)
C_5	$C_{5_{prior}}$	0.0420	0.0330	0.0354	(0.0551, 0.0789)
	$C_{5_{posterior}}$	0.0524	0.0472	0.0433	(0.0645, 0.0793)
	$\|\%\Delta_5\|$	19.8%	30.1%	18.2%	(31.5%, 0.5%)
C_6	$C_{6_{prior}}$	0.1215	0.0088	0.0084	(0.0319, 0.0078)
	$C_{6_{posterior}}$	0.0052	0.0062	0.0069	(0.0237, 0.0086)
	$\|\%\Delta_6\|$	95.7%	41.9%	21.7%	(34.6%, 9.3%)

7.2.6.2 Experiential Learning

The performance data is treated as though they were Accident Precursor Data obtained during the plugging and abandonment operation for the Elgin platform. Their observed evidence is collected and recorded over the seven (7) week period for which the actual hydrocarbon blowout occurred as presented in Table 7-7. The Accident Precursor Data was verified through a thorough peer-review process in a quartile-one journal and further validated by the C-RISE research group to support its applicability. The data indicates the number of trials recorded for each accident contributory factor over the seven (7) week period for which the Elgin platform failed.

Table 7-7 Accident Precursor Data for key performance data

Performance Data / Weeks	B1.1	B1.2	B3.2.1	B3.2.2	B5.2	B6.1.1	B6.1.2	B7.1.2
0	3	-	-	3	2	1	-	-
1	3	2	1	1	2	1	-	-
2	2	1	1	-	2	-	-	-
3	2	1	-	2	1	1	-	-
4	2	-	1	2	1	1	-	-
5	1	1	-	2	1	2	-	-
6	1	1	-	1	-	2	1	-
7	1	-	1	1	-	2	1	1

Incorporating these sets of evidence in the model through probability adaptation technique, the strength of influence on the top event and resulting consequences' reliability was trained or learned within MATLAB and are presented in Figure 7-3.

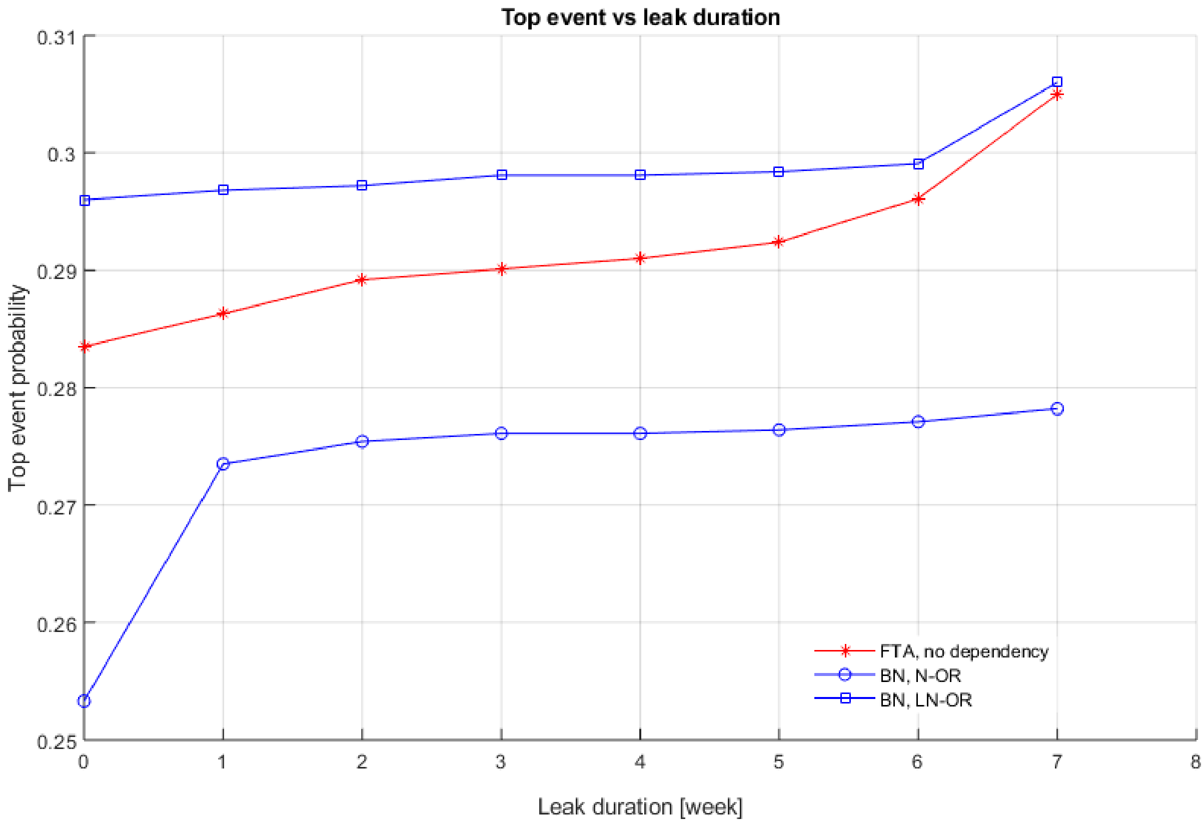


Figure 7-3 Top events evolution over leak duration

Figure 7-3 provides detailed insight into the sensitivity of the top event failure to its causals including how it responds to potential cascade of failures of these causals. A closer examination revealed that the FTA model in BN without dependency (in red asterisk) responded increasingly in a non-linear manner through the overall leak duration. The N-OR model, on the other hand, responded sharply to the performance data trend in the first week before stabilising in a semi-linear manner. In addition, due to the OR-logic gate used to formulate the model, it is apparent that the LN-OR model is a middle-course between *OR* and *And* logic gates, indicating that the FTA model may have been overestimated. The LN-OR model exhibited a similar progressive increment pattern to the FTA model. The marked difference being that the top event occurrence probability was higher than both the FTA- and N-OR models. This notable response is attributed to the incorporation of uncaptured hazards, possible inaccuracy in the modelling assumptions, and parameters uncertainties. Overall, the leak of hydrocarbon to the mudline would have exacerbated in all modelled cases by the end of the seventh week if the well 'kill' would have been unsuccessful. The observation recorded and reported herein paved the way for the need to conduct a comprehensive sensitivity analysis in the dynamic model to support the experiential learning outcomes and consequently, aid a robust decision-making, as shall be seen later in Chapter 8.

7.2.6.3 Diagnostic Analysis

In diagnostic (backward propagation) analysis within BN, the desired information meaningful to decision-makers offshore are the updated (posterior) probabilities, reflecting the specific features of the accident under investigation and, the most probable causes (MPCs) of well P&A failure. To determine the posterior probabilities of the accident contributory factors, a new observation of the overall leak through mudline is necessary. For instance, given that it becomes certain that the well P&A fails, the occurrence probability of the TE is instantiated to unity, i.e., $p(\text{leak thru mudline}) = 1$. The updated failure probabilities of the causations are then reassessed using $p(CE_i|TE = \{T\})$. The results obtained from the FTA, N-OR and LN-OR logics modelled through BN are presented in Table 7-8. It can be seen that the events $B_{1.1}$, $B_{1.2}$, B_2, B_4, and $B_{5.1}$ have the largest posterior occurrence probabilities in all cases. Of these, event B_2 (the leak through upper plug) is the most safety critical, thereby validating the observation noted in Section 7.2.5.1.

To better estimate the most probable causes (MPCs) of the top single failure, the weakest links among interacting events are assessed by using the importance measure (IM) defined by $IM = (p_o/p_i)$ where p_o is the posterior probability and p_i is the prior probability. The further away from unity the ratio, the more responsive the causal event is in contributing to the overall occurrence of the top event. The values of the MPC computation when ran through different relaxation approaches yield up-to-date top event probabilities of 1.00E+00 i.e., the worst-case scenario to update the accident contributory factors.

Table 7-8. Failure probabilities comparison of CEs based on backward propagation.

Events	Mapped FT		IM^{FT}	N-OR		IM^{NOR}	LN-OR		IM^{LNOR}
	Prior	Posterior		Prior	Posterior		Prior	Posterior	
$B_{1.1}$	8.50E-02	1.06E-01	1.25	8.50E-02	9.56E-02	1.12	8.50E-02	9.36E-02	1.10
$B_{1.2}$	1.05E-01	1.25E-01	1.19	1.05E-01	1.15E-01	1.10	1.05E-01	1.13E-01	1.08
B_2	1.90E-01	6.70E-01	3.53	1.90E-01	6.58E-01	3.46	1.90E-01	5.73E-01	3.02
$B_{3.1}$	1.47E-01	1.50E-01	1.02	1.47E-01	1.50E-01	1.02	1.47E-01	1.49E-01	1.01
$B_{3.2.1}$	5.00E-02	5.33E-02	1.07	5.00E-02	5.33E-02	1.07	5.00E-02	5.30E-02	1.06
$B_{3.2.2}$	1.86E-01	1.89E-01	1.02	1.86E-01	1.90E-01	1.02	1.86E-01	1.88E-01	1.01
B_4	2.75E-01	4.93E-01	1.80	2.75E-01	5.22E-01	1.90	2.75E-01	4.77E-01	1.73
$B_{5.1}$	2.95E-01	4.36E-01	1.48	2.95E-01	4.55E-01	1.54	2.95E-01	4.26E-01	1.44
$B_{5.2}$	1.20E-01	1.77E-01	1.48	1.20E-01	1.85E-01	1.54	1.20E-01	1.73E-01	1.44
$B_{6.1.1}$	5.95E-02	6.04E-02	1.02	5.95E-02	6.05E-02	1.02	5.95E-02	6.03E-02	1.01
$B_{6.1.2}$	8.50E-02	8.63E-02	1.02	8.50E-02	8.65E-02	1.02	8.50E-02	8.62E-02	1.01
$B_{6.2}$	1.20E-01	1.22E-01	1.02	1.20E-01	1.22E-01	1.02	1.20E-01	1.22E-01	1.02
$B_{7.1.1}$	1.75E-01	1.77E-01	1.02	1.75E-01	1.77E-01	1.01	1.75E-01	1.76E-01	1.01
$B_{7.1.2}$	2.25E-01	2.27E-01	1.01	2.25E-01	2.27E-01	1.01	2.25E-01	2.27E-01	1.01
$B_{7.2}$	1.20E-01	1.24E-01	1.03	1.20E-01	1.25E-01	1.04	1.20E-01	1.24E-01	1.03

It is observed from Table 7-8 that the posterior failure probabilities for both N-OR and LN-OR are less responsive to the availability of new evidence when compared with the FT similitude mapping results. In addition, the posterior probability for the leak through lower plug (B_2) increased rapidly in all cases, indicating that event B_2 would require higher inspection and monitoring priority. The posterior-to-prior probability ratios are in agreement with the sensitivity pattern observed using the Accident Precursor Data to train the BN model using experiential learning. However, the ratios only represent the relative index between guesstimates and new knowledge and does not provide any intrinsic information to inform risk-based decision making. In a rare accident scenario analysis like decommissioning and abandonment, detailed sensitivity analysis tends to address the components and or subsystems that are critical and to what extent. While the updated probabilities for the mapped FT, N-OR model, and LN-OR model are almost identical in terms of posterior probabilities being larger than their corresponding priors, there is no difference in the order of significance of the accident contributory factors. Mapped FT is modelled with no dependency amongst interacting causal factors with the conditional probability table being binary. The N-OR model results were lower than those of the mapped FT, indicating that uncaptured hazards are a functional variable of uncertainty. The leaky N-OR model provided a more considerable results due to the incorporation of additional uncertainties.

7.3 Discussion on proposed methodology

Based on the results obtained from the model formulation and analysis from conventional PRA to BN comparisons, it can be seen that BN is able to accommodate advanced relaxation techniques to provide failure values corresponding to specific accident models. Overall, the modelled results indicate that FTA and ETA with their corresponding BT equivalent yielded probability values higher than those obtained within the BN using N-OR but lower than those of LN-OR, making the conventional PRA results a middle course vis-à-vis risk analysis. More specifically, the top event failure values characterised by the leak of hydrocarbon to mudline, is demonstrated to be the initiating event for the ETA and the ILN-OR shows how this failure values can be presented as intervals. The interval results presentation allowed for the decision-makers to be able to support their risk response strategy with a lower and upper bound limit.

The developed FT/ET/BT model allowed for a comprehensive and realistic visualisation of the overall system and the interactions among accident contributory factors, which enhanced the addition of new causal events to the system. The system extended the wellbore schematic and its potential leak pathways to include new subsystems such as the barrier contamination, poor mud removal, yielding of casing, and prolong exposure of migrating fluids, among others. The preliminary sensitivity of the top event and associated end consequences to changes in the causal events was demonstrated through predictive (forward propagation analysis) and diagnostic (backward propagation analysis) techniques. Due to the limited evidence offered by a single time-slice, probability adaptation was investigated through experiential learning that took inputs from Accident Precursor Data over the seven (7) week period for which the Elgin platform experienced a blowout.

In addition, the accident scenarios development with FT and BT which was mapped into their corresponding BNs allowed for the flexibility to visualise the accident evolution and can accommodate more accident contributory factors at component and subsystem level. In particular, the ease with which the developed model has been extended to cover additional causations which were not explicitly present in the wellbore schematic contained in the literature and case study adopted, permitted the incorporation of finitely complex cases where any given causal can become a parent to other causals. For illustrative purpose, in the case of the annulus barrier degradation which is both time-dependent and a common cause failure, any one or a combination of its “child” nodes can be triggered in several varying outcomes and in no particular order – a concept referred to as domino effect.

Furthermore, the events analysis of the Elgin platform laid bare the importance of the overall system knowledge because the incident was escalated do to cascading of failures of the mechanical plugs. Several unrelated and unconnected layers of the well failed nonsequentially, necessitating the need to formulate the model in an advanced logical sequence beyond AND/OR gates. These modelling and reservoir dynamics considerations through the implementation of imprecise leaky noisy OR formalism coupled with failure data obtained from Hierarchical Bayesian Analysis with multi-stage refinements, were the focus of this present study. The described methodology presented a robust process for obtaining the top event failure probability with considerable confidence and further aided the identification of the most probable causes of failure that may compromise the integrity of the plugging and abandonment operation.

Instantiation of the predictive analysis algorithm where key performance data were selected to be in their ‘true’ states yielded updated occurrence probabilities for the top event and end consequences with the observation that all formulated models responded incrementally whereas the upper bound of the imprecise leaky noisy-OR showed little to no response. In addition, the instantiation of the diagnostic analysis algorithm where the top event is latched to its 'true' state yielded an expected increase in the occurrence probability of the leak through lower plug, making it the most probable failure capable of initiating the single undesired failure with unprecedented consequences.

The methodology presented here enabled the comparison and contrasting of the strengths of each uncertainty model formulations in describing the accident contributory factors response. Through a comprehensive training of the BN model with accident precursor data, consideration was given to the predictive, diagnostic, and experiential learning capabilities. The models developed demonstrated that the leak of hydrocarbon from the reservoir to mudline would have significantly increased if the well were not 'killed' by the seventh (7^{th}) week. The overall system reliability had reduced considerably even in the quasi-static BN model, necessitating the incorporation of a sensor to capture the accident evolution in real-time. The accuracy to predict the model response over time need to be enforced by a detailed sensitivity analysis as the smaller changes in the posterior to prior probability ratios only offer a superficial insight into the desired trend, and this would be the focus of the succeeding Chapter.

7.4 Summary

This Chapter presented a dynamic method for the safety analysis of a non-sour oil and gas well during decommissioning and abandonment operation. The developed accident model relied upon Hierarchical Bayesian Analysis to obtain and process failure data to address the uncertainty associated with source-to-source variability. Due to the challenges of unknown reservoir condition at the point of production cessation, the model incorporated advanced logics such as noisy-OR, leaky noisy-OR, and imprecise leaky noisy-OR to capture the variables of uncertainty in its entirety. The developed model data was trained within MATLAB and fed into Bayesian networks to conduct probabilistic failure assessment and resulted in a considerably realistic safety analysis. Of particular interest was the capability of the imprecise leaky noisy-OR logic to present the failure probabilities in intervals with upper and lower bounds. The benefit of this intervals is numerous but the notable one being in its ability to offer the decision-makers a robust option to guide against under- or overestimation of the occurrence probabilities.

Chapter 8: Sensitivity Analysis Development

8.1 Outline

The permanent plugging and abandonment failure analysis case study and results were presented in the preceding Chapter where the robust safety methodology provided an insight into the integrity of the wellbore to permit the leak of hydrocarbon to the mudline. In this Chapter, the selected performance data identified are tested using sensitivity analysis to demonstrate how small changes in these data contribute to the occurrence of the single system failure. To establish a failure threshold in order to predict when monitoring is due, the sensitivity analysis results will be compared against the upper-bound failure probability of the top event obtained through the imprecise leaky noisy-OR formalism. The comparison aims to provide a baseline for forecasting well abandonment monitoring regime and to aid decision making to ensure decommissioning safety. Following the brief outline of Section 8.1, the case for safety critical analysis is presented in Section 8.2 and Section 8.3 discusses the model formulation for the selected test runs followed by presentation of results obtained from tested scenarios in Section 8.4, while the concluding remark and Chapter summary are provided in Sections 8.5 and 8.6, respectively.

8.2 Safety critical analysis description

The critical nature of decommissioning and abandonment operations cannot be overemphasised and have been established to be a family of rare accident events consisting of complex and nonsequential failure modes. Therefore, it is important to perform a safety critical analysis to assess the degree of responsiveness of the top event to small alterations in the occurrence probabilities of the selected performance data, in order to support the decision to monitor or reassess the operation shortly before accidents occur. One fundamental argument to justify the critical nature of sensitivity analysis is that risk, in itself, is an unknown unknown, and even the known hazards have some level of uncertainty associated with them. The variables of uncertainty are numerous and often intertwined with the potential to introduce significant error into the tested and validated predictions (Biao and Dawid, 2015). Sensitivity analysis is defined as the comprehensive study of investigating how the uncertainty in a system output can be allocated, qualitatively, or quantitatively, to different sources of uncertainty in the system inputs and how these uncertainties can influence the overall model behaviour (Saltelli et al., 2008; Saltelli, 2002; Zitrou et al., 2013). Sensitivity analysis is especially suitable for examining, quantifying, qualifying, and reassessing the accident scenarios pattern in an abandonment operation due to the limited data and unknown reservoir conditions typically encountered when production has ceased. Sensitivity analysis offers an added advantage for decision makers to track model behaviour and alter the conclusions that may have been true about a model formulation, data sparsity, and or parameters assumptions to consolidate a robust probabilistic safety analysis result.

In the field of uncertainty analysis where Bayesian networks are a commonplace, many researchers have developed and adopted different techniques to conduct sensitivity analysis and can be found in the following literature (Awotwe et al., 2016; Drummond et al., 2015). Zitrou et al. (2013) reviewed and summarised the popular sensitivity analysis metrics defined by their measure of importance, including a comprehensive account of the applications areas. The conclusion drawn from the study favoured the changing of key performance parameter inputs selected within considerable range and then assessing the strength of influence of these variations on the model outputs of interest. While varying these selected performance parameters, the other parameters are kept constant with the intent to rank the input model contributions in their decreasing order of significance, consequently, aiding decision making within uncertain scenarios (Oakley, 2009). It is worth mentioning that this sensitivity analysis approach is relatively straightforward, both in implementation and interpretation, for small- to medium-sized model formulation but computation becomes challenging in complex engineering systems where parameters are finitely large.

As decommissioning and abandonment operations do not generate considerable returns on investment, the cost of implementing sensitivity analysis needs to be minimal. To that end, the use of the common Monte Carlo simulation algorithm cannot be justified due to the sizable numbers of model runs required. Therefore, the three common methods of sensitivity analysis with differing implementation attributes are explored. These methods are the Probabilistic Sensitivity Analysis (PSA), Marginalisation Sensitivity Analysis (MSA), and the Scenarios Sensitivity Analysis (SSA) as contained in the works of Zitrou et al. (2013), Saltelli et al. (2004), and Parmigiani (2002). The PSA is the process of defining a probability distribution for sparse data to quantify the uncertainty in the input parameters using the likelihood function with considerable scale as the distribution basis around the input parameters (Briggs et al., 2006; Briggs et al., 2003; Greenland, 2001). The PSA method thrive on the concept of Hierarchical Bayesian Analysis (HBA) discussed in Chapter 5 where the inputs to be tested within the Bayesian model are the posterior distributions rather than the uninformative priors. The obtained probability distributions for the input parameters are then processed using Monte Carlo simulation. Since this approach had been previously implemented to improve the confidence level associated with the sparse data in terms of mean distribution of failure data, it does not serve the comprehensive purpose intended herein.

The Marginalisation Sensitivity Analysis (MSA) is the process of selecting one or more of the input parameters within an acceptable value limit and varied up to the set limits and its exceedance. MSA allows for the introduction of marginal deviation – where the datasets can be either increased, decreased, or ignored – in the input parameters away from the set limit, making it a flexible sensitivity analysis tool for the study at hand. Therefore, MSA enables the investigation of modeller-defined causal parameter state to predict failure outcomes of interest. The MSA is characterised by, a local sensitivity analysis, due to its capability to selectively examine individual input parameter to learn about the target output.

The scenarios sensitivity analysis (SSA), on the other hand, is the process used to learn the impacts of changing the true value of selected parameters on the results of a model output. Here, the safety analyst selects values and defines relevant scenarios to understand the expected trend of the accident model response. While SSA can be applied to complex but linear engineering systems, it is especially suited to accident models lacking sufficient data size, making it appropriate for the tasks this thesis seeks to address. In addition, the SSA approach is relatively straightforward and cost-effective but does not account for nonlinearity that exist among input parameters, yields unbiased results due to the arbitrary selection of performance parameters, and does not provide information about the probability that the selected parameters would be observed. To control the arbitrary selection of input parameter values, the approach adopted in this study utilises two measures to limit the randomisation effect on the model output. First, the model with the least failure probability values obtained from the N-OR model is selected to test SSA's implementation. Furthermore, the upper-bound value obtained in the imprecise leaky noisy-OR logic i.e., 0.7226 is set as the threshold for which the plugged and abandoned well would be re-entered to conduct inspection and remediation.

Following the selection of the N-OR model Bayesian network, the next step in the SSA implementation approach is to first extend the time-slice to cover 100% utilization of the HBA-processed failure probability from time-slice t_0 to t_i, where $i = 1,2,3,4$ with an increment level of 25%. The justification for the time-variance analysis has been discussed in previous Chapter, however, its purpose is to aid in the robust prediction and diagnosis assessment of the oil and gas well decommissioning and abandonment operation. The underlying selection criteria for N-OR against other developed model is due to its occurrence probability underestimation which may help decision makers learn the parameters evolution trend and draw plausible conclusions. The input parameters of the N-OR Bayesian network after time-slice t_4 are then examined locally, where parameters are varied independently, and globally, where two or more parameters are assumed to be interacting in a nonlinear manner.

8.3 Sensitivity base case model formulation

8.3.1 Model selection

The application of sensitivity analysis to examine finitely complex systems can be computationally intensive, and the system needs to be considered locally to yield better cost-benefit to decision makers. For this reason, the same permanently abandoned and decommissioned well discussed in this thesis would be investigated. This is, especially due to the extensive and nonsequential nature of shut-in and temporarily abandoned wells. As permanently abandoned wells are characterised by the terminal state of the wellbore after subjected to drilling, completion, temporary abandonment, and production phases through its life cycle, the producing horizons are plugged, and the casing strings are severed below the mudline.

The important factors to be considered apart from the degraded well status are the reservoir attributes, well attributes, and host platform attributes.

Reservoir attributes. The reservoir attribute is defined by the reservoir energy, the type of fluid, and the severity of the fluid. The reservoir energy has a significant impact on the size of the leak as this is driven by whether the reservoir is flowing or nonflowing. Where artificial lift is not required to propagate a hydrocarbon-containing fluid from reservoir to the surface, the reservoir energy is said to be sufficient for the well to flow. The fluid can be in a liquid- or gas-phase, and this determines the nature of blowout and the consequence level associated with such leak or seepage. Furthermore, fluid severity is a function of how sour it is, and a sour fluid is prone to increased corrosion with a higher likelihood to fail over time. Therefore, a sour fluid-containing well can pose significant safety risks compared to a non-sour well.

Well attributes. The attributes of both subsea or topside oil and gas wells are affected by the well equipment age and the type of equipment. Due to in-service conditions such as wear, abrasion, tear, corrosion, and cyclic loading on the well, the equipment would deteriorate over time. Ageing of offshore assets and life extension modelling are beyond the scope of this thesis. However, the effect of equipment age on the overall reliability of the well plays an important role in the design-for-decommissioning safety analysis. In addition, each equipment connected to the well such as the Xmas-Tree, packers, casing, tubing, centralizers, etc. has unique mean time to failure associated with it and will contribute to the modelling uncertainty.

Host platform attributes. In regard to the level of exposure of personnel, the environment and the assets, the host platform wherewith decommissioning, and abandonment is carried out consists of the environmental zone, the size of the platform, and the personnel density. The larger the size of the platform, the larger the exposure area and the location of the field would determine the consequence of the leak. An unmanned platform results to zero exposure of personnel to the effect in comparison to a manned platform.

Based on these attributes, the application of N-OR model which incorporates the effect of uncaptured hazards in its formulation offers a better advantage to examine how sensitive the output model is to the input parameters. The application of the N-OR logic gate in the conditional probability table of the Bayesian network model is extended into time-dependence analysis to aid predictive and diagnosis of the dynamic safety analysis to conduct inspection, monitoring and remediation campaigns. The scenarios sensitivity analysis (SSA) is implemented in this study, and different abandonment operational series of developments are demonstrated. In all the tested series of developments, the prior failure probabilities obtained through the Hierarchical Bayesian Analysis (HBA) is considered as base case for the sensitivity analysis. The sensitivity analysis model is set up by systematically varying the base case data following the time-variant analysis to represent real-time dynamic accident evolution of the leak through mudline. The design intents of performing the sensitivity analysis included the following:

- To examine the strength of the dynamic safety model built around advanced logic N-OR formalism to process sparse failure data and perform predictions that differ from base case data.

- To assess the contribution of the input parameters uncertainty on the N-OR model output results and provide threshold for when the first leak would be spotted to aid reliable predictions of inspection interval.
- To investigate failure data states by using stochastic input data in the analysis to simulate the dynamic safety model.

8.3.2 SSA tools and technique

The scenarios sensitivity analysis is intended to provide sets of failure data as the model output of interest. However, the degree of contribution of each input parameter will be estimated using a metric that takes into account the effect of time variation in the analysis. The importance measures metric describes the amount that any single barrier plugs, or a combination of such plugs contributes to the failure probability of the well in its entirety. The metric applicable to such a dynamic safety model is the Fussell-Vesely's formula (Chybowski et al., 2014; Verma et al., 2010; Van der Borst and Schoonakker, 2001) presented in Equation (20) of Chapter 4 and is presented in its refined form to address the variables in this analysis specifically.

$$IM_{B_j}^{FV} = \frac{\partial p_{(B_i)}^{TE}}{\partial p_{(B_j)}} \frac{p_{(B_j)}}{p_{(B_j)}^{TE}} = \frac{p_{(B_j)}^{TE} - p_{(B_j=0)}^{TE}}{p_{(B_j)}^{TE}}$$

As it can be seen from the Fussell-Vesely equation above, the $IM_{B_j}^{FV}$ depends on the top event failure probability as a function of the interacting minimal cut sets. While a portion of the complete permanent abandonment model has been reported in Figure 8-1, the contribution of each accident contributory factor is presented in Table 8-1 and the most probable cause leading to the occurrence of the top event using the Fussell-Vesely importance measure metric, $IM_{B_j}^{FV}$. The $IM_{B_j}^{FV}$ represents the most probable cause of the hydrocarbon leak to mudline and a higher value denotes that the event would more than likely cause the single point failure. The results obtained for the noisy-OR model is similar to those of the FTA similitude mapping, leaky noisy-OR, and the imprecise leaky noisy-OR models. As it can be noted from Table 8-1, the leak pathway compromise is expected to be exacerbated when any or a combination of implemented barrier is lost. The loss of such barrier can be caused by many different factors. While these factors have been attributed to human errors emanating from noncompliance to the relevant guidelines, the subject of human reliability has not been studied in this research work.

Table 8-1 Safety critical failures for abandoned well system

Identifier	Failure Events	$IM_{B_j}^{FV}$
$B_{6.1.2}$	Loss of barrier	0.6593
$B_{1.1}$	Pressure build-up	0.5842
$B_{5.2}$		0.5268
$B_{6.2}$	Annulus barrier degradation	0.5191
$B_{7.2}$		0.5086
$B_{1.2}$	Injection into nearby walls	0.5071
$B_{3.1}$	Prolong exposure to migrating fluid	0.4083
$B_{7.1.1}$	Poor mud removal	0.3035
$B_{3.2.2}$	Geological forces	0.2559
B_{2}	Leak through lower/primary plug	0.2508
$B_{6.1.1}$	Inadequate barrier density	0.2383
$B_{3.2.1}$	Formation fluids load effect	0.1972
$B_{5.1}$	De-bonding of plug & casing	0.1632
$B_{7.1.2}$	Barrier shrinkage	0.1045
B_{4}	Leak through lower/primary plug	0.0844

The leak of hydrocarbon to mudline is significantly affected by pressure buildup which is triggered by the injection into nearby well causing adverse pressure differentials to buildup in the hydrocarbon-containing plugged well. Although, this pressure surge is considered to be insufficient to lead to a blowout but is enough to cause a leak or seepage with huge remediation cost as noted in the Elgin platform failure. The failure will then upset the isolation plug which could alone lead to series of cascade of failures or directly initiates the steel cap compromise at the mudline. The failures leading to the leak through casing assembly (B_5), the leak through the conductor casing (B_6), and the leak through casing hangar (B_7) caused by the degradation of annulus barrier was also identified to be a safety critical subsystem. The degradation of annulus barrier is supported by the de-bonding between the casing and the barrier plug including the contamination of the barrier plug to compromise the casing hangar/assembly, and where such barrier plug has insufficient length the integrity of the conductor casing is undermined. Failure caused by the injection into nearby wells, prolong exposure of unset barrier plugs to migrating fluids, and poor mud removal during the plugging and abandonment operations were also identified to be safety critical factors that may escalate the potential occurrence of the overall system failure.

A closer look at Table 8-1 revealed that loss of barrier is the most critical failure capable of significantly compromising the plugged and abandoned well integrity, evident by its 65.93% contribution. To a lesser extent is the difference in pressure between the reservoir and the pore pressure of the depressurized hydrocarbon causing the top event occurrence and by a visible margin of 58.42%. While the annulus barrier degradation is the third highest accident contributory factor in the investigated model, it is worthy of mention that $B_{5.2}$ contributed to the overall system failure by 52.68%, $B_{6.2}$ contributed 51.91%, and $B_{7.2}$ by 50.86%. This observation is attributed to their different minimal cut sets, and as a common cause failure (CCF) in way of the overall system failure.

8.3.3 Dynamic safety critical analysis

The first step in the sensitivity analysis approach is the computation of the dynamic Bayesian network model to obtain updated failure probabilities for the performance of selected time-dependent parameters, which will then feed into the sensitivity model as input parameters varied over t_i. The dynamic model framework also permits the transitive effect of marginalising a node of interest within any time-slice such that any alteration of such node, in the event of new evidence, will update the failure probability all nodes interacting with the marginalised node. For the N-OR model under study, a portion of the 10-year estimate over four time-slices, indicating monitoring interval of two-and-half year, is given in Figure 8-1 below.

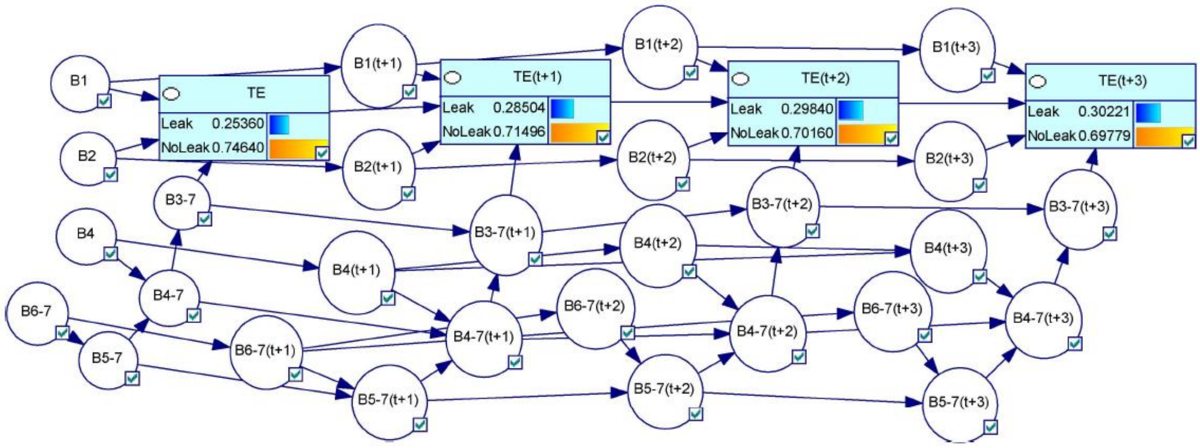


Figure 8-1 Estimated dynamic model for abandonment monitoring over a 10-year period

The results presented in Figure 8-1 above, indicates an increasing probability of leak of hydrocarbon through the mudline. As described earlier, remediation campaign would have to be initiated if and when the unreliability of the plugged and abandoned wellbore coincides with the set threshold of 0.7226 which represents the upper-bound failure probability using the imprecise leaky noisy-OR formalism. Due to the complexity of the overall model, the complete analysis cannot be presented herein, however, the causal events unreliability values are presented in Table 8-2 below.

The results from the dynamic Bayesian network model analysis investigated by propagating the time-slices over a range of $t_0 = 1$ to $t_9 = 10$ represent the ten (10) years interval for which the abandoned well is expected to have been compromised, as noted by Boothroyd et al (2016). If at any time-slice, the resulting failure probability of the top event equals or exceeds the set threshold then the risk profile would have indicated such limit at which monitoring, inspection, and consequent remediation campaign will be initiated. Although, only the first four time-slices of the accident contributory factors have been shown in Table 8-2, the progressive pattern in the risk profile of the top event over the 10-year period revealed that the plugged and abandoned well unreliability level would have increased from 2.53E-1 during the first year of abandonment to 3.80E-1 at the 10^{th} year when the three – that is, Pressure build-up, annulus barrier degradation, and loss of barrier - mechanical barriers in place have failed. It is worth mentioning that the N-OR model have considered uncaptured hazards by way of dependency modelling which is a contributory factor in the accident scenarios analysis. This time-variant analysis relies on the failure of three performance parameters to yield top event failure probabilities below the threshold. However, where there are more interacting events, the top event failure probability will increase considerably due to the modelled dependencies. The failure probability of the top event propagated through the true state of events $B_{1.1}$, $B_{6.1.2}$, and $B_{5.2}$ over the time-slices indicated a progressive increment, making the model output linearly dependent on the confidence level incorporated in the accident scenarios analysis. At the 10^{th} time-slice, the contribution and combinational effects of these causal events will be further investigated in the sensitivity scenarios analysis in the next Section to establish how the top event responds to such variations due to limited confidence and knowledge of the overall interaction in the physical model.

Table 8-2 Summary of barrier failures over time

Events Identifier	Event Description	Time-variant N-OR model failure			
		$t + t_0$	$t + t_1$	$t + t_2$	$t + t_3$
$B_{1.1}$	Pressure differentials	8.50E-2	8.57E-2	8.72E-2	8.82E-2
$B_{1.2}$	Injection into nearby walls	1.05E-1	1.06E-1	1.08E-1	1.22E-1
B_2	Leak through lower/primary plug	1.90E-1	1.94E-1	2.01E-1	2.09E-1
$B_{3.1}$	Prolong exposure to migrating fluid	1.47E-1	1.49E-1	1.54E-1	1.61E-1
$B_{3.2.1}$	Formation fluids load effect	5.00E-2	5.03E-2	5.08E-2	5.14E-2
$B_{3.2.2}$	Geological forces	1.86E-1	1.89E-1	2.09E-1	2.16E-1
B_4	Leak through lower/primary plug	2.75E-1	2.83E-1	2.99E-1	3.31E-1
$B_{5.1}$	De-bonding of plug & casing	2.95E-1	3.04E-1	3.22E-1	3.28E-1
$B_{5.2}$, $B_{6.2}$, $B_{7.2}$	Annulus barrier degradation	1.20E-1	1.21E-1	1.24E-1	1.32E-1
$B_{6.1.1}$	Inadequate barrier density	5.90E-2	5.98E-2	6.05E-2	6.11E-2
$B_{6.1.2}$	Loss of barrier	8.50E-2	8.57E-2	8.72E-2	8.82E-2
$B_{7.1.1}$	Poor mud removal	1.75E-1	1.82E-1	1.97E-1	2.03E-1
$B_{7.1.2}$	Barrier shrinkage	2.25E-1	2.26E-1	2.36E-1	2.41E-1

8.4 Scenario analysis results

The sensitivity scenarios analysis is motivated by controlling the uncertainty through the variation of the base case failure probabilities of selected data to examine the overall failure response of the permanently abandoned well. The failure probabilities obtained through the Hierarchical Bayesian Analysis in its posterior informative forms have been used to propagate the accident model for a period of 10-year, after which, the abandoned well is expected to have deteriorated (Boothroyd et al, 2016). Figure 8-2 illustrates the graphical representation of the sensitivity analysis depicting the different set of inputs and the output for the prediction of the N-OR model.

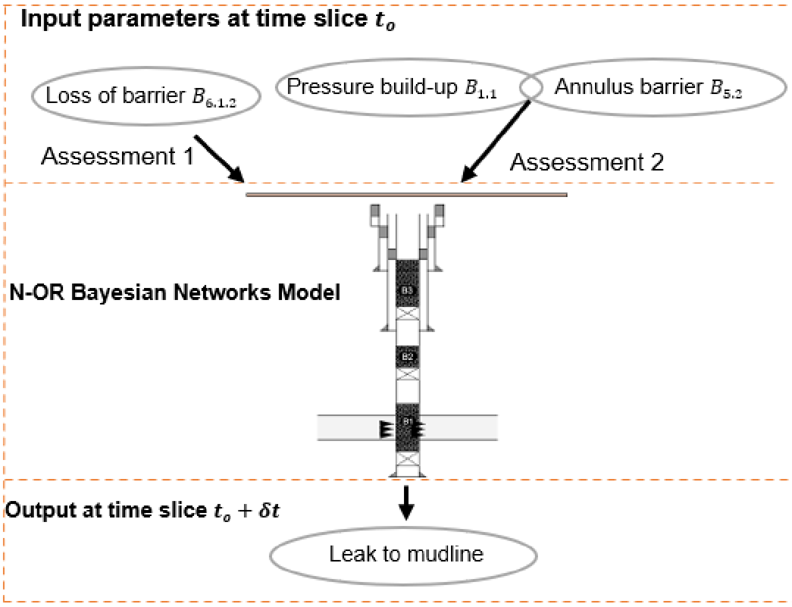


Figure 8-2 Sensitivity assessment setup for input and output responses

8.4.1 Assessment of loss of barrier failure

The failure probability of the loss of barrier failure event is assessed by varying the base case (bc) value over 2% interval for the first three (3) runs and then increased to 5% and 10% for the last two (2) consecutive runs to examine the risk profile of the top event single failure. The loss of barrier failure value ranges used to learn the dynamic safety model are presented in Table 8-3. A total of 11 test runs are performed to study the developed N-OR model outputs. The test runs have been represented as $bc \pm a\%$, where a starts at 2% from bc_1 to bc_3, and then increased by 5% through test runs bc_4 and 10% for bc_5 over a relative difference of 21% positive and negative extremes from the base case.

Table 8-3 Input parameter failure values for the loss of barrier plug ($\boldsymbol{B_{6.1.2} = 0.085}$)

Cases	Runs	Loss of barrier plug [%]
bc_1-	$bc - 2\%$	8.330
bc_2-	$bc - 4\%$	8.160
bc_3-	$bc - 6\%$	7.990
bc_4-	$bc - 11\%$	7.565
bc_5-	$bc - 21\%$	6.715
bc	$bc \pm 0\%$	8.500
bc_1+	$bc + 2\%$	8.670
bc_2+	$bc + 4\%$	8.840
bc_3+	$bc + 6\%$	9.010
bc_4+	$bc + 11\%$	9.435
bc_5+	$bc + 21\%$	10.285

Figure 8-3 shows the test runs results for the loss of barrier plug case study. The error margin for test run bc_1- is found to be 0.21% away from the base case value and continue to decrease over time as the time-step increases. This observation is the first step in the validation of the N-OR model and its response to the slightest shift in the failure probability of the loss of barrier input parameter to proportionately adjust the leak of hydrocarbon to mudline output confirms such capability. It is worthy of mention that the prior failure probability of the loss of barrier is the same as the pressure buildup, making the local analysis of the pressure buildup influence on the output redundant. Furthermore, the consistency in the model output at difference time-step demonstrates the robustness of the dynamic Bayesian network results for each iteration due to the narrow spread of the outputs over the mean and variance of the distribution. Therefore, reducing the loss of barrier plug failure by up to 2% of the base case yields considerable model response.

In addition, bc_2- and bc_3- results show that the leak of hydrocarbon to mudline output is steadily adjusted further away from the base case value and the error margins show a gradual increase due to the increase in the loss of barrier input parameter values from the base case value. For bc_{3^-}, the model output yields a reasonable result as the loss of barrier input value decreases further leading to an increase in the error margin. In support of this observation, Figure 8-3 further reveals that the deviation of the outputs of bc_{3^-} begins to become apparent on the N-OR model with a variance of 6.3% relative to the base case value. The trend is propagated in bc_{4^-} test run and further extended to bc_{5^-} wherein the error margins become notably wide relative to the preceding test runs. Specifically, in test run bc_{5^-} the mean output of the dynamic model response is 8.7% compared to the 4.6% output from bc_{4^-} model run results. Based on these results, inference can be made that the N-OR dynamic model returns an unreliable output in these two (2) excessively fluctuated cases.

For bc_{1^+} and bc_{2^+} test runs, the scenarios sensitivity analysis yields realistic outputs, indicating that the dynamic N-OR model is responsive to input shifts up to 4% for the loss of barrier failure. Furthermore, the results obtained for test run bc_{3^+} indicates the starting point for a reasonable increase in the outputs corresponding to increased input parameter. Moreover, the error margins for test runs bc_{4^+} and bc_{5^+} are expectedly high for the predicted timeline of the abandonment due to the sudden spike in their input parameters which indicate an error margin of +4.6% and +8.7%, respectively from the base case value. However, the mean difference for both test runs remain unchanged, thereby yielding similar outputs.

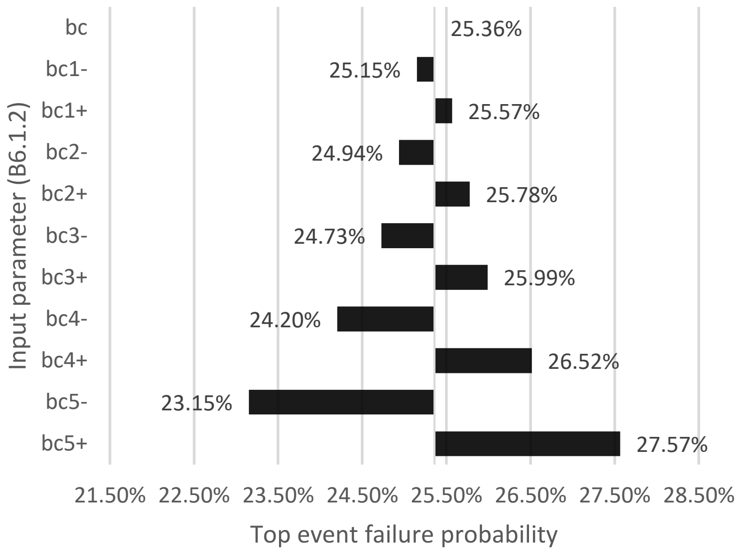


Figure 8-3 Tornado plot for loss of barrier sensitivity case

In the Figure 8-4 below, the datasets aim at supporting the safety critical performance of input parameters due to the shift from the base case value to ranges that may push the output into the unstable model response. While the datasets at varying test runs continue to respond proportionately well over the 10-year period, their unreliability increases progressively for increased input and vice versa for reduced input away from the base case. It is also worthy of mention that regardless of these close-to-identical trends in risk profile, the maximum failure probabilities remain below the set threshold, making it impossible for the permanent well abandonment to leak by the 10th year. Summarily, the results of the sensitivity analysis for the leak of hydrocarbon to mudline demonstrate increased compromise of the plugged and abandonment as the selected time-dependent input parameters deteriorate over time. Therefore, the risk profile validates the current state of knowledge that the lower the reliability of the well components, the lower is the abandonment and plugging integrity of the oil or gas well. The succeeding Section presents the results for a combinatorial sensitivity analysis where two variables strength of influence on the leak of hydrocarbon to mudline is explored.

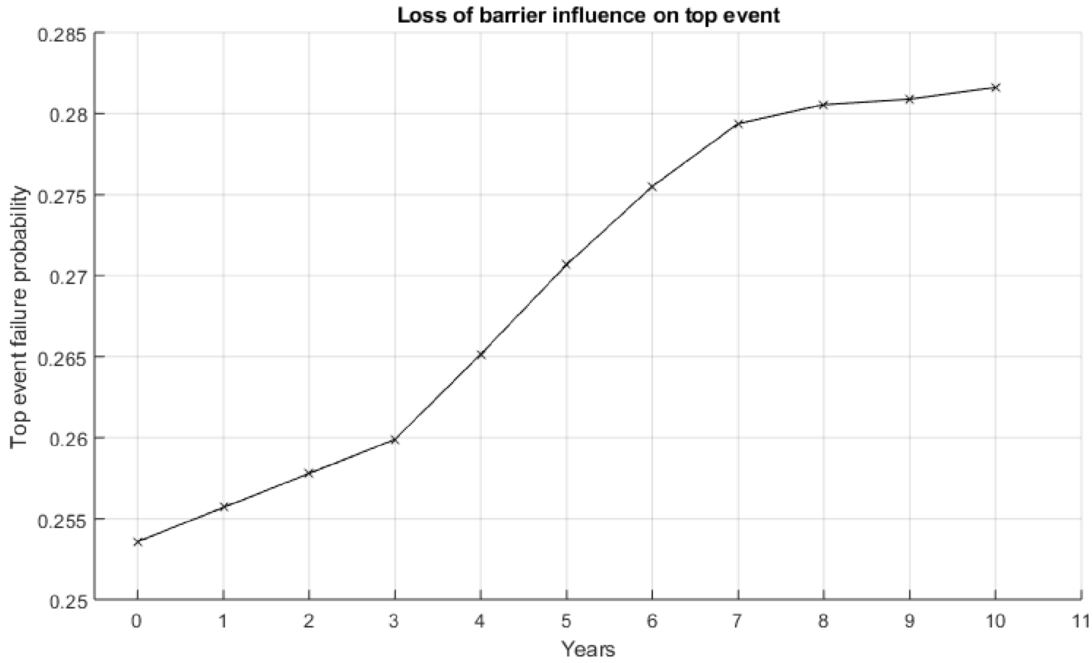


Figure 8-4 Scenario sensitivity analysis response for loss of barrier influence

8.4.2 Assessment of pressure build-up and annulus barrier degradation

In this sensitivity scenario, these datasets are termed “base case (bc)” data and they are assessed with a 5% increment in both positive and negative iterations until the updated probabilities of the causals reach the upper bound threshold of 0.7226 or the predicted results yield a complete failure of the top event i.e., occurrence probability of 100%. Therefore, the sensitivity scenarios run is expressed as $bc \pm a\%$, where $a = 5\%, 10\%, 15\%$ and so on, as can be seen in Table 8-4. It is worth mentioning at this point that the 5% increment was not arbitrary as the sensitivity analysis began with 1% and 2% increments. However, it was observed that the succeeding failure probability predictions showed no marked difference from the preceding results, necessitating the need to increase the accident model variation up to 5%. The 1% increase in a stepwise manner did not yield any notable change as shown in Table 8-5, because the base case values are well below the reference value defined by the FT analysis where each accident contributory factor is assumed to be statistically independent. The timeline defined for this analysis is based on the expected time for which the well abandonment integrity would have been showing signs of deterioration, at which point, the initial leak or seepage is spotted. The first year represents the decommissioning and abandonment year where failure data are collected, and the rest of the years illustrate the prediction of the permanent abandonment lifespan.

Table 8-4 Selected performance parameter variations from base case ($B_{1.1}$=0.085; $B_{5.2}$=0.12)

		Input parameter failure values [%]	
Cases	Runs	$B_{1.1}$	$B_{5.2}$
bc_1	$bc \pm 5\%$	[8.075, 8.925]	[11.400, 12.600]
bc_2	$bc \pm 10\%$	[7.650, 9.350]	[10.800, 13.200]
bc_3	$bc \pm 15\%$	[7.225, 9.775]	[10.200, 13.800]
bc_4	$bc \pm 20\%$	[6.800, 10.200]	[9.600, 14.400]
bc_5	$bc \pm 25\%$	[6.375, 10.625]	[9.000, 15.000]
bc_6	$bc \pm 30\%$	[5.950, 11.050]	[8.400, 15.600]
bc_7	$bc \pm 35\%$	[5.525, 11.475]	[7.800, 16.200]
bc_8	$bc \pm 40\%$	[5.100, 11.900]	[7.200, 16.800]
bc_9	$bc \pm 45\%$	[4.675, 12.325]	[6.600, 17.400]
bc_{10}	$bc \pm 50\%$	[4.250, 12.750]	[6.000, 18.000]

The percentage difference in the increment was extended to 50% in all investigated runs to provide sufficient outputs from which adequate accident response decisions can be made and also, to account for the lack of comparable data for the same purpose. In total, ten (10) cases were set up and fed into the dynamic Bayesian model over a 10-year iteration forecast. The variations of the input parameters provide some level of perturbation by the percentage increase or reduction of each investigated data point and the output is presented in the tornado diagram of Figure 8-5 below. For each iteration, the sensitivity model is instantiated within the dynamic Bayesian network model taking into consideration the impact of computation time to ensure the analysis continues to appeal to the decommissioning and abandonment community.

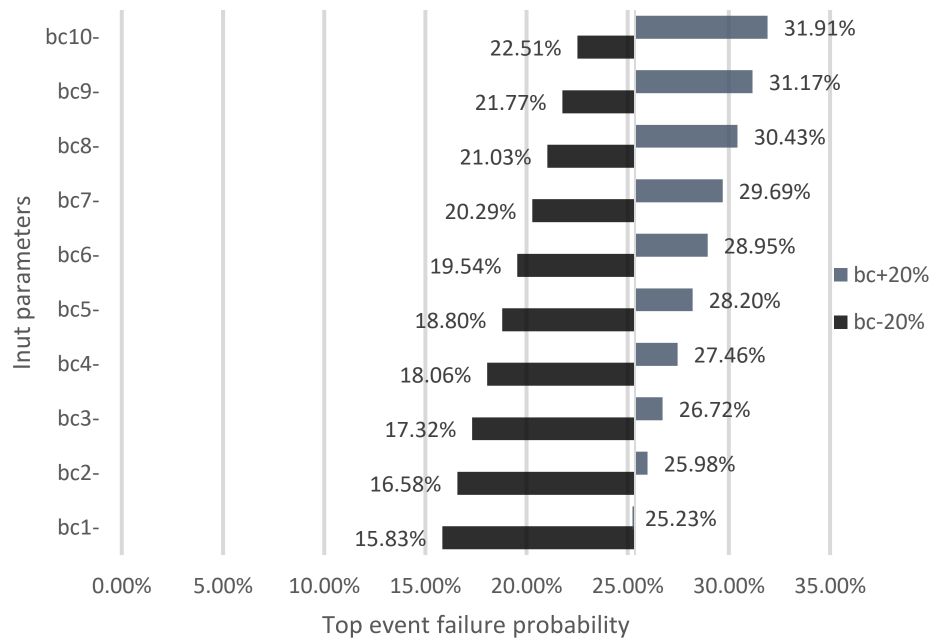


Figure 8-5 Tornado plot for reduced sensitivity cases

As it can be seen from Figure 8-5, the error margins fade off in the case of $bc - 20\%$ as the percentage difference increases, that is, from $bc_{1}-$ to $bc_{10}-$. It is worth mentioning that the values in the bc-20% plot are negative whereas those on the bc+20% are positive, indicating that the error margins become insignificant in the latter plot from $bc_{10}-$ to $bc_{1}-$. These error margins are relative to the top event failure probability base case of 25.36%. Based on these observations, it can be inferred that the dynamic Bayesian network model is flexible and robust without trading off the slightest alteration in the input values and their corresponding output response. Therefore, the results from this sensitivity analysis further supports the argument that an adequately plugged well barriers would ensure the longevity and integrity of the well such that the well may not require re-entry for its intended permanence.

The results from the dynamic Bayesian network analysis for each case examined are obtained and the failure predictions from the upper-bound ILN-OR model of Section 7.2.6.1 is used as the safety threshold for the scenarios sensitivity responses, which when attained the accident model is said to have been extremely unreliable and inspection as well as site remediation plans must be executed. The tested cases have been divided into two categories from $bc_{1}-$ to

bc_{10^-} and bc_{1^+} to bc_{10^+} for ease of presentation. The preliminary top event sensitivity results where the runs are increased by 1% up to 4% only in the positive propagation are as presented in Table 8-5.

Table 8-5 Top event failure trend for base case variations from 1-4%

Years	bc	$bc + 1\%$	$bc + 2\%$	$bc + 3\%$	$bc + 4\%$
0-1	0.25359	0.25359	0.25359	0.25359	0.25359
1-2	0.25360	0.25360	0.25360	0.25360	0.25360
2-3	0.25361	0.25361	0.25361	0.25361	0.25361
3-4	0.25363	0.25363	0.25363	0.25363	0.25363
4-5	0.25368	0.25368	0.25368	0.25368	0.25368

On the other hand, Table 8-5 presents the results for the pressure build-up and annulus barrier degradation influence on the top event for the N-OR model. For the tested cases with bc_{1^-} to bc_{10^-}, it was noted that the obtained model response deviated progressively away from the base case failure probability as the percentage difference increases. More specifically, the failure probability decreased from 0.2536 to 0.1268, indicating an increased reliability of the wellbore. For bc_{1^-} to bc_{5^-}, the results obtained are well below the base case value which further demonstrates that a decrease in the top event failure value by 5% relative to their base case values slightly influence the N-OR model output.

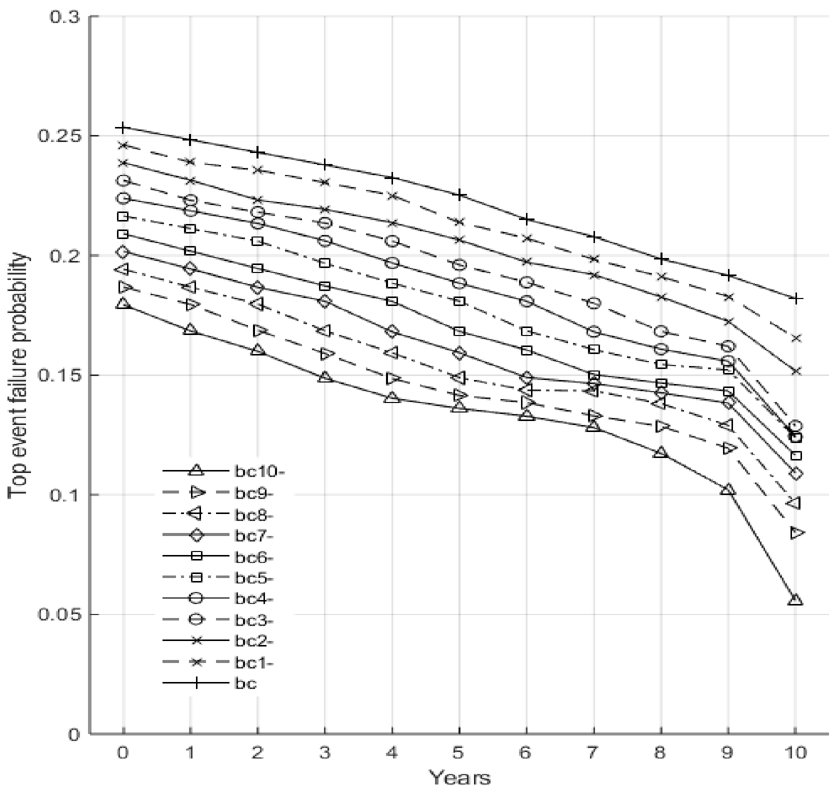


Figure 8-6 Sensitivity scenarios analysis for increased reliability tested cases

In addition, the leak to mudline values in the bc_{6^-} to bc_{10^-} was varied at a steady rate and away from its base case value because of the finite adjustments made to the pressure buildup and annulus barrier degradation values. For bc_{6^-} at the 10th year (Figure 8-6), 1-0.116=0.884 (88.4%) and for bc10- at the 10th year, 1-0.056 = 0.944 (94.4%). In this case, the reliability of the well plugging and abandonment continues to rise gradually at 88.4% and increases up to 94.4% due to the larger parameter ranges incorporated in the investigated model which offered another insight into the capability of the N-OR model to yield outputs that continues to diverge away from each successive failure value optimised and, from the dataset median value. This progressive decrease in failure occurrence necessitated further sensitivity analysis into the positive range between bc_{1^+} to bc_{10^+} to account for all 21 cases and consequently, develop a systematic trend from which safety critical decisions are based.

For that reason, the same procedure is followed for increasing both the pressure buildup and annulus barrier degradation failure values from the base case for test runs bc_{1^+} to bc_{10^+} as shown in Table 8-6. It is worth mentioning that 21 cases are quite large to establish the risk profile based on the scenarios sensitivity analysis for the overall system failure, and only the positive portion of it has been presented herein and the negative runs can be found in Appendix F. However, no analysis is considered superfluous due to the lack of historic or literature data to compare the system performance, and a 10% increment up to 50% in both forward and backward direction provided sufficient information to establish the capabilities of the sensitivity analysis within the dynamic Bayesian network robust computation engine.

Table 8-6 N-OR model sensitivity analysis output for a 10-yr run

Years	bc	$bc + 10\%$	$bc + 20\%$	$bc + 30\%$	$bc + 40\%$	$bc + 50\%$
0-1	0.2536	0.2611	0.2746	0.2851	0.2956	0.3062
1-2	0.2544	0.2645	0.2768	0.2855	0.2957	0.3086
2-3	0.2594	0.2689	0.2795	0.2900	0.2965	0.3092
3-4	0.2659	0.2717	0.2807	0.2909	0.3023	0.3124
4-5	0.2773	0.2845	0.2904	0.3048	0.3093	0.3158
5-6	0.2867	0.2986	0.3072	0.3122	0.3168	0.3273
6-7	0.2907	0.3039	0.3117	0.3222	0.3402	0.3507
7-8	0.2981	0.3113	0.3191	0.3297	0.3476	0.3581
8-9	0.3055	0.3187	0.3266	0.3371	0.3550	0.3655
9-10	0.3130	0.3262	0.3340	0.3445	0.3624	0.3730
10+	0.3204	0.3336	0.3414	0.3519	0.3699	0.3804

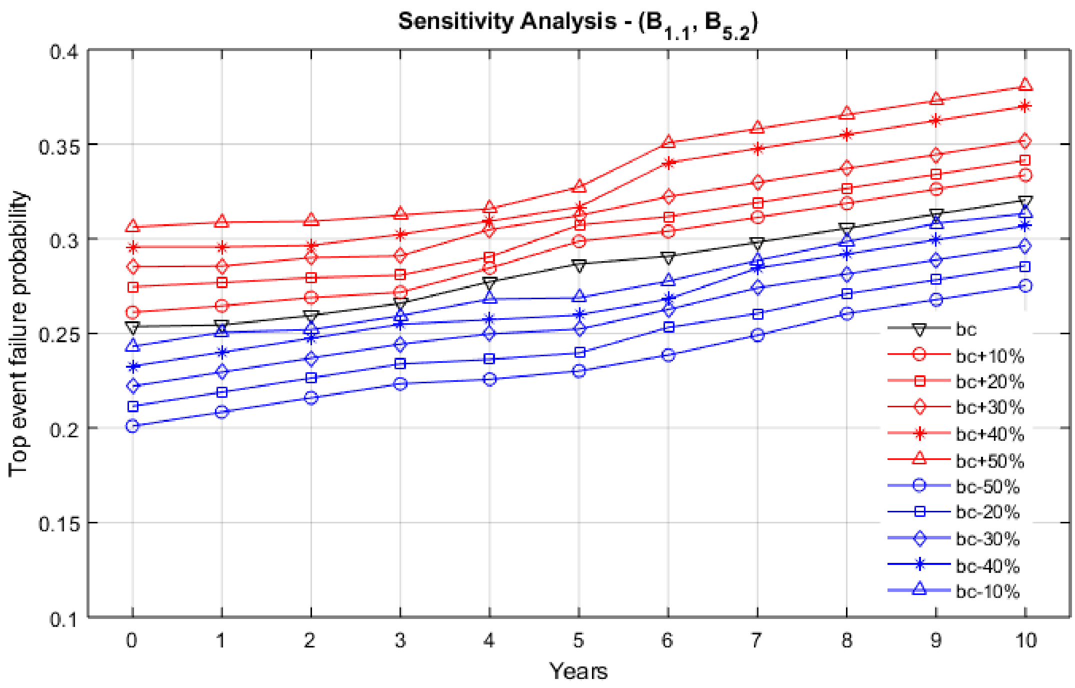


Figure 8-7 Scenarios sensitivity analysis response for bc+a%

As seen from Figure 8-7, gradual alteration of the pressure build-up and annulus barrier degradation values above the base case value have been investigated at 10% intervals until 50% increment is reached over a 10-year abandonment period. While the tested cases all showed progressive increase, it was noted that these output increases were higher and steeper from the third year of abandonment in all cases and tend to be linear after the sixth year of permanent abandonment. Also, as can be seen in Figure 8-7, the maximum failure probability value for the worst-case scenario, bc+50%, had risen to 3.80E-1 by the tenth year period.

From the foregoing, the trend between two- or multi-variable sensitivity analysis and a one-variable scenario presented in the preceding Section, has been established to be in agreement. In all tested cases, the error margin is recorded to be the same across each positive and its corresponding negative run, and this value is found to be 9.4%. Where a physical reliability model becomes available for the evolution of both the pressure buildup and annulus barrier degradation events, a detailed prior failure probability based on real-time monitoring can be fed into the N-OR sensitivity model to predict the safety critical response of the top event occurrence. This would enable systematic comparison between the real-time observation and the data obtained through source-to-source variability.

8.5 Conclusion

The scenarios sensitivity analysis was performed for two (2) case studies where (1) the loss of barrier accident contributory factor ($B_{6.1.2}$) and (2) the pressure buildup and annulus barrier degradation failures, were assessed through percentage incremental variations to examine the degree of responsiveness of the top event failure, characterised by the leak of hydrocarbon to mudline. Both models were built on the previously developed N-OR model which provided the lower-bound top event occurrence probability against a set threshold of 0.7226 obtained from the upper-bound imprecise leaky noisy-OR model. The importance of the upper and lower limit is to guide the analysis in a controlled manner to establish a point where the sensitivity analysis would be halted, indicating a state of 100% compromised integrity of the plugged and abandoned well.

In case study (1), the loss of barrier prior failure probability was altered by 2% increments for the first three (3) runs and by 5% increments for the last two (2) runs in a forward and backward analysis. Moreover, the case study (2) combined and examined the influences of both the pressure buildup and annulus barrier degradation failure probabilities on the leak of hydrocarbon to mudline when these input parameters are varied at a 5% interval and 50% increment over a 10-year period to establish a trend for the risk profile for the model output. In both cases, the procedure for the analysis was preserved to ensure consistency in the obtained risk profile and consequently, serve as a future reference for comparing real-time Accident Precursor Data when they become available.

In general, the scenarios sensitivity analysis proved to be an invaluable tool for assessing the accident evolution capability of the noisy-OR model output. In both the one- and two-variable tested cases, the findings revealed that the N-OR model is adaptable to variations in the accident input parameters and the model output rely on its robustness to response proportionately to the input parameters fluctuations. Due to the single-value error margin obtained across tested runs for case study (2), the N-OR model is capable of adjusting to captured and uncaptured hazards as long as the dependency quantification accounts for such uncertainty. Since the dynamic safety model response is well within the base case set threshold and flexible enough to accommodate arbitrary shifts in the input parameter values, the developed model is robust and adaptable. That is, when the knowledge of the overall risks is known, the model can be extended to a finitely allowable extent.

8.6 Summary

In this Chapter, the capability of the dynamic safety model to conduct sensitivity analysis based on systematic alteration of input performance parameters for the developed noisy-OR accident model was presented. A comprehensive scenarios sensitivity analysis was conducted for the developed N-OR uncertainty model of the dynamic safety strategy based on one-variable and two-variable case studies of the permanent well abandonment accident evolution. The description of the sensitivity analysis methods was presented and the motivation for selecting scenarios sensitivity analysis established – primarily because other sensitivity analysis methods are computationally-challenging which may have huge cost implications and otherwise, not provide any incentive for oil and gas producers. The selection of accident input parameters from the accident model was presented and examined over the leak of hydrocarbon to mudline failure. The model output results in all tested case studies were presented and were supported by a concluding remark. As cost is one of the many justifications for the oil and gas producers to discount selected decommissioning and abandonment operations or options, the next Chapter focuses on the dynamic economic model to estimate and predict the risk value of decommissioning.

Chapter 9: Dynamic economic risk analysis for decommissioning

9.1 Outline

This Chapter presents the last major contribution of this research work. The economic risk of offshore assets removal is conducted to assess the cost of remediating a futile decommissioning operation. The strength of the developed dynamic safety model is demonstrated in terms of cost to provide insight into the financial implication of getting it wrong. The rationale for the need to estimate decommissioning cost based on overall rough order of magnitude along with the assessment framework are described in Section 9.2. The model formulation and concept validation are presented in Section 9.3 and model analysis of the case study is demonstrated in Section 9.4. The obtained results are discussed and concluding remarks are presented in Section 9.5.

9.2 Introduction

The need to estimate the cost of decommissioning and abandonment of offshore assets is driven by economic sustainability. A sustainable strategy is required to assess associated risks of getting it wrong to support oil producers in the development of socio-economic mitigation campaign. The standard procedure for assessing the viability of any decommissioning and abandonment activity is centered around the balance between technological, social, health and safety, environmental, and economic considerations. As the Exploration and Production (E&P) industry rely on the experience – which is often based on analogous knowledge of similar activities – of personnel to address decommissioning concerns, the overall operational lifecycle falls under the unknown unknown assessments category. While the industry has continued to experience advancement in technological development with relatively low record level of social disputes, efforts need be focused on the safety (and health) of personnel, environment, and assets including the cost incurred in the event of a futile decommissioning and abandonment operation. Previous Chapters of this thesis have addressed the safety concerns and the cost aspect requires similar attention.

Although, technical and operational challenges have been extended to post-decommissioning operations such as transportation methods and disposal. In addition, environmental challenges have been broadened to cover efficient energy use and resource conservation rather than merely assessing the direct impacts of spills and the marine environment. However, the technical and environmental considerations are only indirectly addressed in this thesis and are not the primary focus.

Furthermore, the first insight into the estimation of decommissioning cost is related to its Asset Retirement Obligation (ARO), indicating the assets mandatorily required to be dismantled now or in the future and is often contained in financial reports. This type of cost outlook is likely to be underestimated based on the current time value of money and require considerable adjustments with working interest, Net Present Value (NPV), and aggregation of cost. As AROs depend on uncertain market conditions and fluctuations in capital and operating costs, it cannot effectively capture realistic cost model.

A potential solution to this challenging task is the development of a robust cost estimation method that takes input from the overall decommissioning cost to estimate economic risk of the operation based on the impact of each accident contributory factor. The Economic Risk Analysis (ERA) method is an integrated approach which incorporates dynamic safety model, estimated cost based on literature data and a Recommendation-to-Decommission (RtD) algorithm. The ERA is performed for the developed dynamic safety model using Steel Piled Jacket (SPJ) decommissioning case study. The choice of case study is primarily based on the availability of literature data for cost estimate as the Elgin platform's plugging and abandonment breakdown cost is not publicly available to the best of the author's knowledge.

The model formulation for the dynamic ERA concept is presented in Figure 9-1. For the selected SPJ platform, the same failure probability estimate discussed in Chapter 5 will be adopted. The underlying reason for adopting the Hierarchical Bayesian Analysis (HBA) is that the objective statistical data commonly found in offshore database – OREDA – does not include failure information for decommissioning and abandonment components failure.

Decommissioned and abandoned components are often not reassessed once the planned monitoring regime is exceeded, making failure data challenging to obtain. In addition, it would be plausible to use the overall decommissioning cost for an already completed platform removal as cost baseline for estimating the economic risk of individual accident contributory factor at the subsystem or component level and then following preceding probability updating approach to obtain the posterior component-level economic risk profile. The estimation of the top event failure probability of the SPJ complete removal and the immediate hazards leading to its occurrence is based on the comprehensive review of the Brent Alpha decommissioning technical document.

The component-level failure costs and their updated values obtained through the dynamic Bayesian model would be incorporated in the safety analysis and form the basis for which economic decisions are based for future decommissioning and abandonment operation and can be used as guidelines to compare related operations with dissimilar technical and environmental challenges in real-time. This Dynamic Integrated Safety Analysis (DISA) approach would permit the implementation of real-time risk assessment with the potential to incorporate variety of information into a performance metric that satisfies the safety and economic aspects of decommissioning and abandonment operations. The ultimate goal of a safe decommissioning activity is to be able to quantify and assess associated risks to drive down costs and uphold producers' reputations. The costs associated with decommissioning is believed to be as high as those of installation and this could be more in the event of implementing expensive safety measures. Where there are no safety measures in place, the cost of remediating damages would suffice.

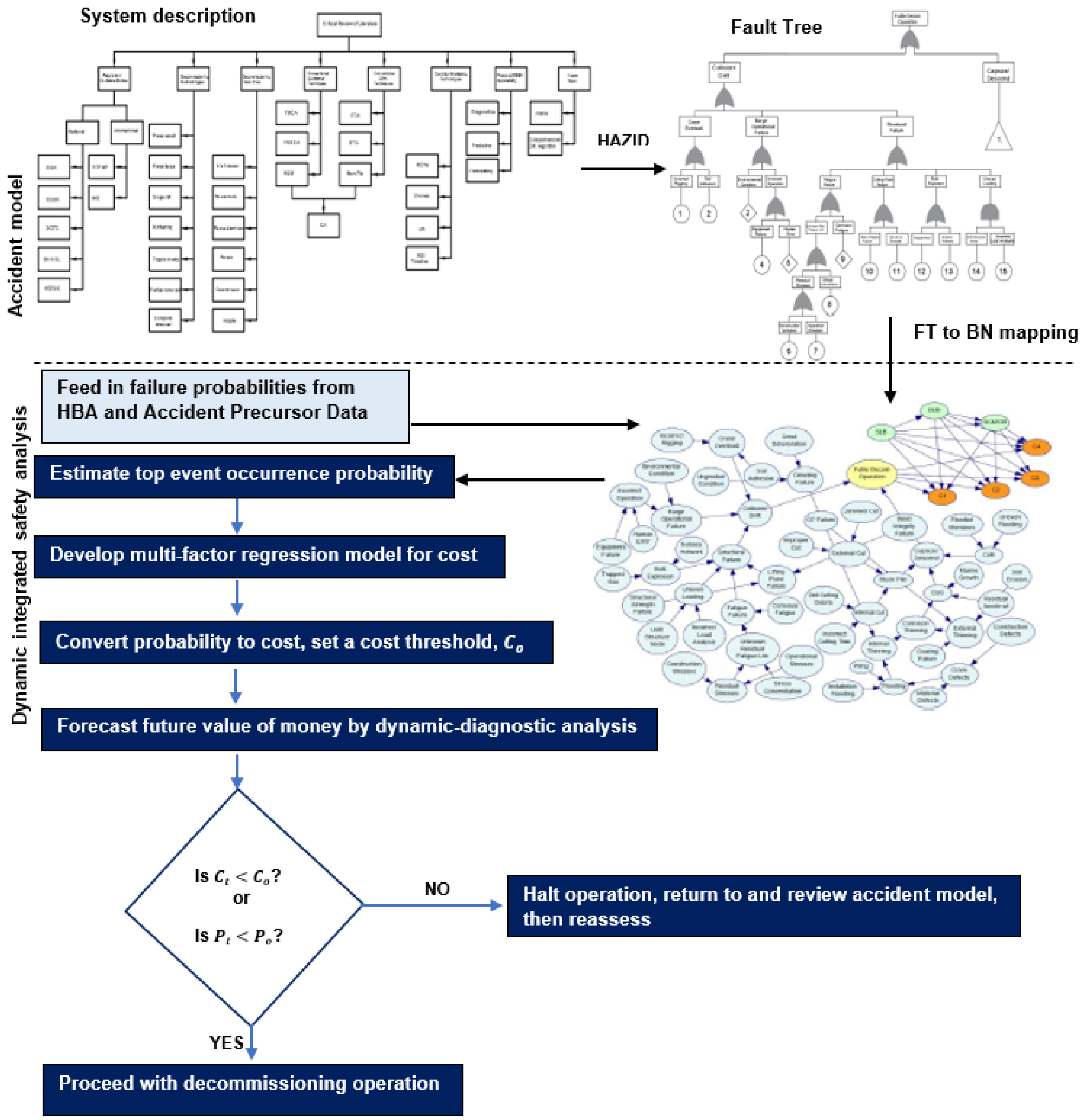


Figure 9-1 decommissioning safety workflow

The main aim of the dynamic ERA is to develop a probability-based cost decision making model for providing the rationale for focusing available decommissioning and abandonment resources on safety critical accident contributory factors. The objectives are to demonstrate the credence of the concept and to verify its applicability to the SPJ decommissioning operational failure.

9.3 Dynamic ERA model formulation

9.3.1 Overview (Step 0)

The parameters of interest are related to the cost of decommissioning for a single oil and gas platform estimated in a specific decommissioning and abandonment campaign. As the operation is, in general, a known unknown rare event due to controllable and often uncontrollable operational circumstances, an empirical model would suffice provided it represents the characteristics of the oil and gas field to be decommissioned. The following assumptions have been considered in order to conduct the dynamic ERA analysis:

- The dynamic ERA is performed for the only steel jacket platform in the Brent field with a service life of 44 years.
- The case study removal operation proposes to leave the footings and drill cutting pile in situ, however, this undertaken evaluates the complete removal of the platform to provide insights into the worst-case scenario.
- While the water depth around the field varied due to uneven seabed, a fixed depth of 140 meters is taken for the analysis.
- There are eight (8) legs and twenty-four (24) piles including approximately fifty (50) spans of horizontal and vertically diagonal members, making the severed conductors a total of 82 (Shell, 2017).
- Brent Alpha platform 28 wells have been plugged and thus, nonproducing with several members severed up to material weight of 8,512 tons estimated to be recycled.
- The cost recovered from re-use and recycling are not accounted for in this analysis.
- The Brent Alpha Jacket (BAJ) weighs over 10,000 tons in air with a deadweight of 28,719 tons.
- The BAJ cutting programme is estimated to take approximately 17 days. For the sake of analysis, the trial is estimated for 24 days in this thesis.

- The economic risk of individual accident contributory factor is calculated based on the £60 million noted for Option 1 decommissioning assessment in the Brent Alpha Technical Document (Shell, 2017). As this value is a rough estimate, a quarter (£15 million) is used in this analysis.
- The cost of chartering the heavy lift vessel (HLV) for the Brent project is £251,000 for each man-year of employment and is included in the overall cost.
- For the dynamic ERA consideration, removal technology is assumed to remain unchanged for the ten-year period from when decommissioning is conceived to when the asset is finally removed.

The general overview of the proposed methodology for the development and validation of the dynamic economic risk assessment model is presented in Figure 9-2. The first step in the process involves the development of the accident scenario description for which the dynamic safety model will be applied. In the second step, Accident Precursor Data are introduced based on exert judgement and inputs from the 24 days observations for the cutting programme noted in the Brent Alpha technical document. In the third step, the cost model is formulated based on a multi-factor regression model. The fourth step converts the failure probabilities obtained through HBA process in Chapter 5 and its extension from step two (2) into expected value (cost) from the regression model in step (3). The fifth step presents a dynamic model based on simulated time step for the ten-year period monitoring of the asset post decommissioning and validation of the concept is achieved. During the sixth step, the recommended risk control measures for each accident contributory factor are provided.

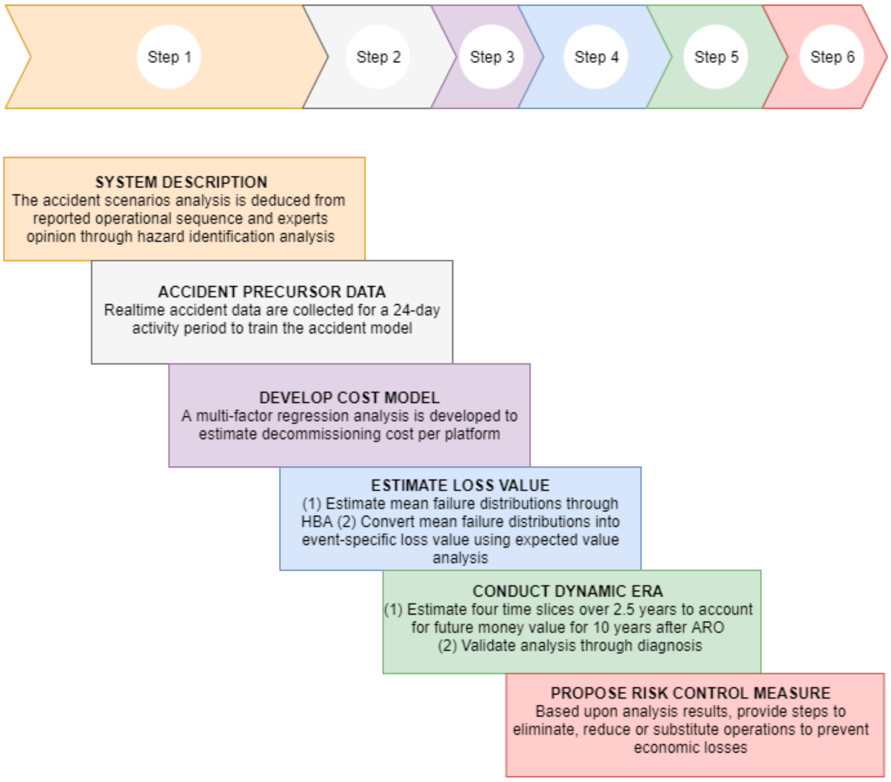


Figure 9-2 Overview of proposed dynamic economic risk analysis

9.3.2 Accident scenario description (Step 1)

The safety analysis of decommissioning Steel Piled Jacket (SPJ) structures for complete removal operation is identified and analysed according to literature reviews (OGUK, 2020; Kaiser and Liu, 2014; Kierans et al., 2004; Bradbeer et al., 2009) and hazard identification is conducted on the operational sequence from decommissioning professionals based on their field experience. To determine the risk of decommissioning offshore jacket structures, all the potential accident scenarios must be captured, analysed and assessed in an integrated manner. Therefore, fault tree (FT) is developed to represent the accident causations of complete removal of SPJs from the description of operational sequence.

9.3.2.1 Operational steps involved in SPJ decommissioning

Phase 1. A route survey is first conducted to determine the locations to position and sever the jacket Sections including the transportation route. The survey also identifies uncharted things underwater such as shipwreck, oyster beds etc.

Phase 2. The topside is removed, and piles and conductors severed. The SPJ is then cut and removed in Sections that the dedicated heavy lift vessel (HLV) can sustain. The SPJ may be made buoyant or de-ballasted to reduce the bottom weight. A suitable severance method is selected based on the technical capabilities available and carried out underwater by divers or remotely operated vehicles. This is the Option 1 (external cutting) as discussed in the BAJ technical document.

Phase 3. The HLV is then rigged to individual module previously severed, removes each SPJ module and loads it to the barge until the SPJ is completely removed. It is worth mentioning that these steps can vary depending on factors such as platform age, location and water depth, platform type and configuration, weight of the lifts and soil strength, among others.

The main processes of the complete removal operation of a steel jacket structure from the fixed position offshore to a recycling yard onshore using lifting barges or HLVs is as shown in Figure 9-3. More information about the safety issues on the lifting barges and HLVs can be found in the works of Abdussamie et al. (2018) and Tan et al. (2018). It is worth mentioning that only the decommissioning hazards relating to the steel jacket structure is considered in this thesis.

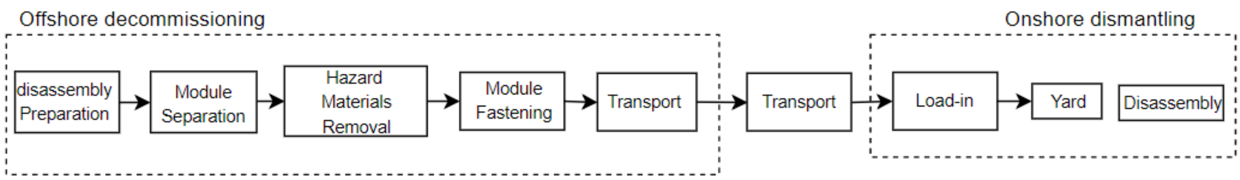


Figure 9-3 Main process of steel jacket decommissioning operation.

The system failure during the steel jacket removal operation is analysed through hazard identification (HAZID) procedure described in Section 9.3.2.2. HAZID is conducted with industry experts from mid- to senior engineers and academic professionals with considerable decommissioning operational knowledge. The process involves subdividing the removal and lifting operation as shown in Table 9-1. In this thesis, emphasis is placed on the lifting safety issues associated with collision (or drifting), loss of stability (or buoyancy) and ascent (or descent). These failures and their causes are used to construct the Bayesian networks used for the dynamic economic risk assessment.

Table 9-1 Hazard identification analysis for steel piled jacket

Hazards	Taxonomy	Deviation	Potential Causes	Potential Effects
Station keeping	Collision	Loss of rig; Damage to barge and jacket	Incorrect rigging; Environmental condition; Human error; Welding integrity of lifting aid; Soil erosion effect on lift; Incorrect load analysis.	Uncontrollable heeling or trimming of Barge; wreckage
	Drifting	Loss of station keeping	Broken mooring line; Soil adhesion on initial lift-off force; Failure of flooded member(s); Soil erosion effect on lift; Uneven flooding effect.	Loss of barge and jacket structure altogether; Snapping of mooring line could lead to injuries.
Loss of stability	Buoyancy	CoG/CoB misalignment	Calculation error; lifting node failure; Marine growth.	Prevents barge from operating safely. Loss of barge.
Sinking	Ascent/Descent	Loss of station keeping.	Grouted or ungrouted conditions; tug impact; human error.	Capsize of lifting barge, Injuries, or fatalities.
Incorrect Standard operation procedure	Noncompliance	High safety risks	Incorrect operation; Improper cutting procedure; Incorrect estimation of cutting time.	Cascading of failures due to chain of events; Increase downtime.
Miscellaneous	Trapped flammable gases	Fire/explosion	Trapped gas due to subsea hot work; Trapped gas in drill cutting debris; Human error	Severe damage to barge, jacket structure and the environment. Injury or fatalities.

9.3.2.2 Model hazards identification

Collision or drift. The collision or drift between the jacket and lifting barge can lead to a futile jacket decommissioning operation as it may result in fire and explosion. Typically, the risk increases when either the lifting barge moves farther from the payload or, both the lifting barge and the payload collide (x_{11}). The lack of decommissioning historic data has necessitated the adoption of Hierarchical Bayesian Analysis integrated with Bayesian network, which is a proven risk analysis tool for estimating the failure probabilities of abnormal events under uncertainty as presented in Chapters 5, 6 and 7.

Loss of stability. The overall effect of this collision alone is independent of whether the lifting vessel capsize due to the misalignment (x_{22}) of the jacket's center of gravity (CoG) and its center of buoyancy (CoB). Improper cutting of the pile (x_{28}) in the footings can cause the differential sticking of pile or stuck-pipe (x_{21}) and consequently leads to capsize.

Ascent or descent. A cut performed in accordance with recommended practice may help to prevent descent or capsize of the lifting vessel; hence, it is situated beside the CoB and CoG in the fault tree in Figure 9-4, which considers the complete jacket removal activity including footings and pile severance. The exact calculation of CoG (x_{18}) can be difficult due to the presence of marine growth (x_{26}), unknown residual anode thickness (x_{25}), and external corrosion thinning (x_{17}). The residual anode may be replaced prior to jacket removal to reduce the number of uncertain variables. Internal and external corrosion thinning are independent events, and the presence of either of them can pose a technical challenge. Grouting prevents the occurrence of flooding in the inner walls of the jacket and pontoon legs. It is, therefore, an important requirement to ascertain the grout's integrity against deterioration (x_{24}), and consequently, prevents internal corrosion thinning (x_{16}). Cathodic protection and coating of such an aged jacket structure are expected to have deteriorated or fail at the instant of removal. They both prevent external corrosion thinning by absorbing soil corrosion effect on the external surface.

Structural damage. The structural failure caused by accumulated cyclic load, lifting point failure (x_4), bulk explosion (x_5), and structural loading (x_7) on the jacket is capable of initiating collision even in the absence of overloading of the lifting crane (x_{10}) or barge operational failure (x_9) (Zhao et al., 2015; Gerwick, 2002). This is particularly due to the breakage of a lifting node on the structure during lifting. The lifting node breakage is imminent if its residual strength is unknown or calculated incorrectly (x_1). To overcome the occurrence of crane overload, the rigging and initial lift-off force due to soil adhesion calculations must be accurate.

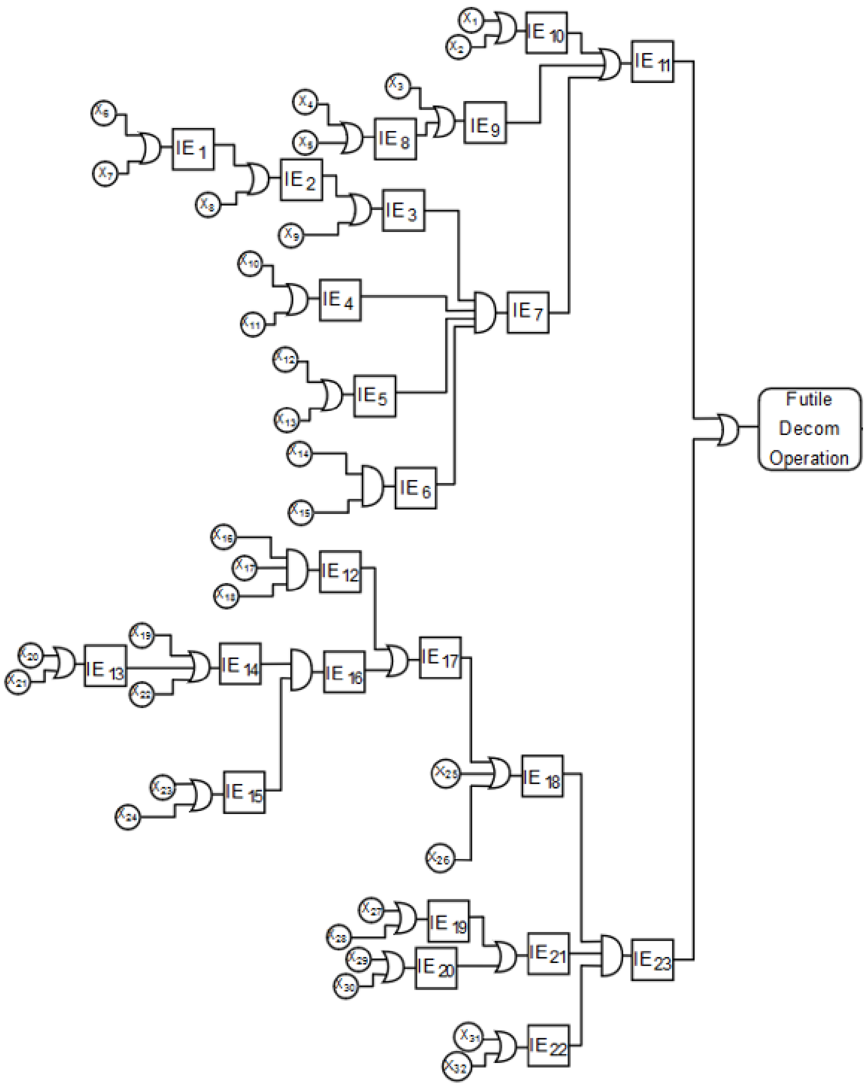


Figure 9-4 Fault tree representation of SPJ accident model.

9.3.3 Development of posterior failure probabilities (Step 2)

Following the estimation of the prior failure probabilities procedure described in Chapter 5, the HBA is used to obtain mean distribution failures with 95% confidence level with the dataset presented in APPENDIX I using the dataset in APPENDIX J. Typically, the proposed dynamic failure model will rely on Accident Precursor Data obtained from decommissioning database or through real-time monitoring using sensor measurements. The application of sensor measurements is prescriptive and a cost-benefit analysis of adopting sensors technology is at the discretion of the platform owners. Specifically, the updated probabilities for the selected accident contributory factors are estimated using equation 9-1, when the concerned event is implicitly represented within the BN, otherwise, the BN node of interest will be set as new evidence. In this study, the new evidence is taken to be implicit since it is believed that the estimation of failure of such rare events is based on expert judgements with associated uncertainty. Using experiential learning, the computation of the new evidence occurrence probability $p(e)$ and consequent updating is estimated for the failure probability of, say, the bulk explosion (x_5) with a prior failure probability value of 0.0517 with an observation of unknown residual stress-induced failure ($p(x_1) = 0.0682$) where, x_1 has been observed nine (9) times and x_5 is observed twice. Then, the evidence occurrence probability is computed as $p(e|9x_1, 2x_5) = \frac{2}{11} = 0.1818$. The observations considered for the dynamic safety model are related to the 24-day trials for the cutting programme taking into account hazards posed by lifting operations, equipment failure, and the weather among other complications that may be encountered, as presented in Table 9-2 for selected failure parameters. The updated (posterior) failure probability of the bulk explosion at the 15th day is given by:

$$p(x_5|e) = \frac{p(e|x_5) \times p(x_5)}{\sum p(e|x_5) \times p(x_5)}$$

$$p(x_5|e) = \frac{(0.1818) \times (0.0517)}{(0.1818) \times (0.0517) + (0.8182) \times (0.9483)}$$

$$\therefore\ p(x_5|e) = 0.0120$$

As economic risk analysis would yield the marginal difference between the expected profit and the expected cost for decommissioning and abandonment operations, four scenarios have been formulated to examine and estimate the economic benefits of the developed dynamic safety model. The approach is demonstrated from the least to the best beneficial scenarios, given that the operation is devoid of complications. Through the application of the dynamic ERA framework in the decommissioning activities work package, the prior failure probabilities could be scaled at quartile intervals.

The calculation procedure for the ERA is performed using the concept of expected value analysis (EVA) for describing the failure costs and corresponding benefits from successful outcome of the implemented safety measures as given in Equation 9-1 below.

$$EV = p(\bar{x}_i) \times p_r - p(x_i) \times c_o \tag{9-1}$$

Where $p(\bar{x}_i)$ is the success probability for events of interest, p_r is the profit accrued for achieving the benefits of such reliability, $p(x_i)$ is the failure probability, c_o is the cost incurred for the unreliability and, EV is the expected value of the decommissioning and abandonment operation. Since the cost of resale from pumps and valves, scraped steel value, and rebates have not been considered, the profit term of Equation (9-1) is excluded from the analysis.

Table 9-2 Accident Precursor Data for selected parameters

Days	x_1	x_5	x_{14}	x_{19}	x_{24}
1	1	-	-	-	-
2	1	-	-	-	-
3	2	1	-	-	-
4	2	1	-	-	-
5	2	1	-	-	-
6	3	1	-	-	-
7	3	1	-	-	-
8	4	1	-	-	-
9	5	2	-	-	-
10	6	2	-	-	-
11	6	2	-	-	-
12	7	2	-	-	-
13	7	2	-	-	-
14	8	2	-	-	-
15	9	2	-	-	-
16	10	3	-	-	-
17	10	3	-	-	-
18	11	3	-	-	-
19	11	3	-	-	-
20	11	3	1	-	-
21	12	4	2	-	-
22	13	5	2	1	-
23	14	6	3	1	-
24	15	7	3	2	1

9.3.4 Determination of decommissioning cost (Step 3)

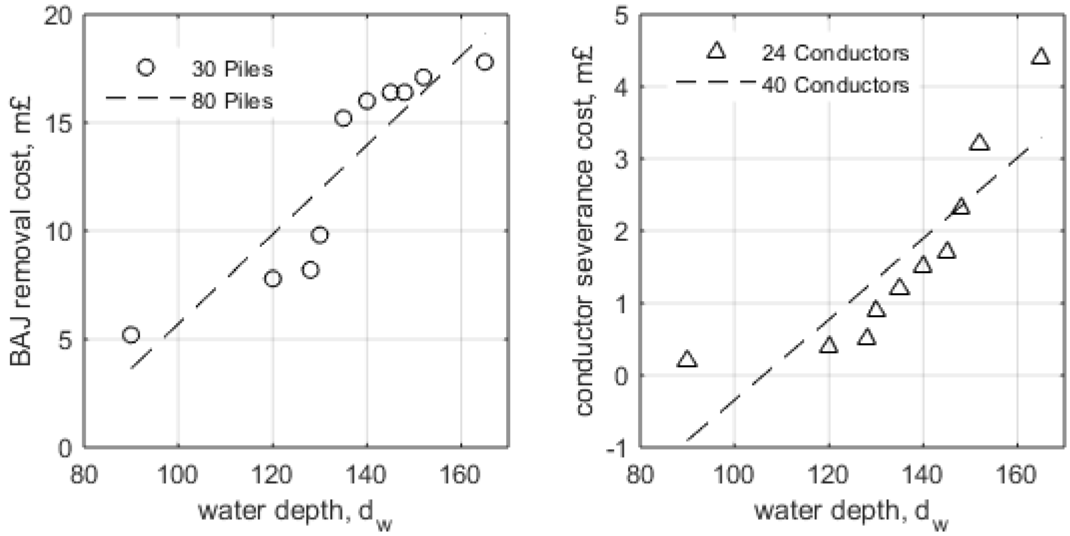
The cost estimation parameters considered for dynamic ERA are implicitly related to the field-specific variables such as water depth, number of piles, conductors, and the level of effort centred around operating costs, for which dataset is generated using "what if" analysis to represent market conditions, as presented in Table 9-3. The declared cost of Asset Retirement Obligations (ARO) for the BAJ includes a set amount dedicated to account for the implementation of DISA to drive decommissioning and abandonment needs. This includes the charter rate of HLVs for the lifting operations, inspection and monitoring cost, and the cost of transportation and dismantling onshore. For the BAJ platform, the cost of conductor severance and steel piled jacket removal have been given more attention. The cost of severing the conductors is considerably less than removing the jacket structure since the cutting operation is entirely performed externally using existing sever- and retrieve technology. However, conductors drive through the entire water column requiring additional cutting time, lifting, and retrieval which tends to increase the cost consequently. The conductor removal cost is calculated considering an average of 24 piles, 8 legs, and 50 bracings.

Table 9-3 Brent Alpha Jacket and conductors decommissioning cost

Platform	Water depth, WD (m)	Legs, piles, and conductors	SPJ removal cost (m£)	Conductor severance cost (m£)
1	90	30	5.2	0.2
2	120	38	7.8	0.4
3	128	40	8.2	0.5
4	130	52	9.8	0.9
5	135	60	15.2	1.2
6	140	80	16.0	1.5
7	145	84	16.4	1.7
8	148	90	16.4	2.3
9	162	96	17.1	3.2
10	165	102	17.8	4.4

For the jacket structural removal, the presence of piles and its quantity further complicates the operation and drive the decommissioning cost further up. The use of explosives to sever the piles have not been considered, to match the technical document operational procedure. The structural removal cost includes platform preparation cost, field clearance cost, and compliance verification cost. Due to the sparsity of data, the decommissioning cost per structure is calculated through a multi-factor cost model based on above data obtained through “what if” analysis in MATLAB. The multi-factor regression model is dependent on specific platform attributes such as removal option, removal technique, water depth, number of conductors, and weather window, among others.

The multi-factor regression model is developed for the specific field with peculiar characteristics (Appendices M and N); however, the model is non-absolute and can be tailored for other fields or extended to characterise an oil and gas field consisting of variety of platforms with dissimilar configurations. In relation to Table 9-3 above, the model response and associated regression model are as presented in Figure 9-5 and Equation (9-2), respectively.



(a) (b)

Figure 9-5 Multi-factor regression model for (a) SPJ removal cost and (b) Conductor severance cost

$$J_{RC} = 36317d_w + 142{,}332n_{l,p,c} - 1{,}524{,}795 \qquad (9\text{-}2)$$

Where J_{RC} is the jacket removal cost, d_w is the water depth and, $n_{l,p,c}$ is the number of legs and piles and conductors that requiring severance. Specifically, for the BAJ which is located at a 140 m depth with overall 80 legs, piles and conductors, the jacket removal cost is estimated at £14,946,145/platform (approx. £14.9 million). Where some of the conductors have been cut and retrieved prior to jacket removal, the regression model based on the conductor severance cost will be added to the estimated value. For the purpose of analysis, 40 conductors have been considered for removal in the Brent field and its regression model

$C_{SC} = 14244d_w + 35{,}605n_c - 2{,}704{,}170$ yields £714,248/platform, therefore, the overall cost of decommissioning a single steel jacket platform based on the multi-factor regression model is £15,911,393/platform in addition to the HLV charter cost. It is worth mentioning that these model parameters and assumptions have been selected following detailed analysis of the Brent Alpha technical document, discussions, and advise from decommissioning engineers and managers including process safety experts.

In addition, the real-time economic risk model that is achievable, to capture the costs incurred by the actualisation of any undesired event, through the application of the dynamic ERA framework will offer the advantage to be able to assess, reassess, predict, and mitigate the risks shortly before they occur. That, in turn, would help decision makers in planning ahead and as such can lead to considerable cost reduction associated site remediation. The dynamic ERA focuses on the evolution of cost on selected accident contributory factors capable of leading to a futile decommissioning operation. The next Section addresses the failure-to-cost conversion methodology.

9.3.5 Failure conversion into expected cost (Step 4)

Following the decommissioning cost evaluation in previous Section, the loss costs due to the actualisation of any one or combination of the accident contributory factor will be calculated in sequence. First, the fault tree of Figure 9-4 is converted into its corresponding Bayesian network as presented in Figure 9-6. Then the BN model is run through to obtain the futile decommissioning operational failure probability ($p(TE) = 0.05233$) which is then utilised, as the new evidence, to estimate the updated (posterior) causal events failure probabilities. As the cost of decommissioning is not free of uncertainty and limitations, the loss costs at time-slice t_i can be presented in terms of economic risk. Therefore, the posterior non-occurrence probability of bulk explosion event (x_5) given the futile decommissioning probability of 0.05233 at the 15th day is given by (See Table 9-4):

$$p(x_5|TE) = 0.05233 \times (1 - 0.0120) = 0.051704$$

The risk value for this event is calculated using the expected value analysis of Equation (9-1) by incorporating the decommissioning cost c_o in Section 9.3.4, thus

$$R_c(x_5|TE) = 0.005434 \times £15{,}911{,}393 = £822{,}683$$

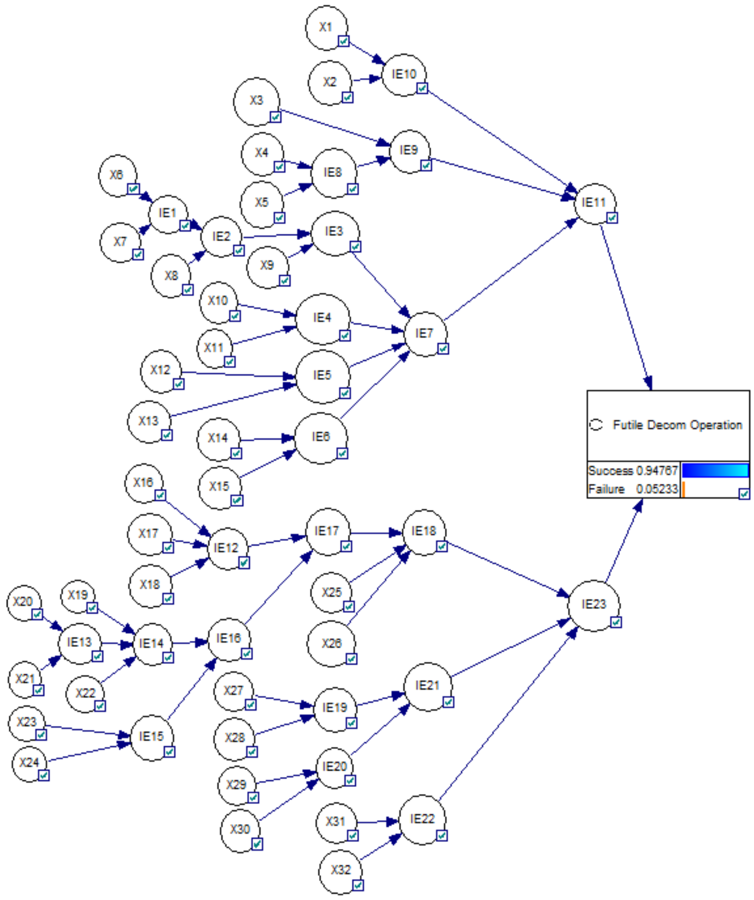


Figure 9-6 Bayesian Network for SPJ/BAJ

To minimize the effect of generic failure data due to source-to-source variability, these probabilities are then compared with a limiting cost of £15m – a quarter of the rough order of magnitude estimated by Shell UK – and a limiting probability against the causal events after a monitoring regime of 10-year period distributed over four scenarios of 25%, 50%, 75%, and 100% occurrence increments. The limiting probability and cost have been set based on literature review of related offshore accidents and advise from process safety experts leveraging on field experiences and/or recommended practices. The steel piled jacket removal operation is continued or suspended if the posterior failure probabilities are lesser than the limiting probability or otherwise. The conditioning algorithm allows for most critical elements of the accident contributory factors to be re-examined and modify as required. The overall safety of the jacket removal activity can be maintained while driving down costs associated with remediation from accidents and downtime.

Table 9-4 Occurrence updated probabilities of end consequences over a 24-day period

Days	x_1	x_5	x_{14}	x_{19}	x_{24}
1	4.88E-2	4.96E-2	4.68E-2	5.11E-2	4.95E-2
2	4.88E-2	4.96E-2	4.68E-2	5.11E-2	4.95E-2
3	4.56E-2	5.09E-2	4.68E-2	5.11E-2	4.95E-2
4	4.56E-2	5.09E-2	4.68E-2	5.11E-2	4.95E-2
5	4.56E-2	5.09E-2	4.68E-2	5.11E-2	4.95E-2
6	4.29E-2	5.14E-2	4.68E-2	5.11E-2	4.95E-2
7	4.29E-2	5.14E-2	4.68E-2	5.11E-2	4.95E-2
8	4.05E-2	5.17E-2	4.68E-2	5.11E-2	4.95E-2
9	4.42E-2	5.12E-2	4.68E-2	5.11E-2	4.95E-2
10	4.29E-2	5.14E-2	4.68E-2	5.11E-2	4.95E-2
11	4.29E-2	5.14E-2	4.68E-2	5.11E-2	4.95E-2
12	4.17E-2	5.15E-2	4.68E-2	5.11E-2	4.95E-2
13	4.17E-2	5.15E-2	4.68E-2	5.11E-2	4.95E-2
14	4.05E-2	5.16E-2	4.68E-2	5.11E-2	4.95E-2
15	3.94E-2	5.17E-2	4.68E-2	5.11E-2	4.95E-2
16	4.21E-2	5.15E-2	4.68E-2	5.11E-2	4.95E-2
17	4.21E-2	5.15E-2	4.68E-2	5.11E-2	4.95E-2
18	4.13E-2	5.16E-2	4.68E-2	5.11E-2	4.95E-2
19	4.13E-2	5.16E-2	4.68E-2	5.11E-2	4.95E-2
20	4.13E-2	5.16E-2	5.19E-2	5.11E-2	4.95E-2
21	4.29E-2	5.15E-2	5.16E-2	5.11E-2	4.95E-2
22	4.40E-2	5.14E-2	5.17E-2	5.23E-2	4.95E-2
23	4.47E-2	5.14E-2	5.15E-2	5.23E-2	4.95E-2
24	4.52E-2	5.14E-2	5.16E-2	5.22E-2	5.22E-2

The above table presents the summary of the risk profile for implementing the Accident Precursor Data (APD) in the monitoring of the removal operation for the anticipated 24-day period. The complications depicted by the selected accident contributory factors are in the order of their likelihood of occurrence and expected severity. The events with lesser observations represented by unfit structure node (x_{14}), installation flooding (x_{19}), and grout deterioration (x_{24}) are a family of events characterised by low probability high consequence events, making them more costly to remediate should they ever occur. As a result, their risk values would be increased by 25%, 50%, 75% and 100% of the expected £15.9m respectively. In addition, the significant reduction in the failure probabilities of the events indicate that more knowledge of the potential undesired events has become available and clearer due to accrued observations and evidence from daily trend as the decommissioning operation progresses.

9.4 Model analysis and results

The risk profile in terms of failure and cost of remediating the failure should it occur are discussed in this Section. In addition, a forecast beyond the 24-day removal period is presented for the four scenarios wherein the decommissioned site is monitored for an extended period of 10 years through backward propagation using the top event as the new evidence for 25%, 50%, 75% and 100% increments.

9.4.1 24-day failure model response

This Section presents the results for the failure profile observed during the 24-day activity period for which the BAJ is being removed following the operational sequence of SPJ decommissioning. The scenario demonstrates the typical Accident Precursor Data collected during operation which is often used to inform lessons learned. Figure 9-7 represents the failure model for the five selected performance parameters with activity being hindered by the occurrence of unknown stress-induced failure observed throughout the entire period, bulk explosion-related event emerged on the third day while a failure related to unfit structure node was spotted on the twentieth day followed by issues of rigging related to installation flooding on the twenty-second and grout deterioration effect on the lifting operation on the last day of removal, all of which are attributed to human error of some degree.

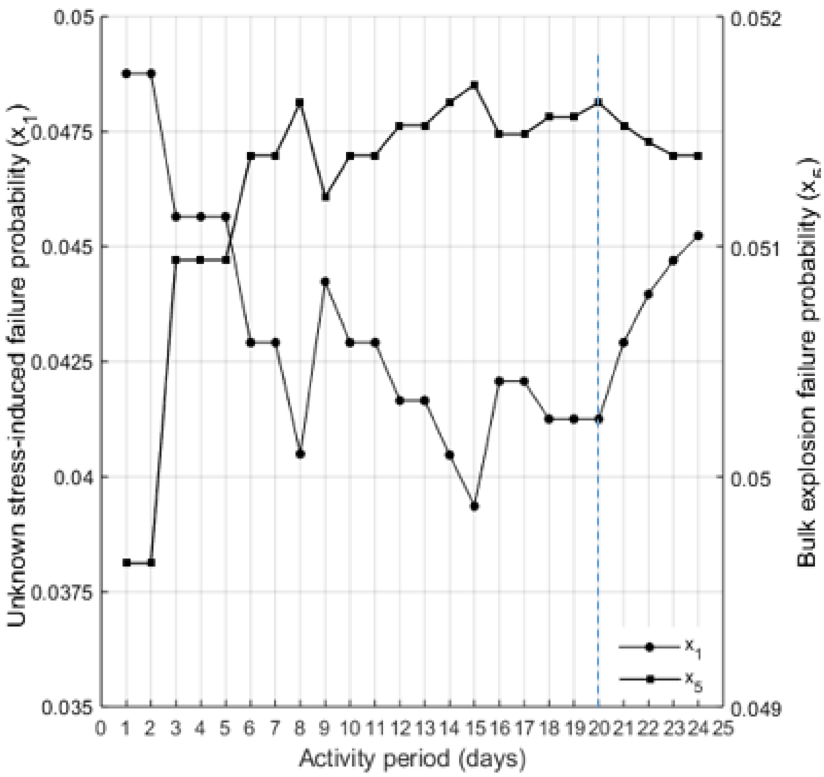


Figure 9-7 Failure profile for unknown stress and bulk explosion occurrences

As it can be seen from the graph, the occurrence probability of the unknown stress-induced failure increases as that of the bulk explosion decreases gradually on the 8th , 15th and just after the 20th day of decommissioning operation. This trend is attributed to the decrease in the failure values obtained from posterior probability estimation within the Bayesian network and the corresponding increase in the case of the bulk explosion related incidents. The increasing level of threats posed by the insufficient knowledge of the jacket structures remaining useful life (RUL) prior to decommissioning could also lead to this observed trend. To account for the RUL influence on the successful removal operation, adequate maintenance record, life extension analysis and relevant rigging calculations er recommended practices are imminent. Limited knowledge of the RUL will eventually trigger an increase in the likelihood of overall system failure. For this reason, it is recommended that RUL be ascertained through inspection and detailed late life extension analysis prior to decommissioning of the jacket structure and improved to avert the observed model response from occurring.

For the other three causal events where, little evidence has been gathered during the 24-day period of decommissioning the jacket structure, the prior occurrence probability of the top event has been relied upon as the new evidence to update their values, as presented in Figure 9-8. For instance, if the limiting probability, p_o for unknown stress-induced failure is set to 0.04375, the jacket removal operation would have been stopped at the 22nd day and the overall activity sequence re-examined and modified as required in accordance with the decommissioning safety workflow described in Figure 9-1. A potential cascade of failure that could trigger the occurrence of the top event through the interactions of any combination of these causations that appeared to be probable on the 24th day would have been prevented.

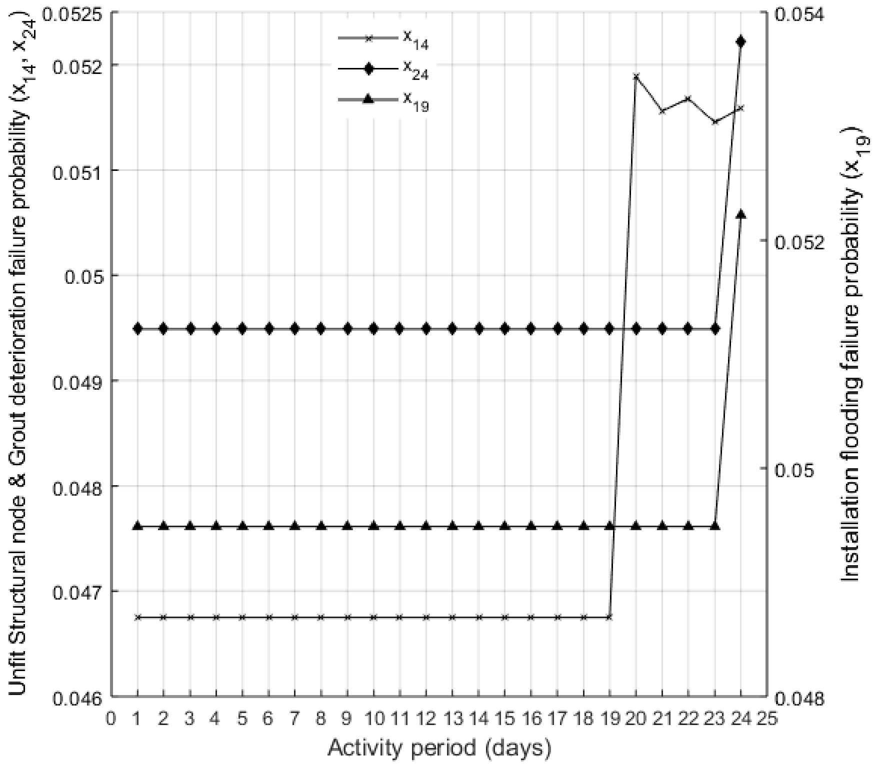


Figure 9-8 Failure profile for unfit structural node, installation flooding and grout deterioration occurrences

Whereas the failure profile depicted in Figure 9-8 showed that both the installation flooding and grout deterioration likelihoods increase abruptly in the same manner until the 23rd day when the unfit structural node began to decrease on the 19th day. Similar to the bulk explosion event, the unfit structural node event is detected by mere inspection and can be averted through the use of adequate supporting structure during the lifting and towing operations. In addition, the same increasing likelihood trend, observed in the case of unknown stress-induced failure holds true for the installation flooding and the grout deterioration events, although, only after the 23rd day. This capability of the dynamic safety model to be able to predict hazards occurrence prior to their occurrence would enable an effective and well-informed decision support during operational decision analysis phase of decommissioning and abandonment with the opportunity to significantly drive down the enormous cost of remediation.

9.4.2 Economic risk values

This Section presents the economic risk results for the selected causations for different loss values estimated at an increasing rate of 25% as the gathered evidence decreases. Figure 9-8 is the risk profile depicting the cost of preventing the identified hazards that may lead to the futile decommissioning operation and other end consequences that may put heavy financial burden on the oil and gas operators in the event of their occurrences.

As shown in the Figure, installation flooding would have escalated and cost the same as the grout deterioration on the 24th day if the operational sequence is not halted, reviewed, and improved as indicated by the risk profile for the 22nd day. The cost of preventing or remediating the installation flooding and grout deterioration failure occurrences increase significantly when the cost related to unknown residual stress continues to rise steadily on the 23rd day. There is a sharp jump on cost associated with the bulk explosion son after the 2nd day of removal operation whereas the unfit structural node failure remained steady until the 19th day and returns to a steady growth over time. Furthermore, the most optimistic cost profile is the bulk explosion model where the failure was spotted and remediated on the second day as depicted by its flat curve followed by the unknown residual stress failure with highest fluctuation seen to remain below the initial cost on day 1.

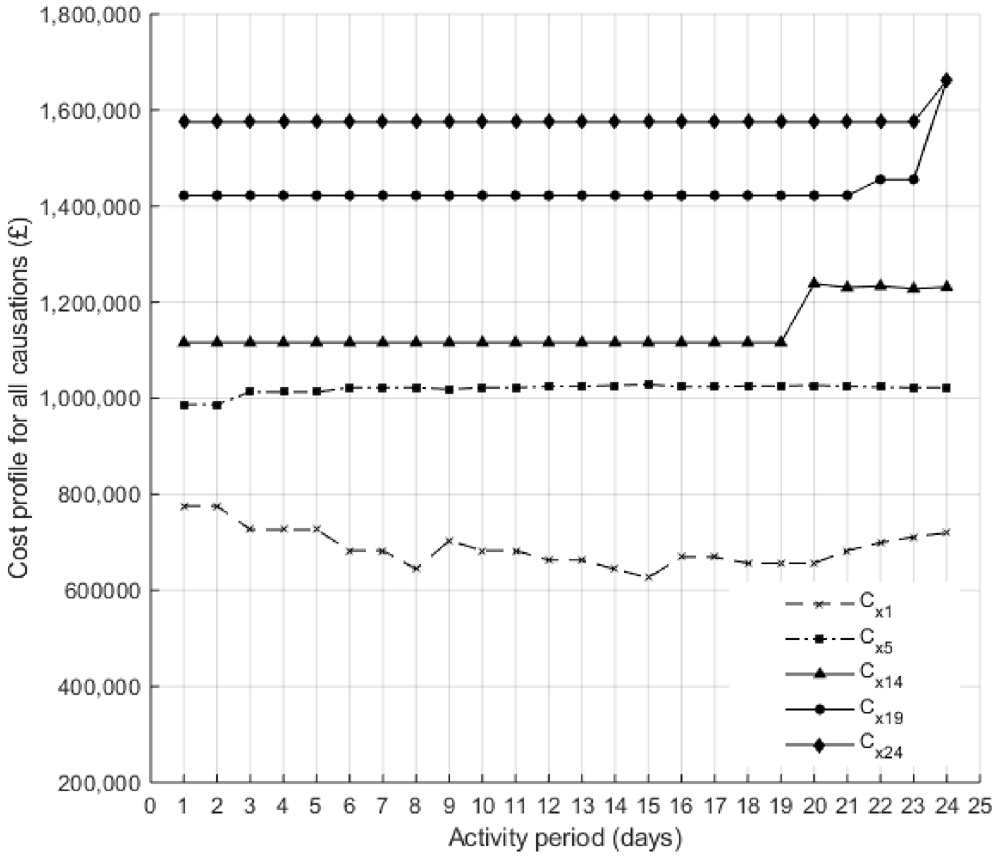


Figure 9-9 Loss value of causations over activity period

The cost profile trend is an indication that the implemented decommissioning safety workflow is efficient as required unless human error characterised by noncompliance is encountered. The level of effectiveness of the risk control measures put in place will influence the potential escalation of the causations in a way that the link between interacting factors is impaired to avert cascade of failure. If the occurrences are not guided against during the 24-day jacket removal period, these cost profiles will be uncontrollably high. Moreover, the grout deterioration cost profile further confirms that the most unwanted event cost more to remediate, making it possible for the decommissioning team to make a well-informed operational decision. Overall, the loss value significantly increases when the top event is likely to be overly impacted by the events with the least probability of occurrence.

9.4.3 Dynamic ERA results

The risk values obtained in Section 9.4.2 are further evaluated in a backward propagation to predict what the risk value would be, in future rate, if the lifting and towing operations were not adequately monitored. This is achieved by dynamically scaling the occurrence probability of the top event over four scenarios of 25%, 50%, 75% and 100% respectively using the 24th day failure data as the starting point to update the loss values. The dynamic ERA results for the four-stage increment are presented in Figure 9-10.

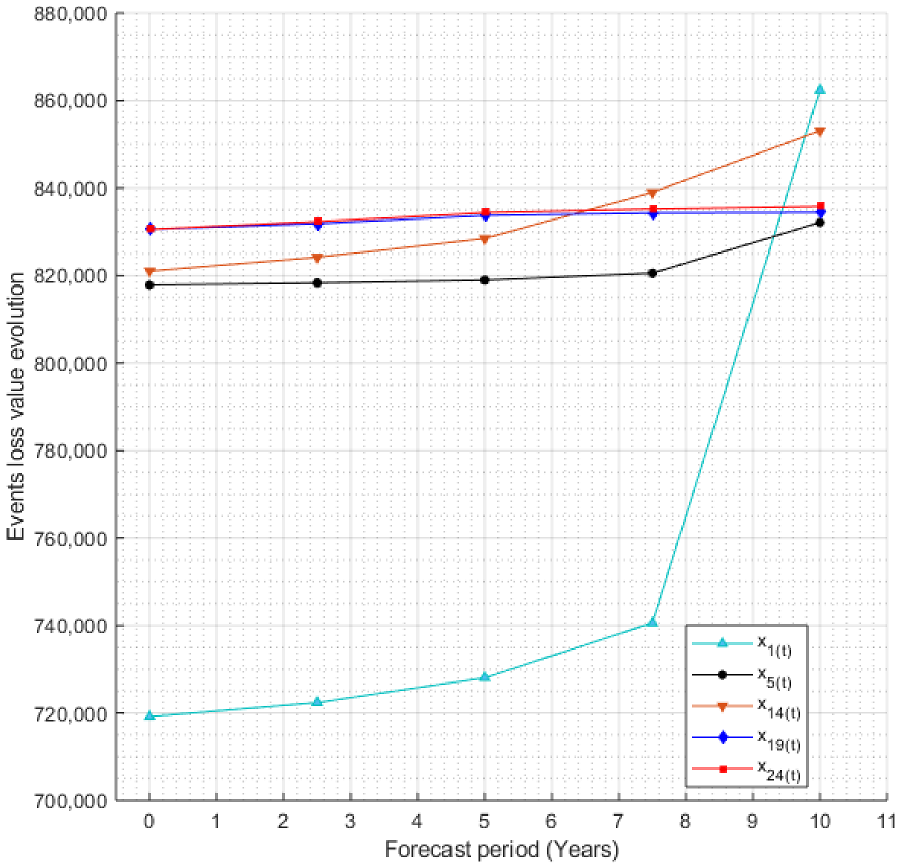


Figure 9-10 Dynamic economic risk prediction over a 10-year period

The loss values for all accident contributory factors are seen to increase over time, although, at varying degrees. For instance, the loss function of unknown residual stress failure, bulk explosion, and unfit structural node failures significantly increase in a nonlinear manner, making their occurrence more expensive to address should appropriate risk control measures be lacking or not implemented. While both the installation flooding and grout deterioration failures initially attracted higher costs to remediate, they both soon become unresponsive to further changes in the occurrence probability of the top event. This implies that when all hazards capable of triggering a futile decommissioning operation have been identified and captured in a robust dynamic safety model such as the type proposed in this thesis, the events with low probability and higher severity (LPHS) would have been prioritised in a similar manner to those with high probability high severity (HPHS). More specifically, the results presented indicated that for a steel piled jacket platform removal estimated for £15.9 million, the least severe mishap would cost approximately £720,000 to remediate whereas the most pessimistic scenario would cost up to £853,100. While these loss values have been based on the multi-factor model taken inputs from the decommissioning and abandonment site, the availability of data from Asset Retirement Obligation (ARO) documents and historical information from database will likely yield higher estimates. Where the limiting cost is set to £1m, the risk tolerance level would have permitted the removal activities to continue or stopped and revised for a relatively lower remediation reserve. Based upon the results obtained, a risk control measure is developed to address some of the many significant accident contributory factors as shown in Table 9-5.

Table 9-5 Risk control measure for steel piled jacket removal

Events	Description	Risk Control Measure	RCM Hierarchy
X_{16}	CP fails	Replace anode prior to decommissioning	Substitution
X_{17}	Soil erosion effect on lift	Inspect structure prior to lifting	Training and supervision
X_{18}	Failure of external coating	Paint affected area	Elimination
X_{19}	Installation flooding	Inspect inner walls of structure prior to lifting	Training and supervision
$X20$	Construction defects	Inspect hidden flaws and add appropriate safety factor during rigging	Engineering control, training, and supervision
X_{21}	Material defect	Reduce the effect of material defects by adding appropriate safety factors in analysis or safety functions prior to lifting	Engineering control and substitution
X_{22}	Piling	Prevent uncontrolled piling through training of offshore personnel.	Training and supervision
X_{23}	Ungrouted condition	Avoid Ungrouted condition in the substructure.	Elimination
X_{24}	Grout deteriorates	Prevent grout deterioration through corrective maintenance or implement real-time maintenance while structure is still operational.	Elimination or Substitution depending on extent of deterioration
X_{25}	Residual anode weight unknown	Replace the anode prior to decommissioning through preventive maintenance routine	Substitution and administrative control

X_{26}	Marine growth	Avoid either over- or under-estimating the effect of marine growth during rigging	Engineering control
X_{27}	Jammed cutter	Prevent operator error through high quality inspection and operating procedure of the substructure cutter and possible training if the cutter jams.	Training and supervision
X_{28}	Improper cutting procedure	Prevent operator error through noncompliance with established cutting procedure	Training and supervision; information and instruction
X_{29}	Drill cutting debris	Prevent drill cutting debris from depositing into the sea through compliance with lifting procedures.	Engineering control
X_{30}	Incorrect cutting time estimation	Prevent operator error through incorrect calculation of vital parameters such as the time required to cut the substructures	Training and supervision
X_{31}	Flooded member(s)	Prevent operator error through incorrect calculation of required flooded members.	Training and supervision
X_{32}	Uneven flooding	Prevent operator error in analysing uneven flooding within the jacket legs and pontoons, capable of toppling the substructure.	Training and supervision

9.5 Conclusion

The presented Dynamic Integrated Safety Analysis (DISA) provides an alternative means to assess the financial implication of a futile decommissioning operation from an economic risk assessment standpoint. It provides a localised approach to obtain loss values for selected accident contributory factors based on a multi-factor regression model that takes input from the decommissioning and abandonment site of interest. The methodology affords the oil and gas producers (OGPs) to gain insights into the cost of getting it wrong and the opportunity to make informed decisions based on quantifiable metrics peculiar to the field where offshore assets removal is required. The selection of accident contributory factors for this analysis is based on importance measure analysis discussed in previous Chapter to support a comprehensive backward propagation analysis to further allow OGPs to locally assess the latent impact of different component-level failures. This would enable the objective selection of key performance parameters needing immediate attention to distort the link capable of leading to cascade of failures.

Furthermore, the developed dynamic ERA model was executed for field-specific parameters such as the water depth and number of conductors, piles, and bracings to be severed. The obtained failure probabilities are then converted into loss values by way of expected value analysis, with all causations exhibiting varying degrees of increase in the losses, given that the failures occur. The cost model is updated through an integrated dynamic diagnosis of the top event to predict the future-day monetary value of the failure occurrences, as presented in Table 9-6 and the posterior probabilities in APPENDIX K. To limit the effect of uncertainties and generic data used in the analysis, a limiting value is proposed for both failure probabilities and loss values based on the organizational risk tolerance level. However, the proposed model does not have control over the limit set and may be within or outside its range if the parameters deviate from observed risk profile or the limit was set independent of the decommissioning-related workflow. In addition, the diagnosis implemented was arbitrarily scaled over four scenarios of 25%, 50%, 75% and 100% to simulate market condition over a 10-year period. Such increment is intended to introduce additional variation into the accident scenario analysis which would, otherwise, require the availability of sufficient historical or real-time data often gathered as the decommissioning and abandonment activity progresses. The adoption of a percentage scaling of the top event based on the availability of new evidence or observation further validates the robust computation engine of the Bayesian networks and contributes to the adaptation capability of the developed model. However, an uncontrolled generic adaptation can introduce noise into the model as it is not based on historical or real-time data, which is why the dependency modelling using noisy-OR and other advanced logics discussed in preceding Chapters remain valid.

The results obtained for dynamic probability updates showed that a limiting threshold set by the OGPs has the advantage to alert the personnel whether to continue the operation or to re-assess, making it a valuable tool for failure benchmarking. It is also observed that the degree of responsiveness for the cost model updating is, for the most part, nonlinear and the less severe events having high occurrence probabilities responded considerably to the stepwise changes in the top event probability. In the same manner, the events x_{19} and x_{24} were less sensitive to the incremental variations even though these two factors had higher occurrence probabilities at the end of the 24th day: indicating the credence of incorporating the dynamic-diagnosis approach in the analysis. Overall, all tested factors for each increment in the top event occurrence probability increase in order of their significance and proportionately from $t_o = p(TE)$ up to $t_4 = 2p(TE)$ as shown in Table 9-6.

The development and validation of the dynamic economic risk assessment require sufficient data for its implementation, which is lacking in the context of decommissioning and abandonment. Detailed ARO is needed to accurately estimate today's money value including the inflation rate and working interest, among others. In addition, Accident Precursor Data was required to implement the dynamic safety model within Bayesian network based on the Bayes' theorem to update the failure probability of causations. As ARO was not available for the selected case study in this thesis, a multi-factor regression analysis sufficed which proved to be invaluable. When sufficient data and observations become available, it is expected that these would be incorporated to address the data-driven limitation. Moreover, the system description presented here for the jacket removal operation was based on author's understanding of the operational sequence as contained in the BAJ technical document and feedbacks from peer reviewed journal. Therefore, future research of the proposed methodology should focus on verification of approach to data application and system validation to support the findings presented herein.

Table 9-6 Summary of dynamic ERA results for cost prediction in current day value

Time slice	Scenarios	x_1	x_5	x_{14}	x_{19}	x_{24}
$t_o = p(TE)$	PoF	4.52E-2	5.14E-2	5.16E-2	5.22E-2	5.22E-2
	Cost (£)	719,195	817,846	821,028	830,575	830,575
$t_1 = 1.25p(TE)$	PoF	4.54E-2	5.14E-2	5.18E-2	5.23E-2	5.23E-2
	Cost (£)	722,377	818,314	824,162	831,848	832,325
$t_2 = 1.50p(TE)$	PoF	4.58E-2	5.15E-2	5.21E-2	5.24E-2	5.24E-2
	Cost (£)	728,064	818,961	828,483	833,757	834,393
$t_3 = 1.75p(TE)$	PoF	4.65E-2	5.16E-2	5.27E-2	5.24E-2	5.25E-2
	Cost (£)	740,589	820,536	839,012	834,330	835,205
$t_4 = 2p(TE)$	PoF	5.42E-2	5.23E-2	5.76E-2	5.25E-2	5.25E-2
	Cost (£)	862,398	832,139	916,746	834,434	835,786

**PoF = probability of failure*

Summarily, the dynamic ERA is data-driven and to benefit from the potential advantages offered by the proposed method, responsible maintenance records and historical data collection through a database should be incorporated in the offshore engineering practices culture from early stage under the design-for-decommissioning (DfD) approach. In general, the dynamic ERA demonstrated its capability to integrate different aspects of safety and cost modelling to provide an insight into the two important areas of the five considerations of technical, social, environmental, safety and economic balances. Furthermore, the decommissioning and abandonment operation can either be continued or discontinued (and reassessed) based on the limiting threshold framework to prevent impending catastrophe shortly before they occur.

9.6 Summary

This Chapter introduced a dynamic economic risk analysis performed by implementing the developed dynamic integrated safety model that took inputs from actual accident scenarios observed and recorded over a period of 24 days, validated through accident precursor data. The dynamic ERA focused on the Brent Alpha field, operational sequence described in the technical document and a robust methodology that provided a route to estimating the loss value of accident contributory factors through the failure probabilities. The dynamic ERA incorporated time-variant analysis and backward propagation analysis to forecast and update the failure probabilities and consequent cost implications of the accident contributory factors selected through the results obtained from importance measure analysis presented in Chapter 8. The results were presented for 24-day failure responses, estimation of the economic risk values characterised by loss values, and the dynamic ERA obtained through the scaling of top event by 25%, 50%, 75% and 100% to replicate scenarios where future value of money, inflation rates and overall knowledge of hazards become available as evidence in the model.

Chapter 10: Research Discussion

10.1 Outline

This Chapter presents the discussion following the trend of outcomes from the research and the capability of the Dynamic Integrated Safety Analysis (DISA) developed. The novelty and contributions of the research are presented, followed by the strengths and limitations offered by the research methodology.

10.2 Novelty and Contribution

10.2.1 Novelty

The novelty of the research work presented herein is achieved from the developed dynamic integrated safety framework. In this framework, inputs from variety of strategies such as hierarchical Bayesian analysis, Bayesian networks and dynamic Bayesian networks were incorporated. In addition, various advanced logic gates were introduced into the conditional probability tables to incorporate dependencies among interacting accident contributory factors and, to model uncaptured hazards. As the research is primarily motivated by data paucity, a method to tackle the effect of small data size was proposed with considerable confidence level, making it a valuable and adaptive tool for wide range industrial application. Due to the rare accident classification of decommissioning and abandonment operations, the developed dynamic integrated safety analysis model can offer a possibility to redirect safety decisions from what used to be an experience-driven activity into a data-driven type, building upon the robust computation engine of the model. One main advantage of the model is in its ability to update failure data within the model and reassess the overall safety as more knowledge, observations, and new evidence become available.

The first level of effort was invested in conducting a detailed evaluation of decommissioning and abandonment-related research through a comprehensive review of literatures, technical documents, and current trends published on DNVGL webpage on the findings of the Joint

Industrial Projects, JIP (ABB, 2017). While there are numerous equipment and components as part of the offshore assets needing to be decommissioned, this research focused on two main aspects, namely:

(i) The plugging and abandonment of subsea wells; and

(ii) The steel pile jacket removal.

The present work explores the focus areas of both peer-reviewed research papers and industry current best decommissioning practices including regional and international standards, recommended practices, and regulations. Through a thorough gap analysis of the literature review, this research bridged the void between theory and practice. The research comprehensively examines the methods, tools and techniques, strategies, inputs and often expected outputs based on financial burdens on oil and gas producers, and the rebates from government to inform modelling assumptions.

Notably, the developed model adopted Hierarchical Bayesian Analysis based on Gamma distribution to process analogous failure data obtained using the source-to-source variability concept and returned the outputs as a mean distribution with 95% confidence level, and with the limiting failure framework the decommissioning and abandonment operation can be halted, reviewed, and reassessed to avert single failure that could jeopardise the entire operation. The limiting failure framework is especially developed as a proposed tool to be fed into a real-time sensor device for monitoring and controlling the operational conditions and safety. In addition, the inclusion and strength of influence comparisons of the N-OR, LN-OR, and ILN-OR models aided in addressing implicit or uncaptured causations during hazards identification stage and also, in the verification of the under- or over-estimation drawbacks inherent in the conventional probabilistic risk analysis tools such as FTA and ETA as these traditional methods are not able to consider dependency or common cause failures without incorporating them with advanced and often expensive logic gates.

Another novel attribute of the proposed Dynamic Integrated Safety Analysis (DISA) model is in the development of importance metrics estimation emanating from the uncertainty analysis to establish the most probable cause of the single undesired failure. The importance measures formulation then set the pace for the time-variant modelling formulated within dynamic Bayesian networks. The DISA model permitted the possibility to marginalise any combinations of performance parameters at specified time slice(s) to be locally diagnosed or predicted over a set period, making it a realistic and flexible failure analysis tool for learning simple- to complex-finite accident scenario networks (APPENDIX L). The prediction of future failure or economic state of selected performance parameters have been made possible through the dynamic model, thereby enhancing component- to system-level monitoring as the decommissioning and abandonment operation progresses. The DISA model is adaptable and allows the localization of any system interactions of interest to be evaluated in isolation or as part of a complex interdependencies including the incorporation of new input causations or existing causation data representing new evidence based on ongoing risk profile tracking or previously uncaptured hazards.

In conclusion, objective quality evidence in systems identification, description, and assessment has been substituted for through the development of various uncertainty improvement strategies at different levels of the DISA model formulation, analysis, and its application to case studies. Moreover, the cause-consequence relationship was first demonstrated on FTA and ETA respectively and visualised through their corresponding bowtie to provide a level of objectivity in the accident formulations prior to mapping these into Bayesian networks through the similitude concept, taking advantage of both conventional and modern qualitative and quantitative assessments.

10.2.2 Contribution

The contribution of the developed DISA model is especially notable in theory and practice. In theory, the systematic transformation of the fault tree and event tree cause-consequence relationships into their corresponding Bayesian networks provided a means to objectively verify the correctness of the accident scenarios and evolutions. In addition, the dynamic safety method has been analysed considering dependency which is, otherwise, a difficult task to accomplish by conventional quantitative assessment methods. The analysis is adaptable and offers opportunity for improving the safety model as more information or new evidence becomes available, paving way for advancement in the existing probabilistic techniques. Further improvement has been proposed to address unknown reservoir conditions, limited data, and even parameters uncertainty through the elicitation of advanced logic gates to relax the model. The paucity of data has been addressed through the application of hierarchical Bayesian analysis, due to the uniqueness of decommissioning and abandonment accident systems which are not captured in offshore accident database like OREDA or marine accident investigation Branch, MAIB report. A new methodology for the quantification of loss values as a measure of financial implications of unsafe operation has been demonstrated to support the decision to continue or revise operational work package, to foster Recommendation-to-Decommission (RtD). A limiting failure probability is proposed to be set for the top event to control the effect of generic data and to determine whether to continue the jacket removal operation or to modify relevant parameters in order to avert catastrophe. This, in turn, provides the advantage of identifying when to halt the operation and consequently, manage the removal activity efficiently while driving down the cost of decommissioning and remediation.

Furthermore, the application of the DISA framework is demonstrated using two case studies based on practical problems directly related to decommissioning and abandonment. The first case study is the Elgin platform permanent plugging and abandonment failure. The failure model consisted of three fundamental leak paths, namely:

(i) The leak through zonal isolation plugs in the production zone;

(ii) The leak through the secondary barrier along the surface casing; and

(iii) The leak through primary barrier along the conductor casing.

Schematics of the design well was examined, and accident model formulated based on the technical issues reported by Total E&P (2013). Due to limited knowledge of the reservoir conditions and limited data, Hierarchical Bayesian Analysis was implemented to obtain failure probabilities for causations at the component level. Considerable effort was implemented to capture all possible hazards through a hazard identification workshop. The HAZID exercise was validated through a peer reviewed process. The case study benefitted from the DISA framework through dependency elicitation within the conditional probability table of the Bayesian networks and further analysis through dynamic modelling motivated by accident likelihood prediction requirement and validated by sensitivity analysis.

The second case study is the Brent Alpha Jacket structure decommissioning characterised by collision or capsize of the lifting vessel based on Shell technical document. This analysis focused on the development of a multi-factor regression model to define the cost of removal of a single jacket structure. The significance of the regression model thrived on the assumption that no external complications exist. An operational scenario spanning 24-day activities formed the basis of the analysis. The cost is then converted to loss values based on the failure probabilities of the accident contributory factors and is further validated through integrated dynamic-diagnostic analysis to predict the future money value of getting it wrong.

In practice, the DISA model can serve as a robust decision support tool for the oil and gas producers and other relevant stakeholders such as the decommissioning personnel, contractors, Oil and Gas Authority (OGA), Oil and Gas UK (OGUK), Health and Safety UK (HSE, UK) and regulatory bodies. The integrated model incorporating different aspects into a single framework makes it possible to dynamically update and adapt the model to current market or technical conditions as new input data become available. More so, a compact safety tool capable of taking generic and accident-specific inputs to provide real-time output on demand would be an asset to decision makers. The current state of knowledge from the safety analysis results for the investigated accident scenarios can be tailored and updated to enhance the decommissioning and permanent abandonment operations. Moreover, the economic risk analysis model can be further improved and tailored to specific sites to be returned to its initial state. Lastly, this safety design approach can be fully developed and adapted to a real-time risk monitoring device for field application during decommissioning and abandonment operations.

10.3 Strengths of Research Methodology

The presented study introduced and justified the importance of adopting an advanced risk assessment technique to handle such a time-dependent activity as decommissioning. In the study, it was established that the proposed DISA model thrive in the transition from conventional fault tree, event tree, and bowtie analysis to its corresponding Bayesian networks which is capable of handling uncertainty, common cause failures, and finitely complex systems based on Bayes' theorem and advanced elicitation of dependency. It was demonstrated that the conventional models, albeit effective and proven, cannot cope with unknown input data without introducing additional uncertainties or handle dynamic accident scenarios where operating conditions change with and/or over time. The dynamic safety model incorporates a holistic approach to capturing the overall systems hazards through comprehensive evaluation of technical documents and publicly available accident reports. For permanent well plugging and abandonment, all the potential leak paths are considered through standardized well schematic. The Brent Alpha jacket structure was analysed in a similar manner and supported by the availability of producer-specific technical document, thus, tackling the issue of objective quality evidence. In addition, the failure data used in the analysis have been collected through hazard identification workshop and processed using advanced statistical methods, and the results of this analysis can be found in the Data-in-brief journal (Babaleye et al, 2020) on Mendeley to foster reproducibility and verification.

The adoption of Gamma distribution function with multi-level failure estimation and conjugate prior offers an unparalleled advantage compared to other studies using FFTA (Lavasani et al., 2015), FTA (Nichol et al., 2000), and OREDA coupled with Bayesian networks (Babaleye et al., 2018; Faber et al., 2002).

The incorporation of Hierarchical Bayesian Analysis and Bayesian networks to conduct safety risk analysis with in-built dependency model is another advantage of the proposed methodology, an approach which has not been explored within the offshore decommissioning industry thus far. This method is oriented towards uncertainty elimination at each phase of the analysis, thus enhancing the safety of the operation in its entirety. The integration method is a strength that can be fully utilised during and post-decommissioning when compared to fuzzy set theory techniques (Shi et al., 2014, Lin and Wang 1998), static layer of protection analysis (Pasman and Rogers, 2013; Markowski and Kotynia, 2011), and bowtie (Yuan et al., 2015; Khakzad et al., 2013; Ferdous et al., 2013).

In addition, the development of a dynamic integrated cost monitoring model based on the combination of hierarchical Bayesian analysis, Bayesian networks, multi-factor regression model, and time-variant diagnostic state modelling to attribute financial value on accident contributory factors to support safety critical elements prioritization is another important advantage compared to the overall decommissioning cost estimation methods (Kaiser and Liu, 2014), which does not account for the cost of getting it wrong and end consequences cost modelling (Fam et al., 2020; Babaleye et al., 2018), which relied on experience-driven or historical loss values.

The applicability of the developed DISA model to both permanent well plugging and abandonment operation and steel piled jacket removal is a justification of the flexibility of the model to be adaptable to other offshore operations such as process safety, drilling, production, and installation and workover control systems (IWOCs) activities.

10.4 Research Limitations and Assumptions

In the research and design of any engineering system, limitations and assumptions are necessary to account for instances that are beyond control to guide the research against design errors and permits continuous improvement. Therefore, the current thesis is also bounded by such constraints. The following are the assumptions and limitations considered in this study:

System description. The identification and description of accident model for both case studies have been based on overly limited literature. In the case of permanent well abandonment, whilst there was publicly available information on the Elgin platform, the accident scenarios analysis and modelling rely on only the typical well design and construction schematic in accordance with NORSOK (2013) and the comprehensive report on risk analysis of shut-in, temporary and permanent abandonment of oil and gas wells submitted to the Mineral Management Services by Nichol et al. (2000). The hazards identified in the literature appeared to be high level and the basic causals, for the most part, have not been provided. In addition, the assumptions underlying the failure probabilities estimation for the basic causals is peculiar to the site for which the research was conducted and thus, is non-absolute. For the steel piled jacket, the technical document provided operational sequence, but the hazard identification and risk analysis performed to obtain the reported Potential Loss of Life (PLL) values cannot be verified. Therefore, the developed safety model relied on the available information and further expanded the accident model, making it more complex than those found in the literature to justify the need for a novel methodology that may attract significant cost to implement.

Computation time and cost. The elicitation of dependency within the conditional probability table can be a challenging task. At the time of completing this thesis, there has been no academic publication focusing on simplification in elicitation process. Therefore, the development of DISA focused on the accuracy of the relationship among interacting events and assumed a reasonable '*leak probability*' of 5% in the analysis in accordance with current best practices. The selection is arbitrary but often between 0 and any value lesser than the lowest probabilities of the interacting causations. While the specification of this value is intended to account for uncaptured hazards, it may unintentionally be a source of uncertainty if not controlled.

Dynamic state modelling. The dynamic state modelling relied on the assumption that each succeeding time slice is conditionally connected to the one immediately preceding, i.e., the Markov chain formalism. A practical way to model dynamic interactions is through the development of a time-based governing equation which will feed into the prior probability at time slice 0 to update successive ones. However, the current model relied on the posterior predictive probability output from the HBA process as a static prior input to update a dynamic state model for analysis in Chapter 8. It is worthy of mention that the Bayesian networks have been utilised to overcome this assumption, as the model would have considerably reduced the errors introduced by the static input data through dependency modelling and new evidence availability.

Accident Precursor Data. Accident Precursor Data (APD) are important output of an offshore related activity to enhance lessons learned and provide a database for investigating accident or incident trend. The specified Accident Precursor Data in this analysis does not represent any practical measurement or even a simulated environment. It is subjective with the goal of demonstrating the dynamic framework capability of the accident model developed in Chapter 9. With more accurate and sufficient data availability from companies or decommissioning operations, the reliability of outputs can be significantly enhanced. One way to address this issue would be via the development of a correlation or regression model to fit the leak probability objectively based on data. Overall, these limitations and assumptions would provide a step in the right direction for further research, as shall be seen in the next Chapter.

10.5 Summary

In this Chapter, the main outcomes of the PhD thesis are discussed in its entirety. The novelty and contributions to the current state of knowledge and its benefits to both the academic community and the oil and gas industry were presented. The strengths of the developed methodology were further highlighted without trading off the limitations and assumptions governing the model setup. The next Chapter describes the conclusion drawn from the summary of findings.

Chapter 11: Research Conclusion

11.1 Outline

The concluding remarks based on the obtained results from this research with respect to the safety and failure analysis of decommissioning and abandonment are presented. The relevant findings are summarised to support the strengths of the developed methodology, followed by the recommendation for future research. The review of aim and objectives are analysed to demonstrate research accomplishment.

11.2 Summary of Findings

Motivation. The current best practices to ensuring decommissioning and abandonment operations are safe revolves around the development of static safety critical analysis and assessment of the activity sequence based upon the work breakdown structure. Typically, the output of such analysis is the risk to personnel measured by the Potential Loss of Life (PLL) using conventional probabilistic risk analysis tools such as FTA for accident modelling and event tree for consequence modelling. The PLL and other metrics based on the balance of technical, social, environmental, safety and economic considerations are then used to develop a comparative assessment (CA) from which a preferred decommissioning option is justified. One major drawback is the subjective nature of the safety assessment process due to lack of information as the operation is experience-driven, thereby introducing uncertainty into the accident scenarios. Another drawback is the assumption that the conditions associated with the oil and or natural gas to be plugged and abandoned, or the platform to be removed are constant and will remain so throughout the activity duration. It is also commonly argued that the abandoned wells have been depressurized to the level that they pose no threat, now and in the future. These assumptions have proven not to be true and necessitates adequate attention and the development of a new method to address these concerns.

Implementation. The integrated model is first implemented through cause-consequence relation accident scenarios within a bowtie building on the benefits of both fault tree and event tree with the single undesired event at the pivot. These techniques have been adopted primarily to provide a preliminary insight into the safety critical accident contributory factors and eventually support the identification of key performance parameters, which served as the input parameters for the rest of the dynamic analysis, through importance measure. It is essential to point out that the conventional FT and ET have not been relied upon for computation in this study, instead they helped in capturing and envisaging the accident model formulation and then transformed into BN where analysis are conducted. However, the results presented in Chapter 7, Section 7.2 are merely to emphasise the credence of adopting the dynamic safety model because the conventional models under- and overestimated the results in areas where dependency ought to have sufficed.

Application*.* The proposed methodology is applied to two different case studies to demonstrate its permanence and relevance to the scientific community and the industry. The capabilities of the noisy-OR, leaky noisy-OR, and imprecise leaky noisy-OR models are further tested with respect to dependency modelling among interacting causations. The noisy-OR model addressed the issues related to uncaptured hazard and returned a top event occurrence probability (0.2533) lower than that obtained through the FTA result (0.2835) based on standard OR-gate, making it a middle course between And- and OR logic gates. The leaky noisy-OR model addressed the concerns related to the occurrence of accident even though all causations are in their '*zero*' states, a scenario quite common amongst rare accidents within the offshore and process industries. On the other hand, the imprecise leaky noisy-OR model accounted for the uncertainties associated with leaky probability value, assumptions related to the model formulation itself, and the parameter failure data . It is important to note that the leaky probability value, 0.05, was chosen arbitrarily instead of developing a correlation and regression model or design of experiment, either of which would considerably lengthen this thesis without added value, thus, should be a topic for further research. The leaky noisy-OR model estimated the top event occurrence probability (0.2960) higher than the OR-gate, indicating that appropriate dependency assumptions would further enhance the accident prediction. The results obtained from the imprecise model is superior compared to all previously considered models. For example, the imprecise model returned both a lower-bound and an upper-bound occurrence probability [0.2377, 0.7226], indicating that real life accident models should be best represented in intervals to provide decision makers the flexibility to design safety thresholds within these limits.

Case study I failure results. Following the demonstrated capabilities of all three noisy models within the BN, the noisy-OR model was selected to preserve consistency in the reported results across all analysis. One reason for this simplification is due to the amount of effort required to elicit the dependencies for complex interactions. For example, the imprecise model required 27 outcomes for denoting the interactions among three parent nodes, and the CPT would exponentially increase as the number of parent nodes increases. The Bayesian network arrangement for the permanent well abandonment case study was trained using the failure data obtained through HBA as prior probabilities to predict the top event failure, characterised by the leak of hydrocarbon to mudline, through a forward propagation analysis formalism. The model was also instantiated in a backward propagation analysis, subject to the availability of new evidence to diagnose causal events faults based on priori knowledge. The new failure results are then compared with the prior to obtain the most probable cause of failure. These predictive and diagnostic benefits make the BN especially suited to uncertainty modelling.

Case study I sensitivity analysis. The sensitivity analysis incorporated the capability of the BN and its model prediction capability to learn from prior failure data to predict the future state of failure. Based on the Fussell-Vesely's importance measure, the small incremental change between the prior (past) and posterior (updated) probabilities were collected and ranked in order of their significance. The parameters with higher significance were then selected as the key parameters , referred to as base case, to learn how responsive the leak to mudline is to changes in the parameters. The SA is an important step in the analysis to investigate and forecast varying conditions that may escalate the overall single failure. The base case model response for a single test , loss of barrier $B_{6.1.2}$, demonstrated that the forecasting precision u to 21% was attained and significantly increased to 50% precision when combined with annulus barrier degradation $B_{5.2}$.

Case study II dynamic economic risk results. The dynamic ERA demonstrated the economic benefit of properly prioritising and managing safety risks within the selected Brent Alpha jacket removal accident model. The model formulation was based on the Brent Alpha decommissioning technical document from which accident scenarios were derived from the sequence of operation. The model results indicated that both low probability high consequence events and high probability high consequence events would eventually incur similar loss values over time due to the future money value affected by working interests and inflations, among other uncontrollable conditions. For example, by the end of the 10-year period following Asset Retirement Obligation to decommissioning, the economic risk of unfit structure node related failure would have rose to £917,764 whereas the grout deterioration with its perceived severity would have been £835,786. The dynamic ERA thrives on a multi-factor regression analysis to estimate the cost of each activity as a function of their failure probability, market condition, and field-specific data. The ERA can be further improved by incorporating the dynamic safety model into a real-time monitoring device for field operation during decommissioning and abandonment.

11.3 Recommendation for Future Research

Based on the outcomes from summary of findings and observation of the limitations emanating from the research and development of the dynamic integrated safety analysis framework, the need for future research into improvement areas were noted. This further research areas will complement and build upon the accomplishments of present thesis to widen its scope and impact. These improvement areas are highlighted below.

Accident model. Although platforms and oil and gas wells vary in their design, construction, and sizes, among other factors. However, a standardised and adaptable accident model should be developed that can be feed into and improved by the scientific community and the industry through a one-size-fits-all flexible hazard identification methods to preserve the completeness and correctness of the accident scenarios model.

Dependency elicitation. The specification of dependency among interacting events should be further investigated and improved to considerably reduce the amount of time needed to completely represent the accident model.

Asset Retirement Obligation. The integration of Asset Retirement Obligation information into accident model could be explored to provide a practical means through which economic risks are evaluated.

Experiential learning. Accident database containing real Accident Precursor Data obtained during decommissioning and abandonment operations could be invaluable to train the Bayesian networks. This would eliminate uncertainties related to data paucity and invalidates source-to-source variability.

Safety culture. A comprehensive offshore decommissioning safety culture could be developed and consolidated with Accident Precursor Data trained within the dynamic safety model in a data-driven or simulated environment.

Physical reliability model. In the absence of publicly available decommissioning-specific accident data, a physical reliability model based on accurate RUL estimation could be developed to and implemented in HBA to improve uncertainty associated with data.

11.4 Review of Research Objectives

The purpose of this thesis is to contribute to the current best practices, in theory and in parametric verification, of decommissioning and abandonment operations. Therefore, the discussion of the research objective effectiveness covered in this PhD thesis are provided below.

Objective (i): To identify gaps in the literature by examining the current state of knowledge related to offshore decommissioning and oil and gas well plugging and abandonment.

This objective has been accomplished evidenced by the detailed analysis of earlier research conducted on the topic as was covered in Chapters 2-3. A comprehensive review of the literature spanned the regulatory bodies recommended practices, method for selecting decommissioning options, opportunities for reuse, processes, and the types of well plugging and abandonment operations including the critical nature of ensuring operational safety. The strengths of each safety risk methodology, their advantages and shortcomings have been scrutinised, from which the research gaps addressed in this present thesis were identified. The comparative assessment (CA) often used to justify the referred decommissioning and abandonment option have been discussed to rely only on static quantitative analysis and requirement for advanced method to capture real-time data based on dynamic safety model presented including the data paucity exacerbated by the limited availability of literature with respect to the development of safety models relating to the decommissioning industry.

Objective (ii): To demonstrate the applicability and suitability of a gamma distribution function using Hierarchical Bayesian Analysis as a tool for estimation of failure data with 95% confidence level.

This objective was covered in Chapter 5. The challenges in the formulation of the Gamma and Weibull distributions were highlighted. The source-to-source variability concept was adopted to replicate typical accident data collected for the decommissioning operation as if it were analogous to existing industrial practice such as the mining, aerospace or nuclear. The same data was adopted to demonstrate the suitability of both methods from which Gamma distribution, due to its multi-level computation capability including its conjugate prior advantage yielded the better outcome. Therefore, this objective was considered accomplished, and the data formed the basis of input prior failure data for the remaining Chapters of the thesis.

Objective (iii): To develop a safety analysis based on hierarchical Bayesian model to quantify the failure probabilities of offshore installations decommissioning operational *hazards and demonstrate the applicability of the proposed dynamic safety framework to permanent abandonment accidents.*

This objective was covered in Chapter 6. The capability and permanence of the advanced logics were demonstrated taking failure input data from the Hierarchical Bayesian Analysis presented in Chapter 5 to estimate the top event occurrence probability. The conditional probability table within the Bayesian networks were elicited to account for dependency among interacting causal events, uncertainty in modelling and assumptions, and the instantiation of the dynamic safety model to obtain failure probabilities that have comparable advantages over the conventional fault diagnosis quantitative models.

Objective (iv): To develop a probabilistic risk analysis for offshore well plugging and abandonment operations built on advanced logic formalism to address the issues of uncertain reservoir conditions and limited failure data.

This objective was addressed in Chapters 6 and 7. Chapter 6 laid the foundation for the safety modelling through the utilisation of advanced logics to relax the limitations of conventional fault tree and event tree analysis. In Chapter 7, the model was entirely solved using conventional FTA for accident modelling and ETA for consequence modelling with the primary aim of gaining insights into the causal events with the most probable cause of the top event which is measured by importance metrics. The events with higher important measures and those that would normally impact the model dynamically such as annulus barrier degradation over time were selected as performance parameters to learn the overall system response in the dynamic Bayesian networks in subsequent Chapters. These selections were based on the minimal cut sets, importance measures, and time-variant events. Therefore, this objective criterion is considered satisfied.

Objective (v): To develop dynamic risk-based sensitivity analysis model that can be applied to each phase of decommissioning and abandonment operations subject to time-dependent accident evolution.

This objective was addressed in Chapter 8. A detailed sensitivity analysis was designed and analysed taking input data from a risk-based standpoint noted in objective (iv) where selection of input data was based on minimal cut sets, importance measures, and time-dependent failure components, indicating that these input data were the most safety-critical and prioritised accordingly. Two sensitivity analysis scenarios were set up for investigating the degree of responsiveness of the model output to fractional changes in input data. Three sensitivity analysis were identified but the selection of scenarios sensitivity analysis (SSA) was justified by the cost impact of adopting a computationally intensive method. The SSA was carried out in a dynamic Bayesian network where the posterior probabilities for subsequent time slices are modelled using Monte Carlo simulation with the 'what-if' method for computing the conditional probabilities. For the single and two-parameter SSA conducted, the model responses were proportionate with the input data variations, although, the two-parameter achieved a higher performance of up to 50% compared to the 21% for single parameter. Therefore, this objective can be considered satisfied.

Objective (vi): To develop a dynamic economic risk analysis based on multi-factor regression model and failure probability to forecast the future value of money in terms of loss values incurred from impact of failure. (Addressed in Chapter 9).

This objective was covered in Chapter 9 by conducting a multi-factor regression analysis to empirically estimate decommissioning cost based on a field-specific design parameter. The economic risk of encountering a failure event is estimated as a loss value using a form of expected value analysis. The lack of public Asset Retirement Obligation documents or cost estimate database necessitated the adopted approach and proved to fall within range of the rough order of estimate contained in the Brent Alpha technical document. Through a dynamic-diagnostic analysis, forecast of the future value of money was provided to give an insight into how the cost of removal would have changed from the time an asset is considered for decommissioning and the time it is removed, due to market conditions, inflation, and working interest, among other factors. Therefore, this objective can be considered satisfactory.

Objective (vii): To summarise the main findings, concluding remarks from obtained results, research contribution, and propose potential outlook for further research.

This objective was covered in Chapters 10 and 11. The summary of findings emanating from this PhD thesis, the concluding remarks, and the research contribution to the current state of knowledge were provided in ***bold italics*** in the preceding Chapter. Following from the notable strengths, assumptions, and limitations drawn from the proposed methodology in this research work, a proposal for the potential outlook for further research was put forward.

11.5 Summary

In this Chapter, the summary of findings emanating from observed results from the dynamic safety model is discussed, followed by the recommendations for future research to broaden the scope and impact of the present thesis. The breakdown of procedures and trends in the observed results for tested case studies were provided. To supplement the details contained in the thesis for further reading, references and appendices are listed in the succeeding pages.

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APPENDIX A: Weibull estimation in MATLAB

%% Weibull Function

```
clear all
close all
clc
a = [-2.66384 -1.72326 -1.20202 -0.82167 -0.50860 -0.23007 0.03292 0.29903
0.59398 0.99269];

b = [0 0 0.693147181 1.386294361 1.609437912 0.693147181 1.791759469 0
1.098612289 2.708050201];

polyfit(a,b,1)
grid on

ans

p\left(y\right)=\frac{\alpha}{\beta}\left(\frac{y}{\beta}\right)^{\alpha-
1}e^{-\left(\frac{y}{\beta}\right)^\alpha}

 y = [2  0  0  0  1  6  2  3  0  5];

wblpdf(1.9,0.24748, 0.05494)

k = (4.50455042)*((y/0.05494).^(-0.75252)).*exp(-y/0.05494).^(0.24748);

k = 0.000567397024;
```

APPENDIX B: Experts Ranking

While it is a common practice to add weighting factor to dataset to differentiate their relative importance, the weighting factor collected for each expert opinion was normalised and assume to carry equal weightage. This is weightage could not be incorporated within HBA model since the statistical formulation already accounted for multi-level aggregates and variations that exist among the datasets.

Table A.0-1 Experts ranking for model and data validation

Constituent	Classification	Rank	Weighting Factor
Position	Senior academic, Manager, Lead	5	1
	Senior, Intermediate Engineer	4	1
	Junior academic, Junior Engineer	3	1
	Technician	2	1
	Artisan	1	1
Experience	≥ 30 years	5	1
	$20-29$	4	1
	$10-19$	3	1
	$4-9$	2	1
	< 3	1	1
Education	Doctorate (PhD, EngD etc.)	5	1
	Masters (MSc, MEng, MPhil., etc.)	4	1
	Bachelor (BSc, BASc, BEng, etc.)	3	1
	Technical Diploma	2	1
	Vocational Training	1	1
Age	≥ 50	4	1
	$40-49$	3	1
	$30-39$	2	1
	< 30	1	1

APPENDIX C: Dataset for plugged and abandoned oil and gas wells

```
##Wed Mar 22 13:00:37 2017
##-----------------------------------------------
##Hazard identification with risk factors ranking techniques
##-----------------------------------------------------------------
##
##by Ahmed Babaleye
##https://data.mendeley.com/datasets/mz3khsphdb/1
##-----------------------------------------------------------------
##
# format number
0
# num of precursor data types
2
#hazid ranking for B1.1
2.0	0.0	0.0	1.0	0.0	3.0	1.0	0.0	1.0	1.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for B1.2
2.0	0.0	1.0	0.0	0.0	4.0	1.0	0.0	1.0	1.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for B2
0.0	1.0	0.0	1.0	2.0	3.0	3.0	4.0	5.0	1.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for B3.1
1.0	0.0	3.0	1.0	0.0	0.0	1.0	0.0	0.0	7.0
#Elgin platform leak duration for each causations
```

1.0 3.0 3.0 1.0 1.0 2.0 5.0 1.0 1.0 2.0

num of sources

10.0

#hazid ranking for B3.2.1

1.0 0.0 0.0 1.0 0.0 3.0 0.0 0.0 2.0 0.0

#Elgin platform leak duration for each causations

1.0 3.0 3.0 1.0 1.0 2.0 5.0 1.0 1.0 2.0

num of sources

10.0

#hazid ranking for B3.2.2

0.0 1.0 1.0 0.0 2.0 5.0 3.0 2.0 0.0 1.0

#Elgin platform leak duration for each causations

1.0 3.0 3.0 1.0 1.0 2.0 5.0 1.0 1.0 2.0

num of sources

10.0

#hazid ranking for B4

1.0 1.0 2.0 3.0 3.0 0.0 4.0 0.0 5.0 7.0

#Elgin platform leak duration for each causations

1.0 3.0 3.0 1.0 1.0 2.0 5.0 1.0 1.0 2.0

num of sources

10.0

#hazid ranking for B5.1

0.0 0.0 2.0 0.0 5.0 5.0 4.0 0.0 6.0 6.0

#Elgin platform leak duration for each causations

1.0 3.0 3.0 1.0 1.0 2.0 5.0 1.0 1.0 2.0

num of sources

10.0

#hazid ranking for B5.2

3.0 1.0 0.0 5.0 0.0 0.0 2.0 0.0 1.0 1.0

#Elgin platform leak duration for each causations

1.0 3.0 3.0 1.0 1.0 2.0 5.0 1.0 1.0 2.0

num of sources

10.0

#hazid ranking for B6.1.1

3.0 3.0 1.0 0.0 1.0 1.0 0.0 0.0 0.0 1.0

#Elgin platform leak duration for each causations

1.0 3.0 3.0 1.0 1.0 2.0 5.0 1.0 1.0 2.0

```
# num of sources
10.0
#hazid ranking for B6.1.2
1.0	2.0	2.0	1.0	0.0	0.0	0.0	3.0	0.0	0.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for B6.2
3.0	1.0	0.0	5.0	0.0	0.0	2.0	0.0	1.0	1.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for B7.1.1
0.0	0.0	0.0	1.0	2.0	3.0	3.0	4.0	5.0	1.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for B7.1.2
8.0	1.0	0.0	1.0	10.0	3.0	3.0	0.0	0.0	1.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for B7.2
3.0	1.0	0.0	5.0	0.0	0.0	2.0	0.0	1.0	1.0
#Elgin platform leak duration for each causations
1.0	3.0	3.0	1.0	1.0	2.0	5.0	1.0	1.0	2.0
# num of sources
10.0
#hazid ranking for hydrocarbon detection sensor (HDS)
0.0	0.0	0.0	0.0	3.0	8.0	4.0	7.0	2.0	1.0
#Elgin platform leak duration for each causations
11.0	13.0	13.0	18.0	11.0	12.0	15.0	12.0	16.0	20.0
# num of sources
```

10.0

#hazid ranking for ignition prevention system (IPS)

1.0 2.0 1.0 0.0 0.0 0.0 4.0 3.0 0.0 0.0

#Elgin platform leak duration for each causations

11.0 13.0 13.0 18.0 11.0 12.0 15.0 12.0 16.0 20.0

num of sources

10.0

#hazid ranking for flame arrestor system (FAS)

1.0 0.0 1.0 0.0 0.0 1.0 4.0 0.0 0.0 0.0

#Elgin platform leak duration for each causations

11.0 13.0 13.0 18.0 11.0 12.0 15.0 12.0 16.0 20.0

num of sources

10.0

#hazid ranking for alarm and sprinkler system (AaS)

0.0 2.0 0.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0

#Elgin platform leak duration for each causations

11.0 13.0 13.0 18.0 11.0 12.0 15.0 12.0 16.0 20.0

num of sources

10.0

#hazid ranking for emergency evacuation system (EES)

0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 1.0

#Elgin platform leak duration for each causations

11.0 13.0 13.0 18.0 11.0 12.0 15.0 12.0 16.0 20.0

num of sources

10.0

APPENDIX D: Noisy-OR Code for Conditional Probability Table

```
n = 10;
y = rand(n,1);
y_= -y;
Y = [y,y_];
P1 = zeros(2^n,n);
P2 = zeros(2^n,n);

for m = 1:n
 for k = 1:2^m
  if (mod(k,2) > 0)
   P1((k-1)*2^(n-m)+1:k*2^(n-m),m) = Y(m,1);
  else
   P1((k-1)*2^(n-m)+1:k*2^(n-m),m) = Y(m,2);
  end
 end
end

for k = 1:size(P1,1)
 val = 1;
 num = find(P1(k,:) > 0);
 if (size(num,2) > 0)
  for m = 1:size(num,2)
   val = val*P1(k,num(m));
  end
  P1(k,n+1) = val;
 else
  P1(k,n+1) = 0;
 end
 P1(k,n+2) = 1;
end

for m = 1:n
 for k = 1:2^m
  if (mod(k,2) > 0)
```

```
   P2((k-1)*2^(n-m)+1:k*2^(n-m),m) = 1-Y(m,1);
  else
   P2((k-1)*2^(n-m)+1:k*2^(n-m),m) = Y(m,2);
  end
 end
end

for k = 1:size(P2,1)
 val = 1;
 num = find(P2(k,:) > 0);
 if (size(num,2) > 0)
  for m = 1:size(num,2)
   val = val*P2(k,num(m));
  end
  P2(k,n+1) = val;
 else
  P2(k,n+1) = 0;
 end
 P2(k,n+2) = 0;
end

P=[P1;P2];
```

APPENDIX E: Data cleaning for elicitation in MATLAB

```
Y = [dataset];
P = [conditional probabilities]; %defined on script
n = size(Y,2);
K1 = zeros(2^(size(Y,2)-1),size(Y,2));
K2 = zeros(2^(size(Y,2)-1),size(Y,2));
for m = 1:n
 for k = 1:2^(m-1)
  if (mod(k,2) > 0)
   K1((k-1)*2^(n-m)+1:k*2^(n-m),m) = Y(1,m);
  else
   K1((k-1)*2^(n-m)+1:k*2^(n-m),m) = 1-Y(1,m);
  end
 end
end
for m = 1:n
 for k = 1:2^(m-1)
  if (mod(k,2) > 0)
   K2((k-1)*2^(n-m)+1:k*2^(n-m),m) = 1-Y(1,m);
  else
   K2((k-1)*2^(n-m)+1:k*2^(n-m),m) = Y(1,m);
  end
 end
end
K = [K2;K1];
for k = 1:size(K,1)
 C_pt(k,1) = K(k,1)*K(k,2)*K(k,3)*P(k,1);
end
```

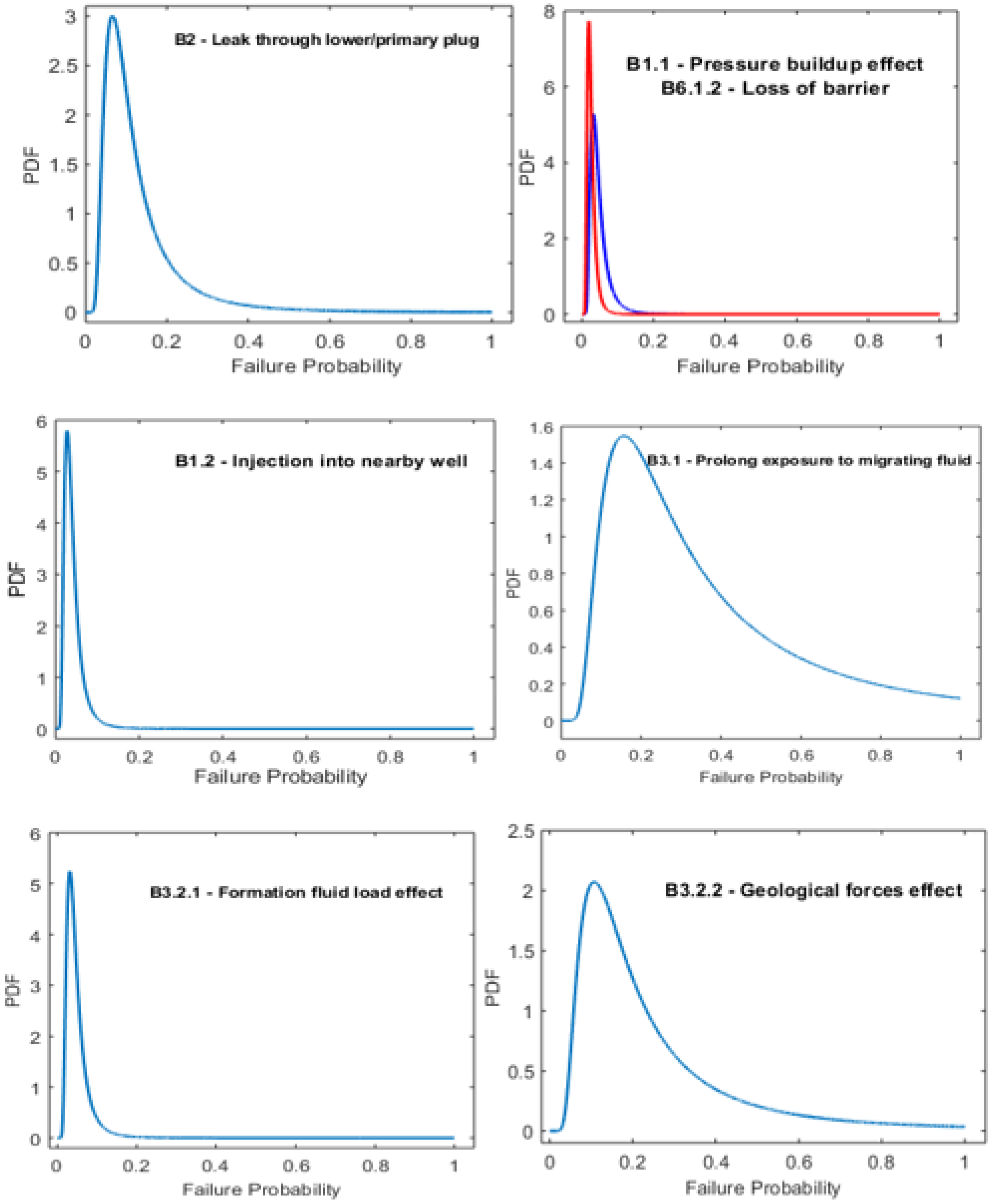
APPENDIX F: Sensitivity Analysis (Backward direction)

Table B.0-1 N-OR model sensitivity analysis output for a 10-yr run

Years	bc	$bc-10\%$	$bc-20\%$	$bc-30\%$	$bc-40\%$	$bc-50\%$
0-1	0.2536	0.2611	0.2746	0.2851	0.2956	0.3062
1-2	0.2544	0.2645	0.2768	0.2855	0.2957	0.3086
2-3	0.2594	0.2689	0.2795	0.2900	0.2965	0.3092
3-4	0.2659	0.2717	0.2807	0.2909	0.3023	0.3124
4-5	0.2773	0.2845	0.2904	0.3048	0.3093	0.3158
5-6	0.2867	0.2986	0.3072	0.3122	0.3168	0.3273
6-7	0.2907	0.3039	0.3117	0.3222	0.3402	0.3507
7-8	0.2981	0.3113	0.3191	0.3297	0.3476	0.3581
8-9	0.3055	0.3187	0.3266	0.3371	0.3550	0.3655
9-10	0.3130	0.3262	0.3340	0.3445	0.3624	0.3730
10+	0.3204	0.3336	0.3414	0.3519	0.3699	0.3804

APPENDIX G: Failure probability results for PA well causations

The mean probability distributions of all causations for the well plugging and abandonment data from analogous sources based on source-to-source variability.



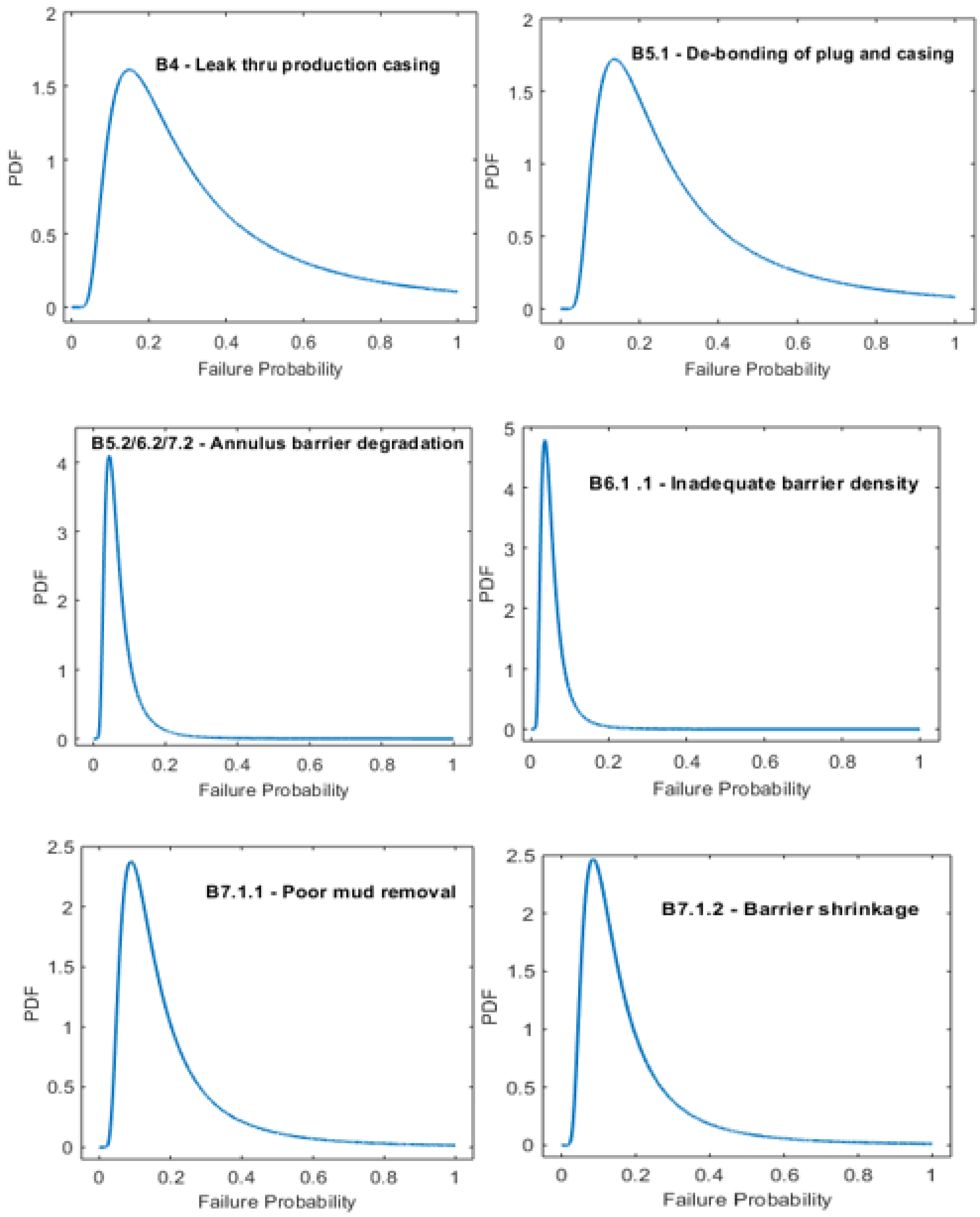


Figure A.0-1 Mean probability distribution for PA well causations

APPENDIX H: Accident Precursor Data for PA well safety barriers

Table C.0-1 Safety barriers APD for well plugging and abandonment

Source	Demands (N_i)	HDS	IPS	FAS	AaS	EES
1	11	-	1	1	-	-
2	13	-	2	-	2	-
3	13	-	1	1	-	-
4	18	-	-	-	1	-
5	11	3	-	-	-	-
6	12	8	-	1	-	-
7	15	4	4	4	-	-
8	12	7	3	-	-	-
9	16	2	-	-	-	-
10	20	1	-	-	-	1

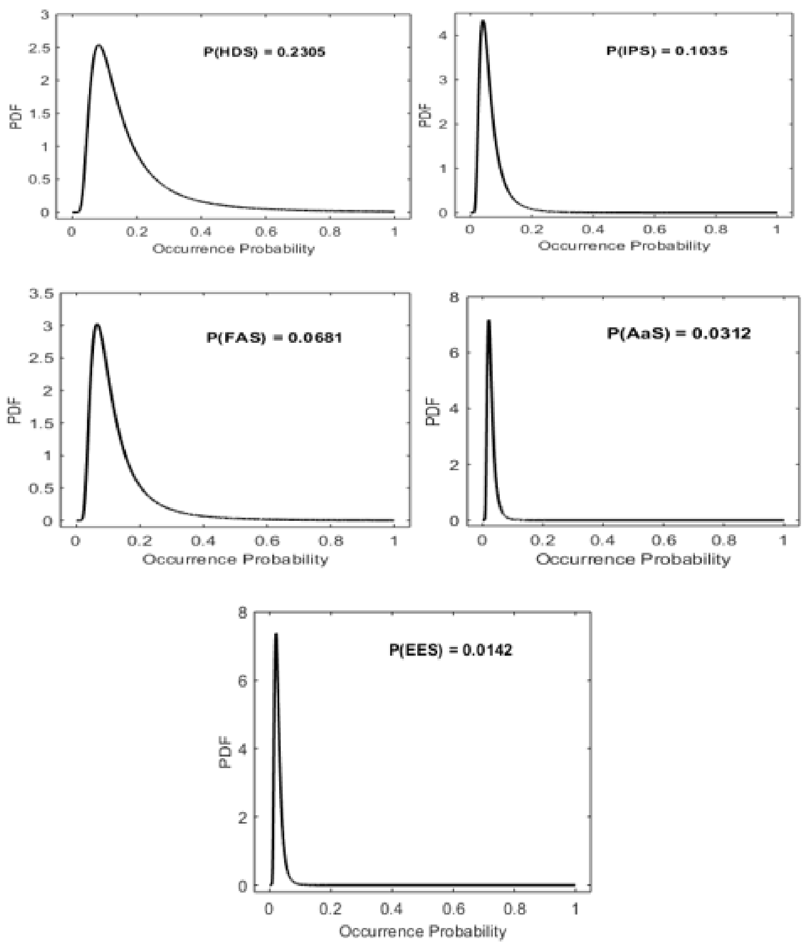
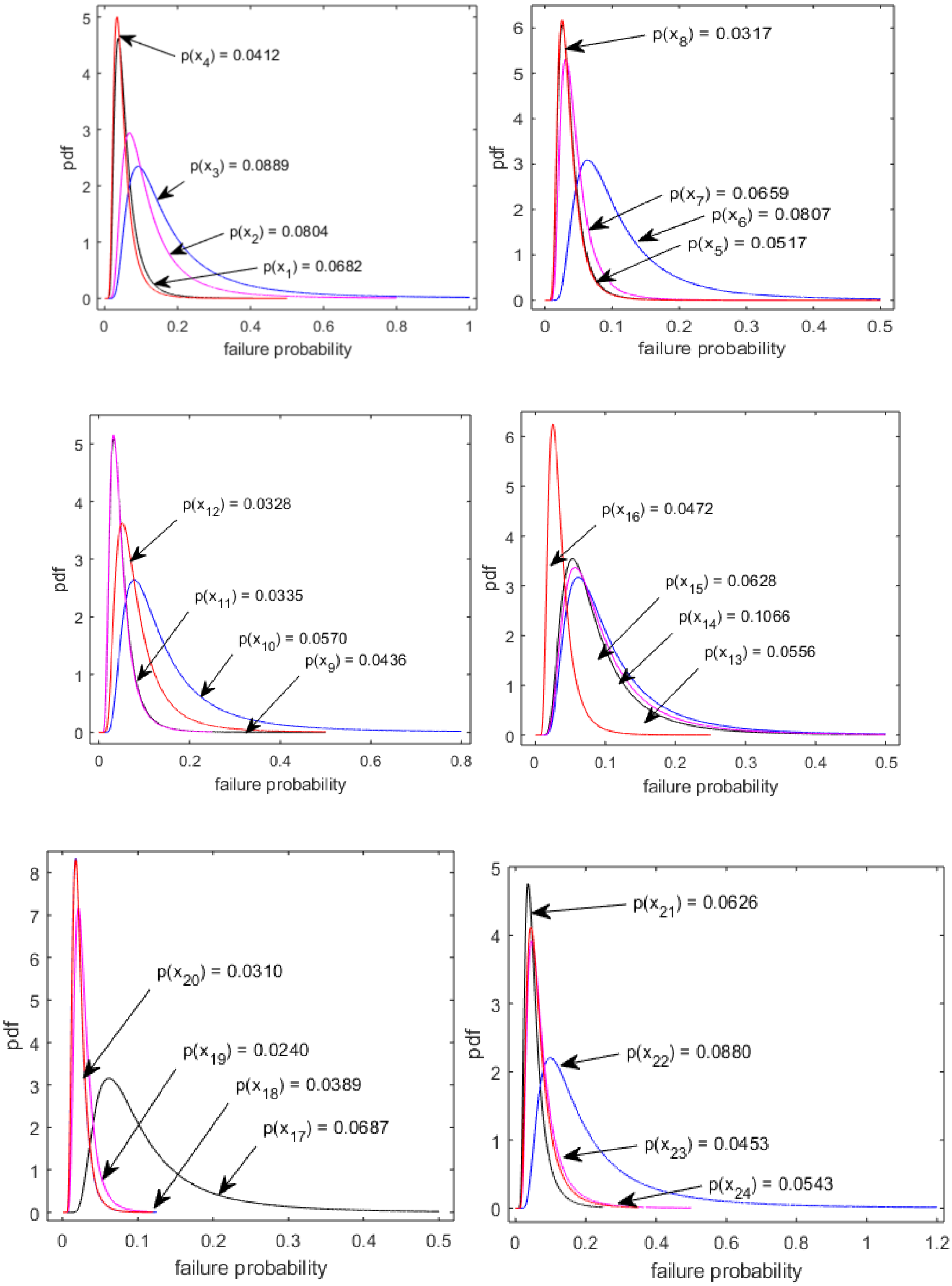


Figure B.0-1 Mean probability distributions for PA well safety barriers

APPENDIX I: Failure probability results for all SPJ causations

Failure probability of steel piles jacket causations obtained from Hierarchical Bayesian Analysis as mean distributions.



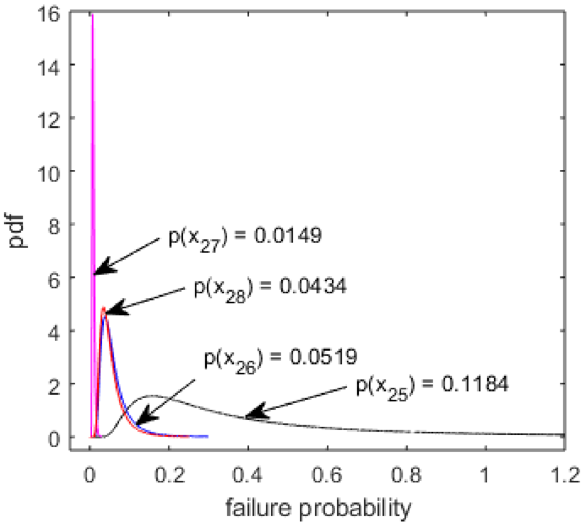


Figure C.0-1 Mean probability distribution of steel piled jacket

APPENDIX J: Dataset for steel piled jacket removal hazards

Table D.0-1 Primary events source-to-source failure data.

Causation	Failure Description	Source	1	2	3	4	5	6	7	8	9	10
		Demand $[N_i]$	14	21	13	14	15	26	17	11	19	20
x_1	Unknown residual stress		0	1	2	2	3	4	5	5	5	7
x_2	Unknown residual fatigue life		0	0	0	3	3	1	6	7	7	5
x_3	Fatigue failure		0	2	3	3	3	4	4	0	0	8
x_4	Lifting node failure		5	2	0	0	0	4	2	5	3	1
x_5	Bulk explosion		2	3	1	2	2	5	5	1	4	4
x_6	Uneven loading		3	7	4	6	0	4	0	5	0	3
x_7	Structural failure		7	6	6	0	4	2	0	4	3	6
x_8	Incorrect operation		7	1	2	1	0	0	4	3	2	2
x_9	Barge operational failure		4	0	4	0	0	1	5	3	3	5
x_{10}	Crane/barge overload		7	1	0	0	6	0	5	3	0	1
x_{11}	Barge collision/drift		0	1	0	0	6	1	2	6	1	3
x_{12}	External thinning		0	0	0	0	1	1	2	3	2	5
x_{13}	Hidden flaws/crack defects		2	2	1	2	1	3	1	1	2	7
x_{14}	Flooding		8	5	8	1	3	3	1	0	4	9
x_{15}	Grouting impact on lift		6	1	5	3	1	0	3	1	1	7
x_{16}	Internal thinning		0	2	4	4	2	4	5	0	2	5
x_{17}	Corrosion thinning		1	2	2	3	4	5	1	0	1	6
x_{18}	Miscalculation of CoG		4	3	4	2	0	3	2	5	1	6
x_{19}	External cut		1	0	0	5	0	1	2	2	3	3
x_{20}	Internal cut		5	2	4	1	1	2	2	2	0	5
x_{21}	Stuck pipe		1	5	2	0	3	3	4	1	6	5
x_{22}	misalignment of CoB		2	1	3	1	1	2	0	3	6	8
x_{23}	Ungrouted condition		2	1	0	0	3	1	4	1	2	6
x_{24}	Grout deteriorates		3	3	1	4	2	5	1	1	0	4
x_{25}	Residual anode wt.		0	0	3	3	1	7	4	2	1	6
x_{26}	Marine growth		4	3	1	5	2	5	0	1	3	1
x_{27}	Jammed cutter		0	2	2	1	2	3	2	3	1	1
x_{28}	Cutting procedure		3	2	4	4	2	4	5	0	2	2
x_{29}	Drill cutting debris		0	2	1	0	3	1	4	3	4	5
x_{30}	Cutting time error		0	1	0	2	3	4	2	1	0	7
x_{31}	Flooded member(s)		1	1	4	1	5	3	6	1	1	6
x_{32}	Uneven flooding		2	3	3	1	4	2	5	1	1	9

APPENDIX K: Probability updating with new evidence

Table E.0-1 Updated probability of causations with new evidence.

Causation	Current knowledge		New evidence		Probability Ratio
	Prior probability	Posterior Probability	Prior Probability	Posterior Probability	
x_1	0.0682	0.0649	0.0590	0.0587	0.99
x_2	0.0804	0.0766	0.0708	0.0693	0.98
x_3	0.0889	0.0889	0.0803	0.0805	1.00
x_4	0.0412	0.0411	0.0371	0.0370	1.00
x_5	0.0517	0.0521	0.0512	0.0511	1.00
x_6	0.0807	0.0805	0.0725	0.0724	1.00
x_7	0.0659	0.0657	0.0592	0.0594	1.00
x_8	0.0317	0.0319	0.0286	0.0287	1.00
x_9	0.0436	0.0432	0.0391	0.0389	1.00
x_{10}	0.0570	0.0548	0.0503	0.0493	0.98
x_{11}	0.0335	0.0322	0.0296	0.0290	0.98
x_{12}	0.0328	0.0315	0.0289	0.0283	0.98
x_{13}	0.0556	0.0534	0.0490	0.0481	0.98
x_{14}	0.1066	0.1030	0.0943	0.0926	0.98
x_{15}	0.0628	0.0606	0.0555	0.0545	0.98
x_{16}	0.0472	0.0472	0.0425	0.0425	1.00
x_{17}	0.0687	0.0687	0.0619	0.0620	1.00
x_{18}	0.0389	0.0391	0.0350	0.0351	1.00
x_{19}	0.0240	0.0239	0.0216	0.0220	1.02
x_{20}	0.0310	0.0310	0.0279	0.0279	1.00
x_{21}	0.0626	0.0626	0.0563	0.0563	1.00
x_{22}	0.0880	0.0897	0.0792	0.0799	1.01
x_{23}	0.0453	0.0455	0.0408	0.0410	1.00

x_{24}	0.0543	0.0543	0.0489	0.0490	1.00
x_{25}	0.1184	0.1185	0.1069	0.1071	1.00
x_{26}	0.0519	0.0520	0.0468	0.0469	1.00
x_{27}	0.0149	0.0160	0.0140	0.0145	1.04
x_{28}	0.0434	0.0464	0.0406	0.0421	1.04
x_{29}	0.0380	0.0408	0.0356	0.0370	1.04
x_{30}	0.0779	0.0834	0.0729	0.0756	1.04
x_{31}	0.0574	0.0585	0.0524	0.1111	2.12
x_{32}	0.0866	0.0882	0.0790	0.1699	2.05

APPENDIX L: Capsize/Descent diagnosis in Bayesian network

Diagnosis of a system level fault defined by capsize or descent failure of the lifting vessel during decommissioning of the steel piled jacket.

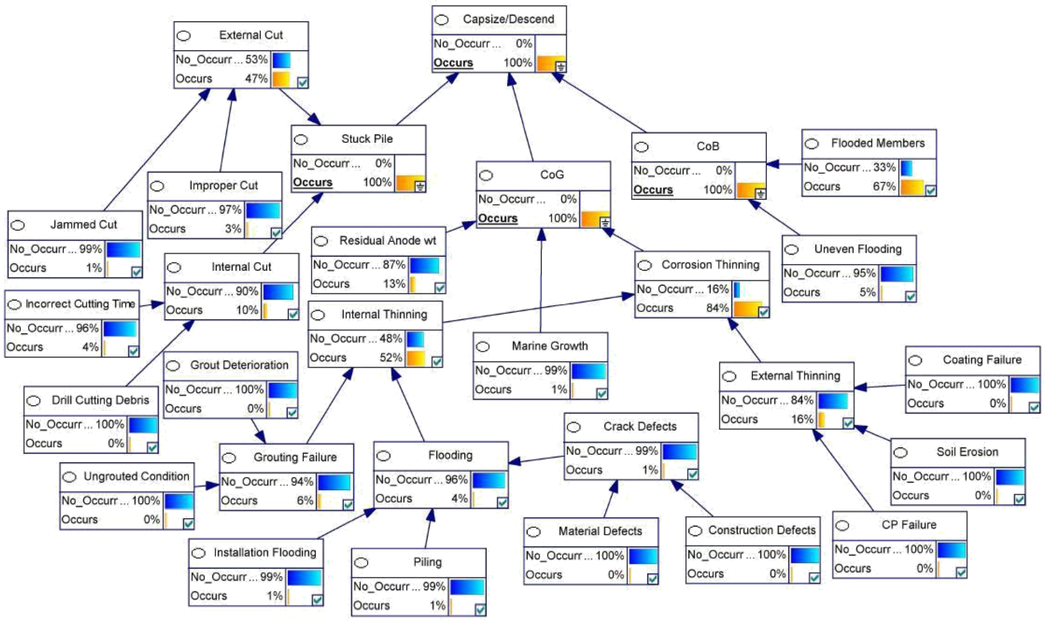


Figure D.0-1 Backward propagation analysis for steel piled jacket removal

APPENDIX M: Multi-factor Regression Analysis for SPJ Removal

Table F.0-1 Regression analysis results for steel piled jacket

d_w	$n_{l,p,c}$	J_{RC}
90	30	5.20E+06
120	38	7.80E+06
128	40	8.20E+06
130	52	9.80E+06
135	60	1.52E+07
140	80	1.60E+07
145	84	1.64E+07
148	90	1.64E+07
162	96	1.71E+07
165	102	1.78E+07

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.957223019
R Square	0.916275909
Adjusted R Square	0.89235474
Standard Error	1538773.845
Observations	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1.81394E+14	9.07E+13	38.30398	0.000169815
Residual	7	1.65748E+13	2.37E+12		
Total	9	1.97969E+14			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-1524795.188	5305935.696	-0.28738	0.782146	-14071339.4	11021749.04
d_w	36317.49192	59816.81077	0.607145	0.562922	-105126.789	177761.7733
$n_{l,p,c}$	142332.1583	49149.28886	2.895915	0.02312	26112.55792	258551.7587

APPENDIX N: Multi-factor Regression Analysis for Conductor Severance

Table G.0-1 Regression analysis results for conductor

d_w	n_c	C_{SC}
90	30	0.20E+05
120	38	0.40E+05
128	40	0.50E+05
130	52	0.90E+05
135	60	1.20E+06
140	80	1.50E+06
145	84	1.70E+06
148	90	2.30E+06
162	96	3.20E+06
165	102	4.40E+06

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.917267
R Square	0.841379
Adjusted R Square	0.796059
Standard Error	605152.5
Observations	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1.35975E+13	6.799E+12	18.565233	0.001589492
Residual	7	2.56347E+12	3.662E+11		
Total	9	1.6161E+13			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-2704170	2086661.684	-1.295931	0.23609	-7638341.18	2230000.464
d_w	14244.42	23524.11606	0.6055241	0.5639394	-41381.2759	69870.11475
n_c	35605	19328.90705	1.8420597	0.1080181	-10100.6025	81310.60223