Risk assessment of decommissioning options for offshore facilities

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RISK ASSESSMENT OF
DECOMMISSIONING OPTIONS
FOR OFFSHORE FACILITIES

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SCHOOL OF MECHANICAL AND
AEROSPACE ENGINEERING

2020

RISK ASSESSMENT OF
DECOMMISSIONING OPTIONS
FOR OFFSHORE FACILITIES

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School of Mechanical and Aerospace Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree
of Doctor of Philosophy

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Summary

Decommissioning is gaining traction globally. Large project management is required to plan and execute an offshore decommissioning operation. There is also increasing interest to adopt risk assessment techniques from other industries for the offshore industry, such as in the area of dependent failure or the role of human error. Finally, piece-wise, segmental risk assessment is based on traditional risk assessment methods, without consideration of long-term effects of a decommissioned structure. This thesis proposes a risk model that consists of three parts: (i) decommissioning options analysis (ii) selected decommissioning activity risk analysis and (iii) long-term monitoring of a decommissioning solution. A case study to a well plugging and abandonment is carried out as that constitutes the largest proportion of decommissioning costs and that well leaks are underestimated.

The thesis has three research objectives. The first objective is to develop an expert judgement process that can consider expert uncertainty and inherent variability in the situation that warrants an expert judgement. Decommissioning projects rely a lot on expert judgement to choose the most apt decommissioning option. The second objective is to model dependencies in terms of time dependent failure (Event 2 failure given Event 1 failure) or Common Cause Failures (CCF) in greater details (material, environment, design). This objective is meant to provide a higher level of detail amongst CCF groups/causes to give insight to relationships between events that is not covered in existing simple CCF-ratio models, where the CCF probability is a ratio of the failure probability of the basic event. The third objective is to develop long-term monitoring to consider accumulative fatigue in the annular fit and the casing strength. This allows the projection of the well barrier failure rate to a decade, which is when a well would most likely fail, if it were to fail.

A risk modelling method that combines and adapts methods from different and/or similar industries have been proposed. The method comprises of the following modelling features in a Bayesian Belief Network (BBN): (i) multiple states in a node (ii) dependency analysis (iii) representation of uncertainties (iv) detailed HRA (v) continuous variables and (vi) temporal variables. Expert judgement is a crucial part of the risk modelling process in the decommissioning field. Such judgement is utilised in options analysis, comparative assessments, human reliability analysis and discrete Markov chain time slices. Expert judgement is the primary input to the BBN. This is a delicate process as it should be comprehensive enough to avoid different types of biases, yet not be overly impractical. The method adapted from the combination of the linear interpolation method and the Bayesian aggregation method can demonstrate dominance of one

factor over the other, or represent different uncertainties in relationships. The modelling is also conducted in two specialised BBN software called GeNIe and Agenarisk.

The model is able to carry out a weighted sum of the probability across all possible intervals and with key values of indication of uncertainty - such as the median value, or the 5th or 95th percentile. The method also utilised linear interpolation to reduce the elicitation burden. The results demonstrate that the interpolation method still manages to capture the dependencies and that the obtained HEP values agrees with other HRA-BBN models. The model also has a dynamic component that can provide insights on long-term well failures. Since fatigue in cement is an accumulative process, dynamic BBN (discrete-time Markov model) modelling has been utilised to investigate the performance of barrier over time, in this case, the annular fit and the casing strength. The model incorporated two common cause failures: (i) changes in wellbore pressure and the (ii) change in annulus pressure acting on top of the cement, which ultimately affects the fit of the cement with respect to the well bore. The results of the sensitivity analysis and backwards diagnostic analysis agree with a statistical study of 103 wells.

Decommissioned structures are meant to last in perpetuity but the proposed solutions usually do not last in perpetuity. The proposed methodology of dynamic Bayesian Belief Networks (1) captured better estimates of a well PA event by incorporating dependencies, and met regulatory requirements by authorities; and (2) utilised the same model to provide long term monitoring of a group of wells linked by common dependencies. This addressed the challenges of underestimating failure probability in plugged and abandoned wells both in the short and long term.

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Nomenclature

β	A ratio of a component, Q_T 's overall failure rate for estimating CCF probability
η_i	Coupling factor strength scaled between 0 and 1 (GDM method)
λ	Failure rate of a component
μ	Repair rate of a component
μ_x	Reference probability value HEP levels
Π_j	$j - th$ element of the posterior probability distribution, $(\Pi = \Pi_1, \Pi_2, ..., \Pi_n)$ of the variable of interest, x
ρ	Spearman correlation values used in a Copula Bayesian Network
$C15$	Event probability in a Fault Tree
f_{ij}	Probability that the realization of the HEP is within interval x_i , given that the median HEP is x_j , with respect to the Matrix F
g_{ij}	Probability that the expert's assessment is x_i when attempting to estimate x_j , with respect to the Matrix G
k	Normalisation factor
$P(A)$	Probability of Event A, usually a failure event
$P(A_i)$	Independent failure probability of Event A
$P(C_i)$	Probability that a cause condition exists, C_i , for cause, i (GDM method)
$P(X_{AB})$	Common-cause failure probability of an event
$P(Y X_0, X_1, X_2)$	Conditional probability of child node Y given the parent nodes X_0, X_1, X_2

$P(Y)$	Joint probability of the child node Y
$P(Y^t X_{(i)}^t)$	Conditional probability of child node Y given parent nodes $X_{(i)}$ over T time slices
p_1	Probability of equipment failure due to environmental considerations in CCF analysis
p_2	Probability of equipment failure due to maintenance considerations in CCF analysis
p_3	Probability of equipment failure due to design considerations in CCF analysis
p_i	Conditional probability that the component fails when testing by cause i (GDM method)
$P_{ave}(C15)$	Industry average OR database average probability of occurrence of event $C15$
P_{high}	Upper limit of probability of event estimated with respect to P_{ave}
P_{low}	Lower limit of probability of event estimated with respect to P_{ave}
$P_{rev}(C15)$	Revised probability of event $C15$
Q_a	Failure probability of Equipment A
Q_i	Values to be utilised for linear interpolation of CPT in the BORA method
Q_t	Combination of component failure probabilities for each failure cause in the GDM method
$Q_{CE,i}$	Common-cause failure component-specific cause condition probabilities (GDM method)
$Q_{E,i}$	Component-specific cause condition probabilities (GDM method)
$Q_{IE,i}$	Independent component-specific cause condition probabilities (GDM method)
W_i	Normalising weights utilised in the HCL method
w_i	Normalising weights utilised in the BORA method
X_i	Parent node(s) in a BBN
Y	Child node in a BBN

$Y_{0:T}$	Joint probability of child node Y over T time slices
y_n	The states of the child node Y
Z_{ij}	Distance measured in units between the states of the parent RIF to the RIF of interest (HCL method)
AHP	Analytical Hierachy Process
ALARP	As Low As Reasonably Practicable
ASEP	Accident Sequence Evaluation Program
ATHENA	A Technique for Human Event Analysis
BBN	Bayesian Belief Network
BEIS	Department for Business, Energy & Industrial Strategy (UK)
BORA	Barrier and Operational Risk Analysis
BSEE	The Bureau of Safety and Environmental Enforcement (USA)
CA	Comparative Assessment
CBN	Copula Bayesian Network
CCF	Common-cause failures
CPT	Conditional Probability Table
EF	Error factor used to define a distribution
EIA	Environmental Impact Assessment
Env B1	Environmental component in a CCF model to Barrier 1
Env B2	Environmental component in a CCF model to Barrier 2
Env B3	Environmental component in a CCF model to Barrier 3
EPC	Error-producing Conditions
ET	Event Tree
FAR	Fatal Accident Rate
FMEA	Failure Modes and Effects Analysis

FT	Fault Tree
GDM	General Dependency Model
HAZOP	Hazard and Operability Study
HCL	The Hybrid Causal Logic Method
HEP	Human Error Probability
HFE	Human Failure Event
IE	Initiating Event
IRPA	Individual Risk Per Annum
LN	Lognormal distribution
Matrix F	The inherent variability of the HEP (Bayesian Aggregation method)
Matrix G	The confidence that the expert provides the correct HEP value (Bayesian Aggregation method)
MOFs	Management and Organisation Factors
MS	Much Stronger (used in AHP)
MSAD	Minimum safe abandonment depth
mu	Graphing estimates for shaping the peak of the elicited probability distribution for the Linear Interpolation Method
MW	Much Weaker (used in AHP)
OGA	UK Oil & Gas Authority
OSPAR	Oslo and Paris Conventions
P&A	Plugging and abandonment
PA Well	Permanently abandoned well
PDS	Paalitelighet og tilgjengelighet av Datamaskinbaserte Sikringssystemer (Norwegian) for Reliability and Availability of Computerized Safety Systems
Petro-HRA	Petroleum industry - human reliability analysis

PHOENIX	A HRA method by Ekanem (2013)
PLL	Potential Loss of Lives
PRA	Probabilistic Risk Assessment
PSFs	Performance Shaping Factors
RIFs	Risk Influencing Factors
ROVs	remotely-operated vehicles
S	Stronger (used in AHP)
sigma	Graphing estimates for shaping the spread for the Linear Interpolation Method
SINTEF	Stiftelsen for industriell og teknisk forskning (Norwegian) for Foundation for Industrial and Technical Research
SLIM	Success Likelihood Index Model
SPAR-H	Standardized Plant Analysis Risk - Human Reliability Analysis
SWAT	Suspended Well Abandonment Tool
TE	Top Event
THERP	Technique for human error-rate prediction
US BOEM	The Bureau of Ocean Energy Management (USA)
USIT	Ultrasonic inspection tool
VMS	Very Much Stronger (used in AHP)
VMW	Very Much Weaker (used in AHP)
W	Weaker (used in AHP)
WOAD	Worldwide Offshore Accident Database

Chapter 1

Introduction

1.1 Preamble

Decommissioning projects are large in scope, and involve multiple phases. Project management in this area is niche due to regulatory requirements surrounding waste management, operational safety, the handling of decommissioning *in situ* items and its societal impact. Decommissioning costs are often funded by the government/public, hence it is prudent to select a decommissioning option based on the following five categories: Safety, Environmental, Technical, Societal, Cost due to its immense scale, and long-lasting effects ([Oil & Gas Authority UK, 2016](#)).

In Norway, the national guidelines recommend the removal of pipelines and cable, but they may be left in place provided that they do not constitute a nuisance or risk for bottom fisheries (Ministry of Petroleum and Energy ([Norwegian Climate and Pollution Agency, 2011](#))). Subsequently, it was reported that a Valhall pipeline of the Ekofisk area which has previously been decommissioned and buried, resurfaced and existed as a free span, posing as an entanglement risk ([Stortinget \(Norwegian Government\), 2000](#)). The free span section of the pipeline is later removed. This highlights that *in situ* decommissioning solutions do require monitoring and that comparative options analysis conducted in the initial stage maybe insufficient.

Thus the research aims to meet the current gaps in decision analysis and risk modelling process that can handle long-term monitoring from integrated historical information.

1.2 Problem description

1. Large-scale project management is required to plan and execute an offshore decommissioning operation

Decommissioning projects commence typically two to three years before production ceases, and involves a review of all records including lease of equipment, production sales agreement, drilling records, and maintenance and inspection records. Field inspection of the equipment such as well-heads and the platform structural condition have to be carried out in order to prepare for detailed engineering analyses on how modules of the structure can be severed and removed in pieces. With the next step taking place a few years later, a good documentation framework is ideal in order to piece information together so that one stage of the research can proceed on to the next stage. The project thus proposes a framework of connecting the stages of options analysis to carry out the activity selected and the long-term monitoring of the particular decommissioned event.

2. Increasing interest to adopt risk assessment techniques from other industries into the offshore industry, such as in the area of dependent failure or the role of human error.

The Bureau of Safety and Environmental Enforcement (BSEE) of the United States published a draft document called 'Probabilistic risk assessment procedures guide for offshore applications' (Cross et al., 2017). This document discusses modelling techniques found to be useful in a range of applications for decision-making pertaining to complex and high-hazard facilities. In section 2.2, the importance of dependence in probabilistic risk assessment is highlighted. Human reliability is elaborated on in section 3.3 of the same document.

A review of decommissioning regulations across five countries was conducted (Fam et al., 2018a). Of these five countries reviewed, three belong to geographic regions deemed to be experienced in decommissioning and two belong to regions considered relatively less experienced in decommissioning. The two less experienced countries are Thailand and Malaysia where Thailand heavily references the USA regulations. Malaysia also references part of their decommissioning regulations from that of USA and UK. This suggests that the trends of USA decommissioning regulations being adopted/referenced could be a trend for countries less experienced in decommissioning to follow.

Another area of interest is on dependent failures and human reliability. There are numerous dependent failure models but the expert elicitation procedure in linking the dependencies

between events may be overly simplistic. There is room to propose a method that can consider uncertainty in the expert judgement. Human reliability in the offshore industry is also limited to binary analysis (Present/Not Present) states of outcome. In real life, the states of outcome could exist in a range rather than in a binary format.

3. Piece-wise, segmental risk assessment based on traditional risk assessment methods, without consideration of the long-term effects of a decommissioned structure

Decommissioned structures are meant to last in perpetuity but the proposed solutions usually do not last in perpetuity. It has been reported in a study ([Boothroyd et al., 2016](#)) of 103 wells that 40 - 80% of decommissioned wells leak within the first decade of decommissioning. The underestimating of failure probability in well needs to be addressed. Since fatigue is an accumulative process, dynamic modelling is proposed to be utilised to investigate the performance of a safety barriers over time. For a plugged and abandoned well, the annular fit and casing strength needs to be examined in order to update the risk profile. Notably, well leaks do not appear in isolation. Thus there is room to address dependent failures across the same well types. Given that a well leak has appeared, how does this affect the risk profile of other wells linked to this well? The links could be similar in terms of abandonment technology, operator or subsea conditions.

1.3 Objectives and scope

The objective of the project is to conduct decommissioning options analysis in a way that integrates with risk management in the short to long term. Piece-wise, segmental risk assessment based on traditional risk assessment methods does not consider long-term effects of a decommissioned structure, which will be of interest as decommissioned solutions are meant to last in perpetuity. The scope of the project was limited to well plugging and abandonment as it constitutes the greatest cost in the decommissioning budget.

The objectives are to:

1. **Develop an expert judgement process that can consider expert uncertainty and inherent variability in the situation that warrants an expert judgement.**

This objective is meant to support the nature of information input in offshore decommissioning. Expert judgment is exercised in options analysis of decommissioning options, Human Reliability Analysis (HRA) and modelling dependencies.

2. Model dependencies in terms of time dependent failure (Event 2 failure given Event 1 failure) or Common Cause Failures (CCF) in greater details (material, environment, design). This objective is meant to provide a higher level of detail amongst CCF groups/causes (Environment, Material and Design) to give insight to relationships between events that is not covered in existing simple CCF-ratio models, where the CCF probability is a ratio of the failure probability of the basic event.

3. Develop long-term monitoring to consider accumulative fatigue

Since fatigue in cement is an accumulative process, dynamic BBN (discrete-time Markov model) modelling has been utilised to investigate the performance of barrier over time, in this case, the annular fit and the casing strength. This allows the projection of the well barrier failure rate to a decade, which is when a well would most likely fail, if it were to fail. Also there are no monitoring plans enforced for abandoned wells, thus the first observed leak is crucial.

1.4 Organisation of thesis

The development of the research model is based loosely on the decommissioning phases. The first phase involves options analysis in order to decide on the most appropriate option for the component to be decommissioned. The next phase involves analysing the chosen activity risk with elements of in-depth human reliability analysis and dependent failure analysis. The third phase involves projecting long-term monitoring into the risk profile. The three phases aim to investigate the hypothesis of the research, which is: failure analysis in offshore decommissioning projects can be improved by considering dependent failures, the role of human error, and having a systematic input of expert judgement into a risk model.

The skeletal structure of the thesis is shown in Figure 1.1.

Figure 1.1: An overview of the work proposed in the thesis.

Chapter 2

Literature Review

2.1 Decommissioning regulations

2.1.1 Decommissioning process

Based on international and national legislation, offshore decommissioning generally consists of shutting down operations, closing the wells, decontamination, making the platform safe and removing, disposing of or relocating facilities, *etc.* A generic decommissioning procedure (See Figure 2.1) for a jacket structure, which is one of the more commonly-used offshore structure (Osmudsen and Tveteras, 2003) is discussed.

The first step involves planning for decommissioning, which typically commences two to three years before production ceases. The planning process involves a review of all records including lease of equipment, drilling records, and maintenance and inspection records. Field inspection of the equipment such as well-heads and the structural condition of the platform is carried out in order to prepare for detailed engineering analyses on how modules of the structure can be severed and removed in pieces. The second step is the preparation of the permits and submission of the decommissioning plan; in short a compilation of the work to be done in the first step as well as the proposed subsequent actions. The third step is the commencement of the physical decommissioning work – the well plugging and abandonment. Wells will be plugged with cement or other materials, and the wellheads severed and removed. The fourth step is the removal of the conductors. Typically, abrasive cutting methods will be used to sever the conductors, and the severed conductors are surfaced and cut into more manageable sizes so that they could be transported onshore. After the conductors are severed, they are dislodged or pulled from below

Figure 2.1: A decommissioning procedure for a commonly-used offshore structure, such as a jacket structure.

the mud line using a casing jack. The fifth step is the preparation of the platform. This requires the topside (the production area) to be decontaminated, and subsequently the termination of piping electrical and instrumentation connections between production modules. Then, sections of the platform will be marked for the construction of new padeyes and lift supports for sectional removal. Below the waterline, inspection will be carried out by divers or remotely-operated vehicles (ROVs) to demarcate the sections of the jacket to be removed. The sixth step is pipeline decommissioning, which involves flushing and cleaning of the pipelines. The pipeline will be severed above the riser bend, and the remaining pipelines are sealed using plugs. Pipelines may be left in place or removed depending on the accepted proposal. Similar to the conductors, the pipelines will be cut into smaller sections for ease of transportation onshore.

As the jacket is now no longer linked to the seabed (with the exception of the jacket piles), the following steps concentrate on dismantling the topsides and jacket structure. The seventh step involves topside removal. Previously, in the fifth step, cutting and lifting points have been identified. Hence the corresponding sections will be removed by cutting at these demarcated sections, and then transporting them onto cargo barges. The eighth step is jacket removal.

The jackets will be sectioned *in situ*, and then removed by a derrick barge. The piles, like the conductors and wells will be severed at a depth below the mud line. The sectioned jacket will then be loaded onto a cargo barge and taken on shore. The final step is site clearance and remediation, which involves conducting pre- and post-decommissioning surveys and preparing close out reports to document the above activities and ensuring that requirements are met.

2.1.2 Decommissioning regulations

A review of the regulations in several countries (Norway, UK, US) which are considered experienced in decommissioning. The review is described in detail in (Fam et al., 2018a) and (Fam et al., 2017). The overall structure of most decommissioning regulations is summarised in a flowchart (see Figure 2.2) extending over six major areas: (i) submission timeline (ii) pre-decommissioning (iii) decommissioning execution (iv) post-decommissioning (v) third party validation and (vi) release of liability. Within item (iii) decommissioning execution, there are further areas governing the different aspects of execution, namely, offshore infrastructure (wells, seabed deposits management, pipelines and associated structures, and structures and facilities), reuse standards, waste management, safety standards and debris survey and clearance.

Figure 2.2: Flowchart of the discussion framework of decommissioning items.

In general, the technical requirements in both regions (North Sea and the Gulf of Mexico) are similar, such as the depth at which structures must be removed, *in situ* pipeline decommissioning (US and UK), waste management and responsibility tied to the waste shipment, as well as the use of options analysis methodology to assess the best decommissioning method for a particular area.

In terms of the legal and technical frameworks for re-use of offshore structures, the US is most advanced in this area. This could be due to the geographic location whereby rigs-to-reef activities could increase productivity in fisheries, such that the reef-to-rigs programme generates income in other ways beyond its role in the offshore industry. The US reef-to-rigs framework also considers the funding of the management of the reefs from the decommissioning costs offset. Usually relocating the structure to a rigs-to-reef location is cheaper than moving it to the scrapyard onshore. In the North Sea, Norway, and UK and thirteen other countries ratified the OSPAR convention and also need to uphold the OSPAR decision of 98/3. Due to the controversy surrounding the Brent Spar case, the OSPAR final guidelines thus excluded non-virgin materials as acceptable reef construction materials, effectively ruling out the use of rigs for reef construction in the North Sea (Jørgensen, 2012). In this area, there could be room for improving the legislation to include a case-by-case determination of the suitability of a structure for rigs-to-to-reef projects.

In terms of health and safety, Norway and UK adopt a goal setting approach, while the US undertakes a more prescriptive approach where the regulator sets out a series of ‘one size fits all’ requirements in which the operator must comply with. However, as of 2017, a draft copy of guidelines titled ‘Probabilistic Risk Assessment Procedure Guide for Offshore Applications’ has been available (Cross et al., 2017), in which the document highlighted that probabilistic risk assessment(PRA) can be carried out for offshore facilities where additional risk assessment needs to be made, suggesting that the US BOEM (The Bureau of Ocean Energy Management (USA)) recognises that the prescriptive regulatory environment may not be a one-size fit all solution for all types of offshore facilities. The guideline references Probabilistic Risk Assessment(PRA) methods from the nuclear and space industries and includes guidance on including dependent failures (stemming from intrinsic and extrinsic common causes) as well as Human Reliability Analysis.

The goal setting approach requires the operator to develop their own objectives, and make a case to the regulator that they are managing safety effectively. Naturally, there are legal boundaries that shape the limits of the respective safety cases. There are also slight differences between the system in Norway and in UK, where by in the former it is called Acknowledgement of Compliance, while in the latter, simply, a Safety Case. Such goal-setting systems only work where relevant statutory provisions are robust enough, both in terms of general management, and technical management. The flexibility in a goal-setting system allows exemptions to be granted, but with justification or identification of remedial measures that demonstrate compliance with overall safety goals. The “as low as reasonably practicable” (ALARP) concept is an important element of the

goal-setting scheme. It is designed to add value as a measure of how far major hazards can be controlled and risks reduced before costs are out of all proportion to the benefit gained. This is important as the onus now lies with the operator to ensure safety, rather than having a prescriptive system where a series of ticked safety items in a form could give a false sense of security on the robustness of a safety management system.

Also, every platform is different and managed differently. Hence, the goal-setting scheme may be more comprehensive. This resonates especially when transitioning from the usual day-to-day tasks of hydrocarbon production to unfamiliar decommissioning activities such as well plugging and, working without full access to all areas of the facility as each area is dismantled section by section.

The economic aspect of the regulations is also crucial as some tax structures imply that the government actually foots the decommissioning bill. In the UK, the 2016 Decommissioning Strategy Delivery ([Oil & Gas Authority UK, 2016](#)) has a focus on optimising the costs of Well P&A activities, whereby the Energy Act 2016 now requires the submission of an abandonment cost estimate, in consultation with OGA before submission, as the Oil& Gas Authority (OGA) Corporate plan also aims to reduce decommissioning costs by 35%. This implies that there is an interest in optimising work flow to meet the conditions of economic viability.

In terms of residual liability, the UK Petroleum Act 1998 ([Oil & Gas UK, 2015](#)) provides a framework for the decommissioning of both offshore installations and pipelines. The Pipeline Safety Regulations 1996 provide requirements for the safe decommissioning of pipelines. There are three acceptable approaches of pipeline decommissioning: (i) complete removal, (ii) leave in place and (iii) monitored or deferral. Pipelines decommissioned in place will be subjected to a suitable monitoring programme agreed upon by the Department for Business, Energy & Industrial Strategy (BEIS) in consultation with other government departments. At the moment, decommissioned wells do not need monitoring, but in the event a spill occurs, according to Section 5-4 ('Liability') of the Petroleum Activities Act (1996), if an offshore facility has been decided to be abandoned, the licensee or owner shall be liable for damage or inconvenience caused wilfully or inadvertently in connection with the abandoned facility. The operator is responsible for the abandoned well and liable for any future problems related to the well. Thus this provides justification to monitor wells, since they are directly linked to the reservoir which is, the source of potential leaks in the future.

In summary, the points of interest arising from the regulatory review study are:

1. Long-term monitoring of decommissioned facilities is required for some structures (pipelines and associated structures) and are of interest for other types (wells).
2. The chosen decommissioning option must meet the conditions of economic viability amongst other safety and technical risks.
3. Increasing interest to adopt risk assessment techniques from other industries into the offshore industry, such as in the area of dependent failure or the role of human error.

2.2 Overview of risk analysis practices in decommissioning

In this section, the thesis provides an overview on risk analysis practices in decommissioning largely based on one of the three countries that are deemed to be established in decommissioning regulations. The US regulations (currently) are prescriptive in nature, so there is no real need to conduct risk assessment outside the scope of the regulations. The Norwegian regulatory requirements are similar to the UK requirements, in that both are goal-setting in nature. The UK regulatory framework and resources are written in English, thus making it ideal for the overview to be discussed based on the UK regulations.

With respect to Figure 2.1 which illustrates the decommissioning procedure for a jacket structure: 'Stage 1. Planning' is where the bulk of the risk analysis is conducted for the remaining stages of 3 to 9: Well P&A, Platforms and Substructures removal. A crucial part of the planning stage is the preparation of the decommissioning plan, which ideally should cover how the operators objectively and transparently assess a number of different decommissioning options. Countries bound by the OSPAR Decision 98/3 are required to conduct a comparative assessment for any potential OSPAR derogation candidate or for all pipeline decommissioning. The presumption in OSPAR Decision 98/3 is that all installations will be removed completely. From there other options are compared with the default position of complete removal. The options are considered against five assessment criteria: Safety, Environmental, Technical Feasibility, Societal and Economic. There is no outright hierarchy among the options. There is also different weights assigned among the options. It is unlikely that cost is accepted as the main driver, unless all other matters show no significant difference.

Descriptions on the types of risk analysis conducted based on the different criteria are listed below:

1. *Safety* - Examples of QRA techniques used include Potential Loss of Life (PLL), Individual

Table 2.1: Comparative assessment criteria and areas of concern

Assessment Criteria	Areas of concern
Safety	Risk to personnel Risk to other users of the sea Risk to those on land
Environmental	Marine impacts Other environmental compartments (including emissions to the atmosphere) Energy/resource consumption Other environmental consequences (including cumulative effects)
Technical	Risk of major project failure
Societal	Fisheries impacts Amenities Communities
Economic	Project costs

Risk Per Annum (IRPA) and Fatal Accident Rate (FAR). Usually comparison is made with the risk levels supported by a regulatory body (e.g. the maximum tolerable level of individual risks of fatality is 1 in 1000 per year ([Health and Safety Executive \(HSE\) \(UK\), 2015](#)))

Under the 'Safety' criteria, a datasheet presented in Tables 2.2 and 2.3 highlights the type of count data required: the number of personnel, the number of man hours, and the calculated PLL, which is a multiplication of the number of persons in a workplace and the Individual Risk Per Annum, which is the probability that a specific or hypothetical individual will be killed due to exposure to the hazards or activities during one year. This value is often obtained from databases or authorities.

Table 2.2: Datasheet for a chosen option for 'Safety' criterion for a comparative assessment

Assessment Criteria	Number of personnel or vessel	Number of Manhours
Offshore Personnel	157	13931
Topsides Personnel	NA	NA
Divers Required	9	1037
Onshore Personnel	20	3337
Legacy Personnel	76	45600
Impact to other users of the sea (Operation) - no. of vessels	4	24.9
Impact to other users of the sea (Legacy) - no. of vessels	2	100

2. *Environmental* - The Environmental Impact Assessment (EIA) is the technique used to evaluate the the effect of decommissioning on the environment. An assessment of the impact of activities at the offshore location and also at the offshore dismantling and disposal site is carried out. A survey of marine mammals and seabirds found in the area is included.

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Table 2.3: Summary of PPL for a chosen option for 'Safety' criterion for a comparative assessment, based on data from Table 2.2

Assessment Criteria	PLL
Operation risk diver	1.01e-3
Operational risk offshore	1.04e-3
Operational risk topsides	NA
Operational risk onshore	4.10e-04
Legacy Risk (out to 50yrs) Fishing	3.00e-3
Fishing Risk	NA - no increase in risk over and above that currently exists for fishing
Overall Risk - ΣPLL	5.46e-03

Underwater noise modelling is usually carried out to ensure that the measures are in place where there may be sensitive receptors.

Under the 'Environmental' criterion, a similar datasheet presented in Tables 2.4 and 2.5 highlights the type of count data required: the number of vessels and operational hours in order to estimate the noise level

Table 2.4: Datasheet for a chosen option for 'Environmental' criterion for a comparative assessment

Assessment Criteria	Number of vessel	Duration (h)
Trawler	1	1
ROV	1	50
Diving support vessel	1	50
Dynamically positioned fall pipe vessel	1	20

Table 2.5: Summary of Sound exposure level, energy use for a chosen option for 'Environmental' criterion for a comparative assessment, based on data from Table 2.4

Assessment Criteria	
Noise -sound exposure level	257 dB re 1mP
Energy use - fuel	1981.8 Te
CO_2	6282.3 Te
NO_x	116.9 Te
SO_2	23.8 Te

3. *Technical feasibility* - Recognised QRA techniques, engineering and operational analysis are used in combination to provide comprehensive, quantitative and qualitative assessment of the options. Comparison is usually made with accepted industry risk assessment criteria for marine operations. Risks are considered in terms of the maximum acceptable probability of a major accident judged against industrial standards or regulatory requirements. There is usually consideration of the technical feasibility of the assessed option based on existing industry experience and available equipment. A few approved Decommissioning Workplans ([Fairfield Fagus Limited, 2017](#)) opted for in situ decommissioning options due to lack of experience for the option of complete removal. Prior to conducting the QRA, a qualitative risk analysis (see Table 2.6) is used to narrow down the which consequences to investigate further.

Table 2.6: Summary of consideration for 'Technical' criterion for a sample decommissioning option for a comparative assessment

Assessment Criteria	
Feasibility	High
Availability of technology	High - off the shelf
Track record	High - extensive history
Risk of failure	Low
Consequence of Failure	Alternate cutting technique / additional rock / limited schedule impact
Emerging Technology	Diverless cutting and recovery of towheads may be an option

4. *Societal* - Usually qualitative in nature and usually referring to fisheries and fishing activity, this is assessed with regard to the level of activity in the area and long-term impacts, the safety of fishermen and mitigation measures so as not to impact the livelihood of the industry.
5. *Economic* - An estimation of cost is important as it is a legal requirement in the UK, under the amended Energy Act 2016 ([Government of the United Kingdom, 2016](#)) that costs are to be minimised. Usually this entails grouping workload together with other platforms in order to enjoy economies of scale in working in the same area where the wells or facilities are located.

2.2.1 Options Analysis/ Comparative Assessment (CA)

Options analysis or comparative assessment is a requirement in the UK, Norwegian, Thai, and Malaysian decommissioning regulations ([Oil & Gas UK, 2015](#); [Norwegian Petroleum](#)

[Directorate, 1996](#); [Petroleum Institute of Thailand, 2008](#); [PETRONAS, 2017](#)) for assessing the most appropriate approach to decommissioning. Options analysis consists of the following steps:

1. *Scoping* - Decide on appropriate method, confirm criteria, identify boundaries, map stakeholders
2. *Screening* - Consider alternative uses and deselect unfeasible options
3. *Preparation* - Undertake technical safety, environmental studies and stakeholder engagement
4. *Evaluation* - Evaluate the options using the chosen CA methodology
5. *Recommendation* - Narrative support explaining key trade-offs
6. *Review* - Review recommendation with internal and/or external stakeholders
7. *Submit* - Usually as part of the decommissioning programme/workplan.

Usually the Multi Criteria Decision Analysis methodology is used as the [Oil & Gas UK \(2015\)](#)'s Guidelines for Comparative Assessment in Decommissioning Programmes, and it has listed this method as an example. It is feasible to utilise other decision analysis methods. The suggested methodology from the guidelines utilises a pairwise comparison system based on the methodologies of the Analytical Hierarchy Process (AHP) ([Saaty, 1987](#)). It is largely qualitative in nature. There can be quantitative analysis involved, if comparing metrics such as Potential Loss of Lives (PLL) numbers or noise emission levels between options.

Within a specific criterion (out of five - safety, environmental, technical, societal and cost), the decommissioning options are compared against one other. The comparative phrases (see [Table 2.7](#), [2.8](#)) help to inform whether a particular aspect was driving a preferred option, or if the preferred option remained the same when the other options were applied, or if the preferred option was effectively reinforced. [Table 2.7](#) explains the comparative phrases and the corresponding score for each option. The score for each option, per criterion(out of five - safety, technical, societal, environmental, economic) was obtained by solving the primary eigenvector of the matrix, and then normalising it as per the weight assigned to that criteria. In some analysis, 'safety' criterion may be given a higher weight than cost. The analyst decides and justifies the weights assigned.

The above method is for a decision analysis over decommissioning options for a greater physical scale, typically referring to pipeline and umbilical components, flexibility and umbilical risers, and whether it should be a partial *in situ* decommissioning with periodic monitoring and remediation as required, or a full removal using reverse reeling (where feasible) so that there is no monitoring

Table 2.7: Definition of comparative phrases and their importance scoring.

Comparative phrase	Definition
Neutral	Equal Importance, equivalent to 1 in the importance scale from 1-9.
Stronger (S) or Weaker (W)	Moderate importance of one criteria or option over the other, equivalent to 3 in the importance scale from 1-9. Stronger = 3, Weaker = 1/3.
Much stronger (MW) or Much Weaker (MW)	Essential & strong importance of one criteria or option over the other equivalent to 5 or 6 in the importance scale from 1-9. Much stronger = 5 or 6, much weaker = 1/5 or 1/6.
Very much stronger (VMS) or Very much weaker (VMW)	Extreme importance of one criteria or option over the other equivalent to 8 or 9 in the importance scale. Very much stronger = 8 or 9, very much weaker = 1/8 or 1/9.

Table 2.8: Example of a pair-wise comparison among three options for the criterion of 'Safety'. The same pair-wise comparison is conducted for the other criteria of Technical, Economic, Societal and Cost.

Safety	Option 1	Option 2	Option 3
Option 1	N (1)	S(3)	N (1)
Option 2	W (1/3)	N(1)	W(1/3)
Option 3	N (1)	S (3)	N(1)

required. Table 2.8 shows an example of a pair-wise comparison among three options for the criterion of 'Safety'. The diagonals of the table will be a 'Neutral' score as it refers to the same option, thus there is no comparison. If Option 1 refers to full removal using reeling, and Option 2 refers to partial *in situ* decommissioning with periodic monitoring and remediation, the expert is likely to assess that Option 2 is safer than Option 1, as the state of the pipeline is unknown after being in the subsea for three decades. There could be a risk of the pipeline failing structurally during the reverse reeling process from internal corrosion. Thus, it has been assessed that in terms of Safety, Option 2 is 'Stronger' than Option 1. Likewise Option 1 is naturally 'Weaker' than Option 2. The scores for 'Stronger' is (3) and 'Weaker' is the reciprocal, thus (1/3).

In well plugging and abandonment, a binary decision tree (Figure 2.3) is used to judge the best action given the state of the well, and then a single elicitation of percentage of success is given. The well abandonment option is chosen based on the following factors (non-exhaustive):

1. Presence of side tracks
2. Presence of restrictions in the well
3. Cement records in the different casings, and if verifiable with documentation
4. Presence of shallow gas
5. Result of pressure test
6. Result of ultrasonic inspection of wellbore

An expert observes the above factors and assigns a chance of success to the possible options taken. This thesis proposes to aid the binary decision tree by incorporating uncertainty in the well condition, for example, in the event tree, it is not always an absolute 'Yes' or 'No' to the question, 'Is 9 & 5/8" casing adequate?' (see Figure 2.4). The expert would need to interpret well logs, and review ultrasonic images which may show that cement behind the casing is only strong in certain sections of the well, and if other information contradicts or supports the test report (such as cement log on the tagged position of the cement barrier).

Figure 2.3: A binary decision tree for assessing permanent well plugging and abandonment options (Lloyd's Register, 2019).

Thus it is proposed that a form of comparative assessment of multiple factors (see Figure 2.4) is used to elicit the chance of success for a task, in order to better capture the intricacies of the decision process.

Figure 2.4: A example depicting the factors which impact a decision point in a decision tree junction and that it is difficult to assign a binary answer to the real situation ([Lloyd's Register, 2019](#)).

2.3 Risk analysis techniques

2.3.1 Overview

Risk analysis techniques are often described in terms of two broad areas, qualitative and quantitative risk assessment. [Cross et al. \(2017\)](#) describe qualitative risk assessment techniques as 'thought processes that aid in defining accident potential' and highlight that despite refraining from using numbers, qualitative risk analysis maintains its ability to generate and rank a comprehensive accident scenario set. Qualitative risk analysis provides inputs to quantitative risk assessment by identifying and grouping initiating events. It is noted that the development of event tree structure is usually aided by techniques known as a Hazard and Operability Study (HAZOP) or Failure Modes and Effects Analysis (FMEA).

HAZOPs are performed in a group setting where a facilitator leads a technically diverse group of experts through an exercise to identify hazards related to equipment or operations of a given system in a given operating mode. The design intent in each operating mode needs to have been specified in sufficient detail to support a sensible discussion of system behaviour; in particular, nominal values need to be specified for all important system parameters. The HAZOP discussion is then cued to analyse the system considering deviations of key parameters in one node at a time, based on applying guide words (e.g., high, low) to each parameter (e.g., flow) characterizing each node (e.g., high flow in Node 32, low flow in Node 32). For each such deviation, the group brainstorms possible causes and possible consequences of each cause, and then may consider other factors relevant to the decision context, including possible recommendations for design changes. An example of a HAZOP conducted for a well plugging and abandonment activity is shown below in Table 2.9 ([Lloyd's Register, 2019](#)).

HAZOP, FMEA, and other methods in this general category promote completeness, which is perhaps one of the most critical issues affecting the performance and application of risk modelling. FMEA promotes completeness by considering (in principle) all failure modes for all components; HAZOP does this by considering (in principle) all physical deviations in all nodes. If design intent is properly specified, then anything that would be considered an accident must represent a deviation from design intent; hence, by considering all deviations, HAZOP creates at least an opportunity for the group to identify any accident potential that is reasonably foreseeable in the context of any given deviation. Moreover, if a similar system has some operating history, we may have a sense of the likelihood of the deviations identified, and we may have at least some perspective on their consequences. However, neither FMEA nor HAZOP is particularly well

Table 2.9: Example of a Hazard and Operability Study on a segment of a well plugging and abandonment activity from [Lloyd's Register \(2019\)](#).

Task ID	Hazard	Consequence	Risk	Risk Reducing Measures
Cement	Too low displacement rate	Low quality cement column or plug, future leak paths	Low-Medium	To condition mud to optimise mud properties. Pump sufficient amount of spacer ahead of cement slurry. Ensure sufficient pump rates can be achieved
Cement	Cement plug not set off bottom correctly	...	...	...

suited to the identification or ranking of scenarios that involve multiple failures, or combinations of failure events with off-normal initial conditions.

2.3.2 Fault Tree and Event Tree analysis (including dependent failures)

A Fault Tree is a deductive logic model where a top event, usually a system failure of interest, is considered. Paths are linked gradually from all subsystems, components, software errors to human actions to this top event ([Cross et al., 2017](#), p 2-25). The simplest block (a basic event) at the beginning of a Fault Tree consists of basic probabilities of failures and is the starting point of the quantification process. Intermediate events are described by logic gates: AND gates (union) or OR gates (intersection) of basic events.

Usually, some modelling rules apply to how the model is set up in a Fault Tree. The top event, usually a system failure of interest, ought to have a defined failure mode of interest (usually only specified ones are to be modelled, *e.g.* insufficient cement in length of plug), and the subsystems are defined according to the operation being performed (cementing), the system the component belongs to (well plugging tool) and its various components (valves, pressure sensors, *e.t.c.*), and failure mode (for *e.g.* failure to transfer cement).

An event tree is a tree-like graphical structure that distils the pivotal event scenario definitions from the initiating event (IE) with scenarios classified according to their consequences. It bears some resemblance to the binary decision diagram in [Figure 2.3](#). It is possible to perform a quantification of the scenarios ([Cross et al., 2017](#), p 2-16). The headings of the event tree are the initiating event (IE), which is the starting point, the pivotal events showing success or failure

Figure 2.5: A fault tree representing a system comprising of two pieces of equipment (A and B) connected by an AND-gate. Each equipment has an independent failure probability (A_i , B_i) and a common cause failure (X_{AB}).

of mitigating/ aggravating events, and lastly the end state referring to the consequence of each scenario. Each individual path through the event tree is a “sequence.” The event-tree’s pivotal events are linked to fault trees, and the pivotal event’s name should match the description of the top event in the corresponding fault-tree top-event. This is because fault trees are tied to the pivotal events and are based on potential failures for that event.

Classical logical modelling (Fault Tree and Event Trees) has some strengths. It is useful for capturing failure modes in systems that depend on support systems in a complicated way. In a complex facility that has, in principle, trillions of combinations of component-level failure modes, even if logic modelling may struggle to generate all of them, it can generate many combinations that are worth knowing. In particular, logic modelling can identify combinations having nominal probabilities that are sufficiently low that they will not typically show up in a simulation-based approach (Cross et al., 2017, p 2-51). One example is that if a particular failure mode has a probability of $1e-5$ of happening, it implies that a simulation-based model will need to be carried out in multiple 100,000s of samplings in order to have a decent chance of seeing them, while a logic model readily identifies the combination of events that lead to this failure mode.

There are some short-comings of classical logical modelling. Dependent failures are not entirely captured in the top event, despite common-cause models which are developed to fit into a Fault Tree. O’Connor and Mosleh (2016) mapped a fault tree with a common cause model

(*Alpha*-model) in a BBN and demonstrated that the Fault Tree model underestimates the top event failure probability due to the independence assumed between the common cause and independent event. Another shortcoming also exists in that logical modelling only considers two states - Success or Failure, whereas in real life, there are system degradations that are difficult to map into discrete logic variables. (Cross et al., 2017, p 2-50) noted that failure can exist in a combination of varying magnitudes, such as a little blockage in a valve or significant degradation in other barriers.

Dependent failures poses a risk at interfaces between components, subsystems and the environment. Failures arising from dependencies are difficult to identify, and if neglected will usually result in an underestimation of the risks. Two events A and B are said to be dependent if $Pr(A \cap B) \neq Pr(A)Pr(B)$. A fault tree includes CCF modelling, which differs from how CCF modelling is conducted in a BBN. Quantification in a fault tree often assumes a system of independence *i.e.* $Pr(A)Pr(B) = Pr(A \cap B)$. However, with dependencies, $Pr(A \cap B) > Pr(A)Pr(B)$, this indicates that ignoring the effects of dependencies will result in an underestimation of the risks.

Dependencies can be classified in many ways. Cross et al. (2017) categorises them as being intrinsic or extrinsic to the system. Intrinsic dependencies refers to a scenario where the functional state of one component is affected by the functional state of another. Extrinsic dependencies refer to situations that are not inherent and intended in the designed functional characteristic of the system.

Some subclasses of intrinsic dependencies are listed below:

1. *Functional requirement dependency* - the functional status of component A determines the functional requirements of component B: B is needed when A fails.
2. *Functional input dependency* - the functional status of component B depends on the functional requirements of component A. Component B is functionally unavailable as long as Component A is not working: dependence of a motor-driven pump on electric power
3. *Cascade failure* - the failure of Component A leads to the failure of Component B: an over-current failure of a power supply that component A and component B are connected to.

Some subclasses of extrinsic dependencies are listed below:

1. *Physical/Environmental* - dependencies due to environmental factors such as a harsh or

abnormal environment: sea states can affect the requirement for the number of the thrusters needed to remain in position.

2. *Human interactions* - dependencies due to human interaction: equipment failure due to a maintenance error

This consequently drives the development of Common-Cause Failures (CCF) in PRA models. CCF is formally defined (Cross et al., 2017) as ‘...the failure(or unavailable state) of more than one like component due to a shared cause during the system mission. Viewed in this fashion, common cause failures are inseparable from the class of dependent failures and the distinction is mainly based on the level of treatment and choice of modelling approach in reliability analysis.’

The most common type of quantitative CCF probability estimation can be grouped into three categories (O’Connor, 2013):

- *Basic Parameter Model* - which calculates CCF basic event probability directly from data. This is not feasible in most cases, as data is not available for every component’s CCF failure.
- *Ratio Models* - estimates CCF probability usually as a ratio of the components overall failure rate
- *Shock Models* - assumes that components within a Common Cause Failure Group receive ‘shocks’ at a constant rate based on a Poisson process, thus each component fails independently with a constant probability.

There are however some short comings in modelling CCF in a logic-based model (O’Connor, 2013). Assuming a typical ratio model, such as a *Beta*-model applied in Equipment A in Fault Tree in Figure 2.5. The probability of event A is calculated below, assuming the following values:

$$\begin{aligned}
 P(A) &= Q_a = 0.2 \\
 \beta &= 0.3 \\
 P(A_i) &= (1 - \beta)Q_a = 0.14 \\
 P(X_{AB}) &= \beta Q_a = 0.06
 \end{aligned}
 \tag{2.1}$$

$$\begin{aligned}
 P(A) &= P(A_i) + P(X_{AB}) \\
 &= 0.14 + 0.06 \\
 &= 0.2
 \end{aligned} \tag{2.2}$$

However, the basic event fault tree (if using Minimal Cut Sets) will calculate event A as:

$$\begin{aligned}
 P(A) &= P(A_i) + P(X_{AB}) - P(A_i)P(X_{AB}) \\
 &= 0.14 + 0.06 - (0.14)(0.06) \\
 &= 0.1916
 \end{aligned} \tag{2.3}$$

The results of Equations 2.2 and 2.3 show the (small) underestimation in the computation method of a Fault Tree.

2.3.3 Bayesian Belief Networks (BBN)

Bayesian Belief Networks (BBN) are graphical structures (directed acyclic graphs) for representing probabilistic relationships among a number of variables and doing probabilistic inferences with these variables (Neapolitan, 2004). A BBN consists of nodes, arcs and probability tables to represent a set of random variables. The arcs also define the conditional relationships between the nodes, and the information embedded is represented in a conditional probability table (CPT). Consider a BBN with the parents depicted by X, and a child node depicted by Y in Figure (2.6). The node Y can take on different states of y_n , where n can refer to the number of states. y_n can take on values; or binary or descriptive states such as True, False, Good, Moderate or Poor. The joint probability distribution of the network is described by Equation 2.4:

$$P(Y) = \prod_{i=1}^3 P(Y|X_i) \tag{2.4}$$

where i refers to the parents of the node of interest Y . The conditional relationship of Y is represented by its parents: $P(X_1, X_2, X_3)$. Equation 2.4 can be expanded by chain rule to:

$$P(Y) = P(Y|X_0, X_1, x_2) \cdot P(X_0)P(X_1)P(X_2) \tag{2.5}$$

Figure 2.6: A simplified BBN where X refers to parent nodes and Y a child node.

Uncertainties can be represented in a BBN, such as the uncertainties of the annular fit of the cement plug at varying levels. The term Y can take on several states such as 'severely', 'moderately' or 'unlikely compromised'. In the case of human reliability analysis, a continuous distribution is considered, and other statistical parameters can be evaluated such as error factors or confidence intervals.

[Kabir and Papadopoulos \(2019\)](#) further highlights the modelling aspects that BBNs can consider (that traditional logical modelling cannot):

- Multi-state systems - Multi-state systems refer to the ability to represent a piece of equipment or event in more than 2 states (Binary states are the norm in FTA). In [Bobbio et al. \(2001\)](#)'s work, it was proposed that the working state of a power supply basic event (originally in a FTA, a node in a BBN) can be represented as three states, with one in-between state of 'Defective but working' other than 'Failure' and 'Success'.
- Dependency among events - Dependency among events can be represented in a BBN by having have a common node that links the events (see Figure 2.7). The common node/s allows the changes in either of the X nodes to be propagated to the other events through Bayes Theorem. For example, by reflecting an observation in X_0 into the model, the posterior probability of X_1 and X_2 is obtained through the propagation of conditional probabilities through node C_2 . An important element lies in the CPTs described in C_2 to link the X events together. Also the greater the common links that is shared between the events X, the greater the dependency. For example, an observation at X_0 will likely have a

greater impact on X_1 than X_2 as X_1 and X_0 are linked by the common nodes C_1 and C_2 . X_2 and X_0 , however are only linked by C_1 .

Figure 2.7: A simplified BBN where X refers to parent nodes and Y a child node. C refers to common nodes which link different X events together

- **Uncertainties** - Uncertainties can be represented in a number of ways. It can be represented as part of the conditional probability table, for e.g. instead of '1' and '0' to mimic an AND or OR gate (see Table 2.17), it can be represented as '0.9' and '0.1' to reflect that it is not absolute that an outcome takes place or not. The second way overlaps with the item on a multi-state system, where an 'in-between' state can be used to describe the non-absoluteness of a 'Success' or 'Failure' state. The third way is an integration of the above two methods - by increasing the number of states in a BBN, whereby each state can be interpreted as an interval/bin of a probability distribution. The elicitation can be carried out through Bayesian methods that includes formal interpretation of uncertainty (variance, error factors) like in the work of [Podofilini and Dang \(2013\)](#).
- **Human reliability** - HRA is a specialised field within Probabilistic Safety Analysis (PSA) that generally consists of Performance Shaping Factors (PSFs) which alter the value of a Human Error Probability (HEP). The nature of the method heavily relies on expert judgement, accounting for dependent failures and multi-level hierarchical analysis on a HEP. BBNs are a natural tool to model that. HEPs are utilised in traditional methods of Risk Assessment, such as in a Basic Event in a FTA. This allows the integration of a holistic HRA into system reliability analysis.
- **Continuous variables** - The variables in the CPTs can be discrete or continuous. If continuous, the mean and variance can be used to describe the conditional relationships. However, to connect a continuous node to a discrete node, the BBN must then be modelled in terms of repeat layers of BBN, usually with only a minimal computation effort increment. This workaround in the model allows the extraction of the value of interest in the continuous

node, i.e. the median/mean/ 95th percentile value of the distribution which can be used as an input to the next discrete node.

- Temporal states - BBNs have the ability to model discrete temporal changes and are further described in the section below on Dynamic BBNs.

BBNs are essentially tools for representing expert knowledge or evidence. They are especially useful for synthesising evidence or beliefs concerning a complex intervention, assessing the sensitivity of outcomes to different situations or contextual frameworks and framing decision problems that involve alternative types of intervention. Bayesian networks are useful extensions to logic maps when initiating a review or facilitating synthesis and bridging the gap between evidence acquisition and decision-making. Formal elicitation techniques allow the development of BNs on the basis of expert opinion. Such applications are useful alternatives to ‘empty’ reviews, which identify knowledge gaps but fail to support decision-making. Where review evidence exists, it can inform the development of a BN.

2.3.4 Dynamic Bayesian Belief Networks (DBN)

In order to consider a BBN’s temporal evolution, a dynamic BBN can be employed to explicitly model changes over time. This can be represented by integrating the traditional BBN with a discrete-time Markov model. Figure (2.8) illustrates how time slices are considered to model the system’s discrete temporal changes. The existing time step is represented by t_0 , and the subsequent steps t_1, t_2, t_T . The relationships between variables at successive time steps are represented by the inter-slice arcs, $Y^{t_0} \rightarrow Y^{t_1}$. Thus, the conditional relationship of $y_i^{t_1}$ is increased to $P(X_0^{t_1}, X_1^{t_1}, X_2^{t_1}, Y^{t_0})$. The resulting joint probability of the DBN over 2 time slices is defined by Equation (2.7):

$$P(Y_{0:T}) = \prod_{t=0}^T \prod_{i=1}^3 P(Y^t | X_{(i)}^t) \quad (2.6)$$

$$P(Y^{t_1}) = P(Y^{t_1} | X_0^{t_1}, X_1^{t_1}, X_2^{t_1}, Y^{t_0}) \cdot P(X_0^{t_1})P(X_1^{t_1})P(X_2^{t_1})P(Y^{t_0}) \quad (2.7)$$

A dynamic BBN has the advantage that it is an extension to an ordinary BBN (coupled with the benefits of modelling in a BBN, taking dependencies and, uncertainties into account) that allows explicit modelling of changes over time. Dependencies can now be introduced from one time state to another - the previous states is utilised for the present reasoning process in present conditions.

 Figure 2.8: A dynamic BBN over T time slices.

2.4 Human Reliability Analysis

Human reliability analysis(HRA) is a structured approach used to identify potential human failure events and to systematically estimate the probability of those events using data, models, or expert judgment ([The American Society of Mechanical Engineers, 2013](#)). HRA is one of the nine elements used to characterise a Probabilistic Risk Assessment, which is defined as qualitative and quantitative assessment of the risk associated with plant operation and maintenance that is measured in terms of frequency of occurrence of risk metrics, such as core damage or a radioactive material release and its effects on the health of the public ([The American Society of Mechanical Engineers, 2013](#), p.18). The history of HRA stems from the use of PRA for nuclear weapons assembly work in the 1960s, and was subsequently adapted for use in risk assessment of nuclear power facilities when it was included in WASH-1400, the original PRA framework for nuclear power.

Two other key definitions relate to 'Human Failure Event (HFE)', which is an integrated logic description of HEPs based on error modes, performance shaping factor assessment and other qualitative information needed to justify a single input to the risk model ([The American Society of Mechanical Engineers, 2013](#)) and 'Human Error Probability (HEP)': which is a measure of the likelihood that plant personnel will fail to initiate the correct, required or specified action or response in a given situation, or by commission performs the wrong action ([The American Society of Mechanical Engineers, 2013](#)).

2.4.1 Introduction of HRA methods

Four HRA quantification methods will be discussed below: (i) Handbook of HRA with Emphasis on Nuclear Power Plant Applications (ii) Accident Sequence Evaluation Program (ASEP) analysis procedures (iii) SPAR-H Human Reliability Analysis Method and (iv) HEART - Heart Error Assessment and Reduction Technique.

The Handbook of HRA with Emphasis on Nuclear Power Plant Applications highlights the THERP method which stands for A Technique for Human Error Rate Prediction ([Swain and Guttman, 1983](#)). THERP is a method that models pre and post initiators in a highly detailed manner. The method utilises highly detailed task analysis and is quantified using an event tree. The event tree consists of possibilities of 'success', 'fail' and in some possible cases 'recovery'. Data in the form of 27 tables is provided in the guideline, consisting of single-point estimates of the nominal HEP with the adjunct error factor (EF). The tables cover information on screening, diagnosis, errors of omission, errors of commission, PSFs, uncertainty bounds and recovery factors. The method encompasses 67 PSFs, divided into three base groups and their subgroups - (i) external factors - situational characteristics, job and task instructions, task and equipment characteristics, (ii) internal factors - organisational factors and (iii) stressors - psychological and physiological stressors. There is also dependency considered between succession of tasks. Modelling using THERP generally requires a system analyst that is a HRA specialist.

The ASEP method [Swain \(1987\)](#) is a simplified version of THERP which can address the quantification of pre and post initiators, in which its intention is to be modelled by non HRA specialist system analyst.

The SPAR-H method decomposes human error probability into contributions from diagnosis failures and action failures. This two groups considers their own nominal HEP. The diagnosis nominal HEP is at 0.01 and characterises the effort of the operator to understand a process of situation on the basis of information resulting from its manifestation. The action nominal HEP is 0.001, and as the name suggests, it is represented by actions, in which it is not necessary to consider the suitability, and intensity of their performance. They are mostly carried out as a process item for e.g. operating the device, start-up of the pumps etc. This framework accounts for the context associated with human failure events (HFEs) by using performance-shaping factors (PSFs) and dependency assignment to adjust a base-case HEP. The method proposes pre-defined base-case HEPs and PSFs, and guidance on how to assign the appropriate value of the PSF based on its negative/positive level. The diagnosis and action failure probability is the base-case HEP

multiplied by the PSF levels and its corresponding factors. The resulting HEP is the sum of the diagnosis and action failure probabilities. The dependency factor is then added on the resulting HEP. The factors correlate to the level of dependency, the greater the dependency, the higher the factor and thus the final HEP. The scale of the dependence level comes from THERP.

The HEART Method defines 9 types of generic tasks with their nominal amount of human unreliability and the 5th to 95th percentile bounds in HEART. Instead of positive/negative PSFs, there are 38 Error-producing Conditions (EPCs) which affect human reliability negatively. Heart suggests strategies and remedial measures aimed at error reduction. The recommendations are linked to the specific EPCs.

2.4.2 Human Reliability Analysis Process in the Oil & Gas Industry

There are numerous HRA methods, most of them developed specifically for PRA in the nuclear industry. One of the typical methods used in the nuclear industry is SPAR-H ([Swain, 1987](#)). There is a method developed for the oil and gas industry, named Petro-HRA ([Taylor, 2017](#)), which is an adaptation of the SPAR-H method. A typical HRA includes the following steps ([The American Society of Mechanical Engineers, 2013](#)):

1. *Select and train the HRA-PRA team*
2. *Familiarise team with facility*
3. *Build initial facility model*
4. *Screen human interactions*
5. *Characterise human interactions*
6. *Quantify human interactions*
7. *Account for dependence and recovery*
8. *Document results*

Step 5-7 are elaborated further as different methods quantify human interactions in different ways.

1. *Characterise human interactions* - determining the factors that may influence the outcome of the human interaction. Many HRA methods classify the human tasks that is being

performed. Beyond the characteristics of particular task types, Performance Shaping Factors (PSFs) are used by many HRA methods to identify what may increase or decrease the likelihood of human error for the HFE. Both task types and PSFs help define the context of the human interactions, which defines what types of human errors are possible. A PSF is defined as a factor that influences human error probabilities such as level of training, quality/availability of procedural guidance, time available to perform an action, etc ([The American Society of Mechanical Engineers, 2013](#)).

2. *Quantify human interactions* - HRA methods are used to estimate the HEP and accompanying uncertainty. The HEP and uncertainty distribution may then be inserted into the overall PRA to determine the contribution of the human to the overall risk.
3. *Account for dependency and recovery* - Dependence is the relationship between two HFEs. In most HRA methods, it is assumed that error begets error—the first instance of human error increases the subsequent chances of error on the next human interaction. Therefore, HRA methods will apply a correction factor to increase the HEP when there is dependence.

[Mkrtchyan et al. \(2015\)](#) conducted a literature review on the use of BBNs in human reliability analysis and summarised that BBNs can be used to address various aspects of HRA, including (i) management and organisation factors(MOF) impact assessment (ii) PSF relationship assessment (iii) HRA method extensions, (vi) HFE dependence assessment and (v) situation assessment.

An example of a model accounting for MOFs is [Vinnem et al. \(2009\)](#)'s model. One approach to consider the influences of MOFs within HRA is to use BBNs to explicitly model their multi-level, hierarchical influences on the HEP. Some PSFs directly influence the HEP, such as the quality of the human machine interface and the time available for the personnel to carry out their tasks. Other PSFs, typically the organisational factors, influence the HEP indirectly. For example the management's commitment to safety influences the quality of personnel training, which, in turn, then directly influences the HEP.

A frequent assumption of HRA methods is that the effects of PSFs on the HEP are mutually independent. Typically, when multiple PSFs are assumed to influence the HEP, HRA methods model the joint influence of the PSFs by cumulating the effect of each factor, as each of them would act independently on the HEP. Indeed, this assumption largely simplifies the development of the HEP quantification models. An example of a BBN model considering an assessment of PSFs relationships is [Podofillini and Dang \(2013\)](#)'s model, which tries to capture joint PSF effects. Joint PFS effects refer to an operator operating under a combination of good performing conditions

together with poor performing conditions. For example, good support from the procedural guidance and an experienced crew can compensate for the challenges of performing a complex task such that a relatively low error probability can be expected (even if associated with a complex task). On the other hand, if a complex task is performed with limited support from procedural guidance and/or without experience, then the failure probability may become very high (much higher than if each of the three factors would be present singularly).

In HRA, dependence analysis refers to assessing the influence of the failure of the operators to perform one task on the failure probabilities of subsequent tasks. There are decision trees designed to evaluate dependencies. A typical approach to model this in the HRA practice is to determine successive conditional probabilities associated with each task along the modelled operator response. The THERP handbook ([Swain and Guttman, 1983](#)) suggests general rules to determine the appropriate dependence level, which is qualified in terms of levels: zero, low, moderate, high, complete. [Podofilini et al. \(2010\)](#) have used BBN to link the similarities of cues and goals to a range of dependency level in order to adjust the HEPs.

BBNs are a natural tool to capture these influences, because of their graphical formalism, which explicitly shows the direct, indirect and general multi-level influences, as well as their modelling approach based on decomposing complex and interrelated relationships into conditionally independent influences.

Some HRA methods or parts thereof have been attempted in the oil and gas. The Barrier and Operational Risk Analysis (BORA) ([Vinnem et al., 2012](#)) method combines the use of barrier block diagrams/event trees, fault trees and risk influence factors (RIFs) to analysis the risk of hydrocarbon releases. HRA is one of the five different groups in the RIFs considered.

[Abaei et al. \(2019\)](#) applies dynamic BBN to a human reliability model for marine and offshore operations in harsh environments. Instead of modelling fatigue in a equipment, the model attempts to model fatigue in a human operator according to four different performance shaping factors: (i) Weather condition characterised by sea state, (ii) extreme roll with a parent link from (i), (iii) noise and vibration and (iv) work condition with a parent link from (i). One key performance shaping factor is that of the weather condition, as that is a parent link to other performance shaping factors as well. The performance shaping factors have three states of severity as well: 'extreme', 'moderate' and 'normal'. The difference between [Abaei et al. \(2019\)](#)'s model and [Chang et al. \(2019\)](#) is that there is a stochastic wave profile determined, and then discretised into weather conditions of varying states 'extreme', 'moderate' and 'normal' based on wave height and peak spectrum of wave period. In [Chang et al. \(2019\)](#)'s model, the expert assigns

the judgement on when a particular operational scenario is considered 'severe' or 'moderate'.

[Liu et al. \(2015\)](#) also utilises dynamic BBN to analyse human error across three categories of factors: (i) individual factor barrier failure, (ii) organisational factor barrier failure and (iii) group factor barrier failure. The dynamic nodes considers repair and no repairs, and selected nodes with the option for repairs drives its dynamic nature. For example, a node 'Control system failure at t=0' updates itself for the node 'Control system failure at t=1'. With repair, the conditional probability table takes on values of exponential distribution of repair time.

The above mentioned are further discussed in Section 2.5 Review of some Hybrid models utilising BBN in Risk Analysis.

2.4.3 Performance Shaping Factors

In 2017, the Petro-HRA method ([Taylor, 2017](#)) was developed to provide a method of qualitative and quantitative assessment of human reliability in the petroleum industry. It is largely based on an adaptation of the SPAR-H method with documented justification of the changes to the definitions of Performance Shaping Factors (PSFs), PSF levels and PSF Multipliers. One such example is on the PSF found both in SPAR-H and in Petro-HRA, which is 'Available Time'. One difference is on what is defined as time adequacy in terms of industry norms. The description of Extra Time (for Diagnosis) for both SPAR-H and Petro-HRA is between 1 and 2 times of the nominal time and greater than 30 minutes. The 30-minute criterion should be evaluated in the context of the time required for Action (*i.e.*, after accounting for the Action portion). In SPAR-H, the PSF level of 'Barely adequate time' is calculated as as 2/3 the average time (30 minutes in SPAR-H) required to diagnose the problem , *i.e.* 20 minutes. The authors of Petro-HRA indicated that for the PSF level of 'Barely adequate time' in the context of the petroleum industry, 10 minutes makes for a better reference than 20 minutes ([Taylor, 2017](#), p. 192).

The Petro-HRA, in summary, is an adaptation of the SPAR-H method with some revisions to the PSF levels and multipliers. Some differences in the PSFs between SPAR-H and Petro-HRA are summarised in Table 2.10:

The two PSFs that are slightly different or additional, with respect to SPAR-H are: 'Teamwork' and 'Physical Working Environment'. 'Teamwork' includes team leadership, backup behaviour, shared mental models. In the drilling cabin, which is where most of the well performance is monitored, backup behaviour which is defined as the ability to anticipate other team members'

Table 2.10: Performance shaping factors (PSFs) in SPAR-H and Petro-HRA.

	PSFs in SPAR-H	PSFs in Petro-HRA
1	Available time	Time
2	Stress/Stressors	Threat Stress
3	Complexity	Task complexity
4	Experience/Training	Experience/Training
5	Procedures	Procedures
6	Ergonomics/Human Machine Interface	Human Machine Interface
7	Fitness for duty	Attitudes to Safety, Work and Management Support
8	Work Processes	Team work
9	-	Physical working environment

needs through accurate knowledge about their responsibilities, is a crucial component to detecting well kicks. This is because one crew member will monitor the stats, while the other carries out the well activity, such as well perforation.

‘Physical working environment’ refers to the working conditions of the person performing the task, and usually refers to tasks outside of the control room. The work on a platform can include working under extreme working conditions, or work that is performed in an inaccessible/hard to reach place or physically demanding tasks such as trying to open a stuck valve.

Some aspects of ‘Work Processes’ in SPAR-H are covered under ‘Attitudes to Safety, Work and Management Support’ in Petro-HRA. ‘Work Processes’ in SPAR-H can be defined as aspects of doing work, including inter-organisational safety culture, work planning communication, management support and policies. It also includes a broader definition of how work is planned, communicated and executed. The Petro-HRA PSF narrowed down ‘Work Processes’ to ‘Attitudes to Safety, Work and Management Support’ as this is deemed a crucial factor that ought to be discussed on its own, in the petroleum industry. The PSF ‘Fatigue’ has been removed from Petro-HRA ([Taylor, 2017](#), p. 220) as the team behind Petro-HRA noted that impairment due to fatigue, illness, drug use *etc.* is rarely documented in event reports, and that there are sufficient mechanisms to prevent drug or alcohol abuse. The remaining, most relevant factor under ‘Fitness for duty’ is thus fatigue. However the multipliers for the effect of Fatigue are much lower than for other PSFs. Hence, due to the lower level of influence of Fatigue, and that there are measures in place for other impairment leading to a lack of fitness for duty, this particular PSF has been removed.

[Vinnem et al. \(2012\)](#)’s BORA-Release model uses Risk Influencing Factors (RIFs), which in principle are similar to Performance Shaping Factors, as RIFs refers to human, operational and

organisational factors that influences accident sequences. Table 2.11 describes these RIFs.

Strand and Lundteigen (2016) adopted Vinnem et al. (2012)’s RIFs for assessing HEP in a well drilling operation. The descriptions for the RIFs were specific to drilling. The evaluation criteria for HMI is described in Table 2.12 (Strand and Lundteigen, 2016).

Some analysis has been conducted on the WOAD database (DNV GL, 2017), a data repository that provides principal information on accidents, such as their causes, chain of consecutive events (*e.g.* a dropped object resulting in fire and oil spill), location of accident facility, and year of accident. The WOAD database has also been built on merging information from existing databases such as the Offshore Blowout Database (Norway), MAIB accident database (UK Marine Accident Investigation Branch) and the COIN/ORION database (UK HSE – Offshore Safety Division).

The data is categorised according to information usually found in an accident report. It is emphasised that the data quality and manner of reporting is inconsistent as the information is sourced from multiple avenues. Under the category ‘Main Operation’, the particular activity ‘Well Workover’ was selected and the corresponding Accident Category and Human Cause looked in detail.

Under ‘Accident Category’, there are four possible assigned states: Accident, Incident/ Hazardous Incident, Near Miss, Unsignificant. The data in WOAD appear as a discrete counts. Each time an accident is reported, the counts are updated. These factors are ordered in terms of severity of the events. The state ‘Accident’ is more severe than a ‘Near Miss’. The event ‘Unsignificant’ is misspelled on purpose as the notation used in the database is ‘U’. The notation ‘I’ is used for ‘Incident’. It also simplifies the data analysis as the severity of the accident category coincides with the ascending alphabetical order of the notation used.

Under ‘Human Cause’, the assigned states are more random in nature, and do not seem to follow established PSFs from known Human Reliability Assessment methods. Based on the ‘Comments’ category, the human causes are extracted from the Accident Investigation Report by the United States Department of the Interior (2007). Further delineation of the ‘Human Cause’ is analysed by searching for the particular accident report (Figure 2.9), which in this case could be explained by unsafe procedures.

There was a total of 251 accident entries (see Figure 2.10). Most of them had insufficient information to provide insights on the potential PSFs involved. The entries with insufficient information had information on where the accident was reported. If the accident happened in

Table 2.11: Descriptions of risk influencing factors in Vinnem et al. (2012)’s BORA-Release model.

RIF group	RIF	RIF descriptions
Personal characteristics	Competence	Competence, experience, system knowledge, training of personnel
	Working load/stress	Sum of all tasks and activities on persons
	Fatigue	For <i>e.g.</i> night shifts, extensive overtime
	Work environment	Physical working environment like noise, light, vibration, use of chemical substances
Task characteristics	Methodology	Methods used to carry out a specific task
	Task supervision	Supervision quality
	Task complexity	Complexity
	Time pressure	Time pressure in the planning, execution and completion of a specific task
	Tools	Availability and operability of necessary tools in order to perform a task
Technical system characteristics	Spares	Availability of the spares needed to perform the task
	Equipment design	<i>E.g.</i> flange type (ANSI or compact), valve type, etc
	Material properties	Properties of the selected material with respect to corrosion, erosion, fatigue, gasket material properties, <i>etc.</i>
	Process complexity	General complexity of the process plant as a whole
	HMI (Human machine interface)	Human-machine interface such as ergonomic factors, labelling of equipment, position feedback from valves, alarms, etc.
	Maintainability	Maintainability of equipment and systems like accessibility to valves and flanges, space to use necessary tools, etc
	System feedback	How errors and failures are instantaneously detected, due to alarm, failure to start, etc
Administrative control	Technical condition	Technical conditions
	Procedures	Quality and availability of permanent procedures and job/task descriptions
	Work permit	The system for work permits, like application, review, approval, follow-up, and control
Organisational factors/operational philosophy	Disposable work descriptions	The quality and availability of disposable work descriptions including safe job analysis (SJA) and isolation plans
	Programs	The extent and quality of programs for preventive maintenance (PM), condition monitoring (CM), inspection, third party control of work, use of self control/checklists, etc. One important aspect is whether PM, CM, etc. are specified
	Work practice	Factors like whether procedures and checklists are used and followed, whether shortcuts are accepted, focus on time before quality, etc
	Supervision	The supervision on the platform including the follow-up of activities, plans, deadlines, etc.
	Communication	The communication between different actors such as area platform manager, supervisors, area technicians, maintenance contractors, CCR technicians, etc.
	Acceptance criteria	The definitions of specific acceptance criteria related to for instance, condition monitoring, inspection, etc.
	Simultaneous activities	Number of simultaneous activities conducted, either planned (like maintenances and modifications) and unplanned (like shutdown)
	Management of changes	Aspects related to changes and modification

Table 2.12: Specific evaluation criteria for drilling by [Strand and Lundteigen \(2016\)](#).

RIF	RIF evaluation criteria
HMI	Ability to interpret <i>in situ</i> wellbore flowrates Ability to interpret <i>in situ</i> pressures along the wellbore Ability to initiate and provide feedback on successful BOP activation and closure Ability to locate tool-joints in the work string Ability to help diagnose and identify the root cause of well barrier failures for purpose of well barrier restoration Ability to help interpret effects from changes made to well drilling parameters, also described as the performance of actions

the US region, it is likely that accident reports exist and these can be used to supplement the information. A total of 60 entries could be studied further, mostly through sourcing secondary accident reports like the one written by the US Department of the Interior. These additional 60 entries have been summarised in (see Figure 2.10). The database had no structure for PSFs, but there were five categories. The five possible PSFs are (i) Adverse weather, (ii) Human (which refers to an operator action error), (iii) Improper design, (iv) Unsafe act due to lack of procedures and (v) Unsafe procedures. It can be observed that unsafe procedures make up the majority of accidents across all states of severity. The PSFs relating to human operator action and lack of procedures make up the majority of accidents occurring at the incident level.

Hypothesis testing was conducted using a chi-squared distribution ([Agresti, 2002](#)) for categorical data analysis for a number of causes as identified in the database (see Figure 2.11).

It is usually said that if the p-value is > 0.1 , it is considered statistically insignificant, and the hypothesis that the particular cause leads to the accident can be rejected. Each cause in the filtered WOAD data is hypothesized to lead to an accident based on the count data analysis. The causes are: collision, corrosion, (improper) design, equipment malfunction, human, ignition, procedures- maintenance, procedures-operation, unsafe act, unsafe act due to poor procedures, unsafe procedures and weather. Those that are rejected are mostly due to small counts. The ones in bold are considered to be statistically significant in causing the accident registered in the database. Understandably, these are factors that led to the accident. Strictly speaking these are not performance shaping factors (as the database collation is haphazard in the accident entry). However, they do provide some insights on the possible performance shaping factors/risk influencing factors that can be identified for well work - it is apparent that procedures on maintenance/operation, shift work are performance shaping factors that are worth looking into ([Fam et al., 2018b](#)).

**UNITED STATES DEPARTMENT OF THE INTERIOR
MINERALS MANAGEMENT SERVICE
GULF OF MEXICO REGION
ACCIDENT INVESTIGATION REPORT**

1. OCCURRED
DATE: **04-AUG-2006** TIME: **1200** HOURS

2. OPERATOR: **Newfield Exploration Company**
REPRESENTATIVE: **Larry Moerbe**
TELEPHONE: **(281) 389-0734**
CONTRACTOR:
REPRESENTATIVE:
TELEPHONE:

3. OPERATOR/CONTRACTOR REPRESENTATIVE/SUPERVISOR
ON SITE AT TIME OF INCIDENT:

4. LEASE: **G01898**
AREA: **ST** LATITUDE:
BLOCK: **148** LONGITUDE:

5. PLATFORM: **B**
RIG NAME: *** COIL TUBING UNIT**

6. ACTIVITY: ☐ EXPLORATION (POE)
☒ DEVELOPMENT/PRODUCTION (DOCD/POD)

7. TYPE:
☐ HISTORIC INJURY
☐ REQUIRED EVACUATION
☐ LTA (1-3 days)
☐ LTA (>3 days)
☐ RW/JT (1-3 days)
☐ RW/JT (>3 days)

8. CAUSE:
☐ EQUIPMENT FAILURE
☒ HUMAN ERROR
☐ EXTERNAL DAMAGE
☐ SLIP/TRIP/FALL
☐ WEATHER RELATED
☐ LEAK
☐ UPSET H2O TREATING
☐ OVERBOARD DRILLING FLUID
☐ OTHER

18. LIST THE PROBABLE CAUSE(S) OF ACCIDENT:
The rig crew had trouble controlling the tubing during the time it was being lowered out of the v-door and catwalk other than manual guiding. The roustabouts believed that manually guiding the tubing joints was part of their job. Laying out singles and manually unlatching the elevators was not the best procedure for this job.

STRUCTURAL DAMAGE
CRANE
OTHER LIFTING DEVICE
DAMAGED/DISABLED SAFETY SYS.
INCIDENT >\$25K
H2S/15MIN./20PPM
REQUIRED MUSTER
SHUTDOWN FROM GAS RELEASE
☒ OTHER **Choke stem, Gas Buster, Piping**

6. OPERATION:
☐ PRODUCTION
☐ DRILLING
☒ WORKOVER
☐ COMPLETION
☐ HELICOPTER
☐ MOTOR VESSEL
☐ PIPELINE SEGMENT NO.
☐ OTHER

Figure 2.9: A snapshot of the generic indication of a human error indicated in an accident report by the [United States Department of the Interior \(2007\)](#). The cause of the accident identified as ‘Human Error’ is looked further in depth and listed as procedural in nature based on the above comment

2.5 Review of some Hybrid models utilising BBN in Risk Analysis

The thesis proposes to use BBN as a tool for modelling risks. Thus some examples of hybrid (quantitative & qualitative) models (see Tables 2.14 and 2.15) have been categorised according to whether these models considered the six desirable features (which can be modelled in a BBN) of (i) multi-state systems, (ii) dependency, (iii) human reliability analysis, (iv) continuous variables and (v) temporal states. Multi-state systems refer to the ability to model more than two states. Traditional logic modelling is limited to binary states (Failure, Success). Dependency refers to occurrences of events from a common factor, or the ability to calculate the union of 2 events that are not assumed to be independent of each other. Human reliability analysis refers to the ability to consider the form of analysis involving performance shaping factors and, dependence between performance shaping factors (and that human error is not just reflected as a simple basic

Figure 2.10: Number of recorded events by the work operation found in WOAD (DNV GL, 2017).

event). In some cases, a continuous distribution describes the phenomena in a better light. Thus, if the model can consider a continuous distribution and have a mechanism for propagating the information towards the interest of analysis, it would be an ideal model. Temporal states refer to the ability to consider a time period of interest, and dependencies from one time state to another.

The hybrid models are further discussed according to whether they consist of the six features listed, and their strength and weaknesses according to the following subsections: (i) offshore-specific model (ii) mapping traditional models in a BBN and (iii) extending model capabilities having mapped traditional models in a BBN.

Figure 2.11: Number of recorded events (Accident, Incidents, Near Miss, Unsignificant) by filtered according to the 'Well Workover' operation from WOAD. Table 2.13 show that 'procedures-maintenance', 'procedures-operation', 'unsafe procedure', 'human', 'day shift', 'night shift', 'equipment failure' and 'ignition' are of interest. (DNV GL, 2017).

Table 2.13: Result of chi-square test for a corresponding organisational, operator or equipment cause to the Accident Category. If p-value is > 0.1 , it is considered not statistically significant, and the hypothesis that organisation, operator or equipment cause significantly affect the occurrence of the accident can be rejected.

	dataframes created in R	χ -squared value	df	p-value	Accept (Y) or Reject (X)
Procedures-Maintenance	table.ac.hu1pm	20.333	2	3.843e-05	Y
Procedures-Operation	table.ac.hu2po	47.571	2	4.677e-11	Y
Unsafe act	table.ac.hu3ua	0.33333	1	0.5637	X
Unsafe act / No procedure	table.ac.hu3un	1.2	3	0.753	X
Unsafe Procedure	table.ac.hu3up	7.8824	2	0.01943	Y
Procedures-Human	table.ac.hu3ph	1	1	0.3173	X
Improper design	table.ac.hu3id	2.6667	1	0.1025	X
Human	table.ac.hu3hu	3.2667	1	0.0707	Y
Adverse Weather	table.ac.hu3aw	3.25	2	0.1969	X
Day Shift	table.ac.sh1	45.628	3	6.805e-10	Y
Night Shift	table.ac.sh2	57.972	3	1.594e-12	Y
Equipment malfunct./fail.	table.ac.eq1ma	100.7	3	$< 2.2e-16$	Y
Struct.fail/fatigue/corr.	table.ac.eq1sf	0.88889	3	0.3458	X
Ignition	table.ac.eq1ig	12.8	1	0.0003466	Y

Table 2.14: Summary of hybrid risk assessment models. Part 1/2

Model/Technique	Description	Authors	MSS	Dep.	Unc.	HRA	Con't	Temp.
							Var.	
BORA-Release Method	Hydrocarbon leak analysis by coupling FT and ET with BBNs. Platform specific conditions of technical, human, operational, and organisational are termed risk influencing factors which could impact the barrier performance.	Vinnem et al. (2009)	X	X				
The Hybrid Causal Logic (HCL) Method	Coupling FT and ET with BBNs. BBN is used to model Risk Influencing factors from the BORA-Release Model. Different probability elicitation from BORA-Release method.	Røed et al. (2009)	X	X	X			
Mapped FT and ET into BBN	Consequence analysis results are used to aid decision analysis between types of drilling tech options, or analysis of critical events.	Bobbio et al. (2001) ; Bearfield and Marsh (2005) ; Bhandari et al. (2015) ; Abimbola et al. (2016)		X				
Mapped FT into a BBN with dependency modelling (General Dependency Model).	The focus on using BBN is in improving Common Cause Failure models typically used in reliability analysis. The proposed dependency model consists of three parameters for each failure cause, which relate to physical attributes of the system being modeled, i.e., cause condition probability, component fragility, and coupling factor. strength.	O'Connor (2013) ; O'Connor and Mosleh (2016)	X	X	X			
Mapped FT and ET into BBN with non-linear, copula-based dependency modelling	The degree of correlations (negative and positive) is represented by pairwise Spearman correlation coefficients (-1 to 1) between nodes, all of which compose a correlation matrix.	Chang et al. (2019)		X				

Table 2.15: Summary of hybrid risk assessment models. Part 2/2

Model/Technique	Description	Authors	MSS	Dep.	Unc.	HRA	Con't	Temp.
							Var.	
Mapped FT and ET into Dynamic BBN	The temporal BBN is set up in a standard discrete self-linking transition CPTs. The transition CPTs are elicited by expert judgement.	Chang et al. (2019) ; Abaei et al. (2019)					X	X
Dynamic BBN for human factors modelling for offshore blowout	The temporal BBN is set up in a standard discrete self-linking transition CPTs. The transition CPTs and human factors are elicited by expert judgement.	Cai et al. (2013)				X		X
Expert-elicited probabilities in human reliability analysis	The analyst is only required to rate the performance factors, and the Human Error Probability (HEPs) are produced by the model. The performance factors and HEP are multi-state and can presented its level of uncertainty.	Podofillini and Dang (2013)	X	X	X	X	X	

2.5.1 BORA-Release Model

BORA-Release is short for 'Barrier and Operational Risk Analysis', and it combines the use of barrier block diagrams/event trees, fault trees and risk influence factors (RIFs) to analyse the risk of hydrocarbon release from a set of hydrocarbon release scenarios (see Figure 2.12). The risk influencing factors are made up of five different groups that covers platform specific conditions of technical, human, operational, and organisational factors. The five groups are personal characteristics, task characteristics, technical system characteristics, administration control and organisation factors.

The RIFs form an arc directly with the basic event (C15) in the fault tree (see Figure 2.13) which modifies the original basic event probability according to the relative weight assigned to the particular RIF ranging from 0 to 10, which is then normalised to 1. The scores of the RIFs, ranging from A (best standard) to F(worst practice), where C corresponds to the industry average. This modification is, strictly speaking, equation based and not encoded as conditional probability values. Some examples of weightage assigned can be seen in the column w_i in Table 2.16. The RIFs are by default set at industry standard (Grade C) so it does not alter the probabilities. A workshop is used to elicit grading of the RIFs from A to F.

Figure 2.12: Conceptual model of how RIFs link to a basic event. The part highlighted in red refers to Figure 2.13.

The RIFs forms an arc directly with the basic event (C15) in the fault tree (see Figure 2.13) which modifies the original basic event probability according to the relative weight assigned to the particular RIF ranging from 0 to 10, which is then normalised to 1, and the scores of that RIF, ranging from A (best standard) to F(worst practice), where C corresponds to the industry average. This modification is strictly speaking, equation based and not encoded as a conditional probability values.

Figure 2.13: Detailed conceptual model of how RIFs link to a basic event. The basic event in this example is labelled as C15 'Corrosion not revealed due to poor inspection reliability'.

The purpose is to assign platform specific values to the input probabilities/frequencies allowing for platform specific conditions of the RIFs. The industry average probabilities/frequencies are revised based on the risk influence diagrams through an assessment of the weights and the status of the RIFs. Based on the RIF identified in Figure 2.13, let $P_{rev}(C15)$ refer to the 'installation specific' probability for the occurrence of event C15. $P_{rev}(C15)$ is determined as follows:

$$P_{rev}(C15) = P_{ave}(C15) \cdot \sum_{i=1}^n w_i Q_i \quad (2.8)$$

where $P_{ave}(C15)$ refers to the industry average / database average probability of occurrence of event $C15$, w_i denotes the weight (0 - 10 then normalised to 1) for RIF no. i , Q_i is a measure of the RIF no. i and n is the number of RIFs.

Q_i can take on a variety of values which differ from one another in a linear manner. $Q_i(C)$ referring to the industry standard will always have a value of 1. $Q_i(A)$ and $Q_i(B)$ are each <1 , while $Q_i(D)$, $Q_i(E)$, $Q_i(F)$ is >1 depending on how the expert estimates the possible values P_{low} and P_{high} with respect to the P_{ave} .

$$Q_i(A) = P_{low}/P_{ave} \quad (2.9)$$

$$Q_i(C) = 1 \quad (2.10)$$

$$Q_i(F) = P_{high}/P_{ave} \quad (2.11)$$

$$Q_i(B) = \frac{P_{low}}{P_{ave}} + \frac{(S_B - S_A)(1 - P_{low}/P_{ave})}{S_C - S_A} \quad (2.12)$$

$$Q_i(D) = 1 + \frac{(S_D - S_C)(P_{high}/P_{ave} - 1)}{S_F - S_C} \quad (2.13)$$

where $S_A = 1$, $S_B = 2$, $S_C = 3$, $S_D = 4$, $S_E = 5$, $S_F = 6$.

The Hybrid Causal Logic with BORA method (Røed et al., 2009) is a new approach for the probability assignment process applied to the BORA method. There is a greater consideration for multi-level BBN modelling (See Figure 2.14), based on the following assumption: the greater the deviation between the parents states and the child state (RIF in focus), the smaller the probability that should be assigned. This is done through a probability distribution elicitation based on a type of exponential distribution that is then normalised such that the six states (A to

2.5. REVIEW OF SOME HYBRID MODELS UTILISING BBN IN RISK ANALYSIS

Table 2.16: Industry average probabilities, weights, scores and revised probabilities for the RIF in relation to the basic event of Figure 2.13

Basic event	P_{ave}	P_{low}	P_{high}	Basic event/RIFs	w_i	$Q_i(S_{A,...,F})$	$\sum_{i=1}^n w_i Q_i$	P_{rev}
C15	0.03	0.006	0.15	P(Corrosion not revealed due to poor inspection)			1.27	0.038
				C151 Size of Corrosion	2	C		
				C152 Accessibility	2	C		
				C153 Procedure for inspection	10	C		
				C154 Time pressure	6	D		
				C155 Competence of inspector	10	C		

F) sum up to 1. The second part of the BBN modelling refers to when the RIFs link directly to the basic event and is similar to the linear interpolation approach by Vinnem et al. (2009) with reference to equations 2.9 to 2.13.

Figure 2.14: Conceptual model of how different layers of RIFs link to each other before linking to a basic event.

In consideration of the sub-BBN of RIF1, RIF 1a and RIF 1b in Figure 2.14, a linear, weighted formulae is used to reflect the distance from the state of the RIF being considered, and the weighted average of the parents' states. The Parent states refer to RIF 1a and RIF 1b. The RIF being considered is RIF 1. The distance is quantified in the following manner:

$$Z_j = \sum_{i=1}^n |Z_{ij}| W_i \quad (2.14)$$

where Z_{ij} represents the distance measured in units between the states of the parent RIF to the RIF of interest. The distance between a and d is three states. If RIF 1a (weight = 0.5) has state c and RIF 1b (weight = 0.5) has state d , then $Z_{RIF1=a} = 0.5 * 3 + 0.5 * 2 = 2.5$. The other values of $Z_{RIF1=b}$, $Z_{RIF1=c}$, $Z_{RIF1=d}$, $Z_{RIF1=e}$ and $Z_{RIF1=f}$ can be calculated in the same way.

The distance between the weighted parents states and the child states is translated into a probability distribution that is described in the following way:

$$P_j = \frac{e^{-RZ_j}}{\sum_{j=a}^f e^{-RZ_j}} \quad (2.15)$$

where R is determined by the expert. The authors recommend $R = 0, 1, 2$ and the conditional probabilities are demonstrated in Figure 2.15. Higher values of R results in narrower probability distributions, which are a way to express expert certainty.

Figure 2.15: Example of calculated probability distributions for three values of index $R=0,1,2$.

The elicitation method in both the BORA-Release and HCL method is simple to adopt, and importantly, the elicitation burden only increases linearly as the number of nodes increase. The improvement of the HCL method applied to the BORA-Release model is in the ability to express uncertainty in the conditional probability elicitation, which is done by varying the R -index. As the nodes can include feedback over a scale of A to F, this suggests that a multi-state system of varying scale can be considered. However, the HCL method is still not ideal as it cannot capture the effect of dominance of one factor in one state - that the HEP is 'very high' independently of

the state of the other factors. As long as the dominant PSF remains on an 'error-forcing' state, the states of other PSFs should not affect the HEP judgement assessed. In Røed et al. (2009)'s model, the distance between the child and the parent is fixed as a 'count' of states and thus cannot capture this type of dominant factor relationship. In addition, the model cannot adopt different uncertainties in the different pairs of parent-child nodes. Podofillini and Dang (2013)'s method which will be elaborated in the next section highlights these features in the elicitation method.

2.5.2 Mapping FT and ET into BBNs

Bobbio et al. (2001) documented a way of reflecting logic gates in a BBN through a series of '0's and '1's. For the BBN of Figure 2.16, the respective OR and AND gates are represented below in Table 2.17 and 2.18.

Figure 2.16: A BBN with two parent nodes X_0 and X_1 and a child node Y .

Table 2.17: OR-gate expressed as conditional probability tables of X_0 , X_1 and Y which are assumed to have only 2 states, Success or Failure.

X_0	X_1	Y	
		$Y = \text{Success}$	$Y = \text{Failure}$
<i>Failure</i>	<i>Failure</i>	0	1
<i>Failure</i>	<i>Success</i>	0	1
<i>Success</i>	<i>Failure</i>	0	1
<i>Success</i>	<i>Success</i>	1	0

The benefit of mapping FT and ET is the ability to reflect evidences to update the failure probability.

Bhandari et al. (2015) mapped the FT and ET into the BBN and used it for a decision analysis

Table 2.18: AND-gate expressed as conditional probability tables of X_0 , X_1 and Y which are assumed to have only 2 states, Success or Failure.

X_0	X_1	Y	
		Y = Success	Y = Failure
<i>Failure</i>	<i>Failure</i>	0	1
<i>Failure</i>	<i>Success</i>	1	0
<i>Success</i>	<i>Failure</i>	1	0
<i>Success</i>	<i>Success</i>	1	0

between the types of drilling technology options based on the outcome of the consequences of the respective methods. The two techniques involved are (1) Managed pressure drilling and (2) Underbalanced drilling.

Both methods lead to the initiating event of interest, which is an uncontrolled release of pressure ('kick') that could lead to well blow outs. However the paths that lead to this initiating event is different between the both methods, so the consequence profile for both methods would be different. The BBN becomes a decision aid to consider the advantages over its risks. For example, despite the higher probability of kick and blowout, Under Balanced Drilling has some advantages over Managed Pressure Drilling operations. A Down-hole Deployment Valve is used in the practice of Under Balanced Drilling as a tool to isolate bottomhole pressure from the rest of the well; this is especially useful when tripping in and out, without the need of a snubbing unit.

Mapping the FT and ET to the BBN allows the backwards analysis of looking at which root events contributed to the respective consequences, in view of other observations/evidence. The backwards analysis allows for the comparison of the percentage contribution of the root events to the most severe consequence 'Blow out'. Therefore it is possible to understand which of the two drilling options has a higher percentage contribution to a 'Blow out'.

However the model stops there, it can be observed in Figure 2.17 that the nodes are binary states, and no dependencies are mapped. Abimbola et al. (2016) similarly mapped FT and ETs to BBN to analyse the risks of a well casing operation failure. This model includes an additional feature of considering dependent failures from common events such as the impact of human error on multiple operations. This model only considers binary states in the nodes. In this model, human error analysis, a large topic and scope in itself, is only represented as generic number.

Figure 2.17: A Fault Tree and Event Tree mapped into a BBN in which the consequence analysis is used to determine which drilling option has lower risks.

2.5.3 Additional analysis of mapped FT and ET into BBNs

The following models to be discussed, apart from mapping the FT and ET into BBNs, also proposed amendments to the modelling technique to tap on the benefits of BBNs. There are two models to be discussed which have more elaborate dependent failure models (O'Connor, 2013; O'Connor and Mosleh, 2016; Chang et al., 2019). Other modelling improvements include modelling uncertainty in the BBN, and being able to express the probability of interest (HEP) in terms of a continuous distribution with information on its 5th, 95th and median value (Podofillini and Dang, 2013). There is also feasibility to add a temporal factor to the BBN so that a dynamic model in terms of time steps can be used to provide risk insights over a time period, such as an operational or monitoring duration.

Dependent failure models

O'Connor (2013); O'Connor and Mosleh (2016) proposed a dependent failure model called 'General Dependency Model (GDM)' to model probabilistic dependencies between components. The model introduces three parameters for each failure cause, which relate to the physical attributes of the system being modelled, i.e., cause condition probability, component fragility, and coupling factor strength.

The GDM model seeks to model asymmetrical components and dependency relationship with the following structure of component failure probability, which consists of component dependency and the propagation of cause condition. The component failure probability, Q_t is defined as the combination of component failure probabilities for each failure cause. For a particular component, each cause is independent of all other causes and the component failure probability can be

calculated as depicted in Figure 2.18.

Figure 2.18: The General Dependency Model of common cause with description of equations involved in each node.

In Figure 2.18, the failure of EDG_1 and/or EDG_2 is due to a cause, identified as $C_{EE}^{[E_i]}$ which could refer to a failure cause due to maintenance procedures, installation procedures, location of equipment, *e.t.c.* The probability that a cause condition exists, C_i , for cause, i is:

$$P(C_i) = Q_{E,i} \quad (2.16)$$

With p_i is the conditional probability that the component fails when testing by cause i , then the probability of component failure due to cause i is

$$Q_{t,i} = p_i Q_{E,i} \quad (2.17)$$

The GDM separates the cause conditions for each component. Component-specific cause conditions can propagate to other components probabilistically using a coupling factor strength, η_i . The coupling factor strength, η_i , is scaled between the following two extremes:

- when $\eta_i = 0$, there is no chance that the component-specific cause condition at one component can propagate to the second component.
- when $\eta_i = 1$, a cause condition is present at both components simultaneously.

As the GDM model splits the component-specific cause condition probabilities, $Q_{E,i}$ into independent ($Q_{IE,i}$) and common failure ($Q_{CE,i}$) probabilities, they can be expressed in the

following way:

$$P(X_i) = Q_{CE,i} = \eta_i Q_{E,i} \quad (2.18)$$

$$Q_{I_i} = Q_{IE,i} = (1 - \eta_i) Q_{E,i} \quad (2.19)$$

For each cause, the model is fully specified once the three parameters p_i , $Q_{E,i}$ and η_i are known, either through expert judgement or from a reliability database.

[Guo et al. \(2018, 2019\)](#) proposed a Copula Bayesian Network (CBN) to capture the non-linear correlation among initiating events and safety barriers in a Bowtie model. The degree of correlations is then represented by pairwise Spearman correlation coefficients between nodes, all of which compose a correlation matrix. Its ρ value is between -1 and 1, determining different strengths of correlation between two variables, with -1 indicating deterministically negative dependence, 0 showing complete independence while 1 representing deterministically positive dependence.

The authors have described a ρ value of 0.8 as significant dependence, and a ρ value of 0.6 as moderately dependent. The authors have only used the values 0.6, 0.7, 0.8 and 1 in the correlation matrix. A sample correlation matrix with nodes in [Figure 2.6](#) would be:

Table 2.19: Spearman correlation parameters between the X_0 , X_1 and X_2 nodes

	$P(X_0)$	$P(X_1)$	$P(X_2)$
$P(X_0)$	1	0.6	0.6
$P(X_1)$	0.6	1	0.6
$P(X_2)$	0.6	0.6	1

The benefit of the model is in its ability to consider a wide range of dependent relationships, but in doing so will require extra consideration in translating the dependent relationships into the correlation matrix. The authors [Guo et al. \(2019\)](#) did not fully utilise the flexibility of the copula functions - the correlation matrix elicited only considered three correlation values of 0.6, 0.7 and 0.8. It would be tricky to consider negative correlation in dependent failures, since most assumptions on dependent failures consider that as the likelihood of failure of one component increases with the failure of another similarly maintained, installed, or located component. Thus for dependent failures analysis, it is usually not necessary to consider negative correlation. Since the model does not fully utilise the flexibility in the copula functions, it may not be worth the additional time and work to write a separate programme to analyse it.

Continuous 'Discretised' variables

Although the model by [Podofilini and Dang \(2013\)](#) has been primarily used for determining human error probability in a full Human Reliability Analysis, it has many segments worth exploring to provide new dimensions to risk analysis. The model (a sample in Figure 2.19) considers dependent failures (the same performance shaping factors could affect multiple operator actions), and the elicitation process considers uncertainties through two matrices that represents the inherent variability of the HEP (Matrix F) and the confidence that the expert provides the correct HEP value (Matrix G). In addition, the elicitation process is able to consider multiple states.

Figure 2.19: A BBN of a simplified HRA model. The nodes have multiple states.

The basic assumption for the method is that the HEP is distributed according to a lognormal distribution with unknown parameters values. The expert opinion is then used to update on the values of these parameters. The expert opinion is manifested as estimates of specific realisations of the quantity of interest ([Podofilini et al., 2015](#)). The HEP node consists of five states ranging from 'Very high' to 'Very low'. The model basically considers the case (shaped by different performance shaping factors) in which the BBN is used to predict the order of magnitude of the HEP (each state covers a factor of 10 in the HEP ranging from 1 to 1e-4).

If considering a discrete probability distribution, the Bayesian model can be written as :

$$\Pi_j = k^{-1} L(E|j) \Pi_j^0 \quad (2.20)$$

for $j = 1, 2, 3, \dots, n$.

where Π_j is the j -th element of the posterior probability distribution, $(\Pi = \Pi_1, \Pi_2, \dots, \Pi_n)$ of the variable of interest, x (*e.g.* HEP). Then $(\Pi^0 = \Pi_1^0, \Pi_2^0, \dots, \Pi_n^0)$ is the prior distribution, updated in light of the evident, $E = i_1^*, i_2^*, \dots, i_N^*$ where N is the number of experts. The expression is normalised by Factor k over j to a probability distribution.

The likelihood term $L(E|j)$ is interpreted as the probability of evidence E , given that the actual value of x is x_j . This is described as a function of the following two elements:

- Matrix F - the inherent variability of the HEP
- Matrix G - the confidence that the expert provides the correct HEP value

The elements of the matrices F and G are determined in the following manner. Each reference value $x_i = 1, 2, \dots, 5$ of Table 2.20 is interpreted as the median of an HEP uncertainty distribution. $i = 5$ refers to the five states of the HEP ranging from 'Very high' to 'Very low'. Thus the HEP assessment problem becomes that of assessing which of the five x_i 's best represents the median, based on the expert estimates. The error factor (square root of the 95th and 5th percentiles) of the uncertainty distribution is assumed to be known and equal to 5. With the error factor defined, only one parameter needs to be assessed - the median. This simplifies the assessment procedure. It has been investigated that the value of 5 for the error factor represents a commonly accepted confidence range for HEPs (Podofillini and Dang, 2013).

The element f_{ij} is the probability that the realization of the HEP of the specific HFE considered by the expert is within the interval represented by x_i , when the applicable probability (or reference value or reference judgment, depending on how the variable x is expressed) is represented by x_j (x_j could be for example the mean, the median, or just an indication of the order of magnitude). For example, element f_{12} is the probability that the HEP would realised within interval 1 given that its median is in interval 2. (1e-2).

Table 2.20: Elements of matrix F, f_{ij} = probability that the realization of the HEP is within interval i , given the realization of the HEP is within interval j .

i	j				
	1	2	3	4	5
1	8.8e-1	1.2e-1	2.1e-4	2.0e-9	8.8e-17
2	1.2e-1	7.6e-1	1.2e-1	2.1e-4	2.0e-9
3	2.1e-4	1.2e-1	7.6e-1	1.2e-1	2.1e-4
4	2.0e-9	2.1e-4	1.2e-1	7.6e-1	1.2e-1
5	8.8e-17	2.0e-9	2.1e-4	1.2e-1	8.8e-1

For the G matrix, a lognormal distribution with an error factor of 10 is assumed as the confidence

that the expert provides the correct value of the HEP. This corresponds to being 90% confident that the expert estimate would deviate within less than a factor of 10 above and below the correct value. The elements of the G matrix (Table 2.21) are therefore interpreted as follows: g_{ij} = probability that the expert assessment of the HEP is x_i , when the realization is x_j .

The element g_{ij} is the probability that the expert assesses $X = x_i$, when attempting to estimate x_j (i.e. when attempting to quantify the HEP of an HFE with HEP represented by x_j). For example, element g_{12} is the probability that the expert would assess the HEP to be in the interval 1, when its realisation is in interval 2. The elements of Matrix G are then modified to avoid probabilities that are too low (i.e. below 1e-2) and deviate by more than two intervals from the appropriate one, as suggested in Podofilini and Dang (2013). Therefore, elements with values below 1e-2 are set to 1e-2 as reported in Table 2.21.

Table 2.21: Elements of matrix G, g_{ij} = probability that the expert's assessment is x_i when attempting to estimate x_j - modified distribution tails with 1e-2 residuals.

i	j				
	1	2	3	4	5
1	7.7e-1	2.1e-1	1.0e-2	1.1e-2	1.0e-2
2	2.0e-1	5.8e-1	2.0e-1	1.0e-2	1.0e-2
3	1.0e-2	2.0e-1	5.8e-1	2.0e-1	1.0e-1
4	1.0e-2	1.0e-2	2.0e-1	5.8e-1	2.0e-1
5	1.0e-2	1.0e-2	1.0e-2	2.1e-1	7.7e-1

In the single expert case, the peak of the probability distributions is the value assessed by the expert (the uncertainty on the distributions combines the level of confidence in the expert estimates and the intrinsic variability of the HEP. As an example, for an expert-passed judgement that a HEP is Very High (see Figure 2.20), the distribution derived is such that it represents a distribution across the other possible HEP levels. The general idea is that the state that was described as most likely, by the expert would have the greatest probability density to it.

The end result for the node HFE1 would be a distribution of the elicited human error probability across the five levels of HEP, ranging from the states 'Very High' to 'Very Low' (Figure 2.21). This represents the posterior probability distribution of the knowledge of the median HEP in light of experts opinion. In most qualitative exercise, the median HEP draws the greatest interest. The median value of the expected density function of the HEP is obtained by weighing the probability density function with the median and an error factor of 5. The probabilities expressed in percentages are the weights (the percentages or probabilities in HFE1 or HFE2) used for each corresponding distribution.

Figure 2.20: Probability elicited from an expert judgement of HEP = Very High.

Figure 2.21: Results of Podofilini and Dang (2013)'s method, where the final HEP can be expressed a median with its corresponding 5th and 95th percentile values.

Generally, a BBN's primary use is the representation of knowledge and decision support under uncertainty; The main benefit of this model is the ability to present the elicited HEP in with (1) uncertainty, and if is required to quantify a HFE, a weighted sum of the distribution is considered which provides (2) a single median value with considerations of uncertainties incorporated in it.

Dynamic BBN

A few researchers also extended the use of BBNs in risk modelling to Dynamic BBN. The extension of ordinary static BBN to Dynamic BBN maintains the merits of handling uncertainty, in addition to modelling the dynamic behaviour of a system by introducing temporal dependencies in the

network, as well as having the opportunity to use the previous states for the present reasoning process in the present condition (Chang et al., 2019).

Chang et al. (2019) applies dynamic BBN specifically to an expert elicited transition probability data on the degree of fatigue accumulation in the subsea wellhead. The degree of fatigue accumulation stems from some uncertainties and can be categorised in terms of (i) loadings, (ii) operational parameters and equipments, (iii) fatigue capacity, and (iv) critical fatigue position of the subsea wellhead. The node which drives the dynamic analysis is the node on the degree of fatigue accumulation, split into three states 'severe', 'moderate' and 'low' (Figure 2.22). The temporal order is '1', implying that the current state, t only affects the $t + 1$ state. If the temporal order is '2', it implies that the current state only affects the $t + 2$ state. If the model is unrolled out in terms of the number of time steps, it will resemble Figure 2.23.

Figure 2.22: Truncated version of Chang et al. (2019)'s dynamic BBN model modelled in Genie (BayesFusion, 2018). Only the immediate parents nodes to the dynamic node 'Fatigue Accumulation' is shown.

Figure 2.23: A model based on Chang et al. (2019)'s dynamic BBN model unrolled up to three time steps and modelled in Genie (BayesFusion, 2018). Only the immediate parent nodes to the dynamic node 'Fatigue Accumulation' are shown. The transition conditional probability table for 'Fatigue accumulation' is in Table 2.22.

Abaei et al. (2019) applied dynamic BBN to a human reliability model for marine and offshore operations in harsh environments. Instead of modelling fatigue in an equipment, the model attempts to model fatigue in a human operator according to four different performance shaping

Table 2.22: Transition Conditional Probability Table (elicited by experts) for the event 'Degree of fatigue accumulation' over time, beginning at 'Step2' in Figure 2.22 in Chang et al. (2019)'s Dynamic BBN on fatigue in a subsea wellhead.

Violent Wellhead Response	Long operation	Fatigue accumulation (t-1)	Fatigue accumulation (t)		
			Severe	Moderate	Low
<i>True</i>	<i>True</i>	<i>Severe</i>	1	0	0
<i>True</i>	<i>True</i>	<i>Moderate</i>	0.9	0.1	0
<i>True</i>	<i>True</i>	<i>Low</i>	0.8	0.2	0
<i>True</i>	<i>False</i>	<i>Severe</i>	1	0	0
<i>True</i>	<i>False</i>	<i>Moderate</i>	0.8	0.2	0
<i>True</i>	<i>False</i>	<i>Low</i>	0.1	0.8	0.1
<i>False</i>	<i>True</i>	<i>Severe</i>	1	0	0
<i>False</i>	<i>True</i>	<i>Moderate</i>	0.8	0.2	0
<i>False</i>	<i>True</i>	<i>Low</i>	0.1	0.8	0.1
<i>False</i>	<i>False</i>	<i>Severe</i>	1	0	0
<i>False</i>	<i>False</i>	<i>Moderate</i>	0	1	0
<i>False</i>	<i>False</i>	<i>Low</i>	0	0	1

factors:(i) weather condition characterised by sea state, (ii) extreme roll with a parent link from (i), (iii) noise and vibration and (iv) work condition with a parent link from (i). One key performance shaping factor is that of the weather condition, as that is a parent link to other performance shaping factors as well. The performance shaping factors have three possible states of severity : 'extreme', 'moderate' and 'normal'. The difference between Abaei et al. (2019)'s model and that of Chang et al. (2019) is that there is a stochastic wave profile determined, and then discretised into weather conditions of varying states 'extreme', 'moderate' and 'normal' based on wave height and peak spectrum of wave period. In Chang et al. (2019)'s model, the expert carries out the judgement on when a particular operational scenario is considered 'severe' or 'moderate'.

Liu et al. (2015) also utilises dynamic BBN to analyse human error across three categories of factors: (i) individual factor barrier failure, (ii) organisational factor barrier failure and (iii) group factor barrier failure. The dynamic nodes considers repair and no repairs, and the option for repairs at selected nodes drives its dynamic nature. For example, a node 'Control system failure at t=0' updates itself for the node 'Control system failure at t=1'. With repair, the conditional probability table takes on values according to the exponential distribution of repair time.

A sample transition probability table between a node with self link (Table 2.23):

Table 2.23: Transition Conditional Probability Table with repair for the event 'Control system failure' over time in [Liu et al. \(2015\)](#)'s Dynamic BBN on human error in offshore operation.

Control system failure ($t = 1$)	Control system failure ($t = 0$)	
	<i>True</i>	<i>False</i>
<i>True</i>	$e^{-\mu T}$	$1 - e^{-\lambda T}$
<i>False</i>	$1 - e^{-\mu T}$	$e^{-\lambda T}$

2.6 Software review

There are a number of software specialising in analysing BBNs. The ones with a graphical user interface are easy to get started with, because of the click-and-draw interface. Two examples reviewed are GeNie ([BayesFusion, 2018](#)) and Agenarisk ([Agena Ltd, 2019](#)). There are also command-line software options of R, BUGS, Matlab, Python etc. As the nature of the research does not require custom programming in order to conduct the analysis, the ones with graphical user interface is used to analyse the model. In most papers where BBN is employed, specialised software with graphical user interface has been used. The models mentioned in the above section (see Table [2.14](#) and [2.15](#)) all make use of specialised BBN software.

In this thesis, the software GeNie is used initially up until it is required to extract a value from a continuous distribution. GeNie is extremely intuitive and easy to use, however it does not allow for the extraction of a value from a continuous distribution. The software Agenarisk, while less intuitive, allows the extraction of practically any statistical value from a continuous distribution, which makes it useful for the HEP elicitation (see Figure [2.24](#)).

A simple test case is run in both GeNie and Agenarisk to illustrate that the software is able to calculate simple system reliability models correctly, such as a Fault Tree analysis. The data used in the Fault Tree is found in Table [2.24](#).

Table 2.24: Data used in the Fault Tree in Figure [2.26](#)

Fault tree events	Probabilities
P(Equipment 1)	0.1
CCF β -factor	0.02
P(E1)/ P(E2)	$(1-0.02)*0.1 = 0.098$
CCF	$0.02*0.1 = 0.002$
P(Failure)	$= E1, E2, X(12) = 0.098*0.098 + 0.002 = 1.16e-2$

Table 2.25: CPT of the control node.

	No cause	Fail				Not Fail			
	Independent cause	Fail	Not Fail	Not Failed	Not Failed	Fail	Not Fail	Not Failed	Not Failed
	Common cause	Fail	Not Fail	Fail	Not Fail	Fail	Not Fail	Fail	Not Fail
Control node	No cause	0	0	0	1	0	0	0	0
	Independent	0	0	0	0	0	1	0	0
	CCF	0	0	0	0	0	0	1	0
	N/A	1	1	1	0	1	0	0	1

Figure 2.24: A comparison of the BBN software GeNie and Agenarisk. Agenarisk is less intuitive, but allows the extraction of practically any statistical value from a continuous distribution.

Figure 2.25: Mapping a Fault Tree into a BBN (in GeNie)

2.7 Knowledge gap and proposed model

In summary the problems faced by the industry are the following:

1. Large-scale project management and multi-pronged options analysis required to plan and execute an offshore decommissioning operation
2. Increasing interest to adopt risk assessment techniques of other industries for the offshore industry, such as in the area of dependent failure or the role of human error.
3. Piece-wise, segmental risk assessment based on traditional risk assessment methods, without consideration of long-term effects of a decommissioned structure

Thus it is proposed to have a framework for conducting Options Analysis for decommissioning options which includes a traceable form of expert judgement, and the ability to reflect evidence with multiple factors of unknown status. A BBN is proposed to be used as it allows the representation of knowledge and decision support under uncertainty. A BBN can also be used to model dependencies in system reliability concepts, thus this overcomes the underestimation of risks in existing methods which assume independence between events.

An outcome of the analysis could be what is shown in Figure 2.27. In Figure 2.27, Activity 1 could refer to a chosen decommissioning option that represents the best solution (at that point in time, and given the technological development and amount of resources). Modelling it in a BBN allows the model to have input from location-specific information, and the consideration of dependencies, and thus a higher, more likely risk profile. Industry average risk is likely to be underestimated (if calculated from traditional methods). However, the converse is also true where a second Activity (Activity 2, Figure 2.27) could reflect a risk profile lower than the industry average risk, as it is specific to the activity and local conditions. The consideration of Human Reliability Analysis and Dependent Failure Analysis will be able to differentiate the risk profile between activities.

It is proposed to utilise the expert elicitation method by Podofillini and Dang (2013) where the quantitative and qualitative scale of HEP is anchored to the initial calibration points for the experts mentioned in the ANTHENA method (J. Forester et al., 2007), as the model is able to present the elicitation with uncertainty, and then quantify with consideration of uncertainties incorporated in it (such as specifying the Error Factor, or the median, 5th and 95th percentile values). Its other merits is also summarised in Tables 2.14 and 2.15 where it can also consider multiple states, and continuous variables. Also, this eliminates one element of subjectivity

required of the analyst, i.e. the determination of the impact of the performance factors on the error probability (which is computed by the model).

Current industry practices skew towards *in situ* decommissioning options and regulations warrant monitoring for the majority of decommissioning options. In order to consider the long-term effects, it is proposed to use a dynamic BBN with the method by [Chang et al. \(2019\)](#) method to estimate accumulative fatigue effects to postulate the risk profile in the future. At any given point in time if an evidence is observed, example, that there is a leak in a permanently abandoned well, then this could imply that the risk of leaks from other wells abandoned in a similar manner (same crew, same technique, same subsea conditions) could also leak, and preemptive action could be taken to minimise the spread of leaks.

Thus the remainder of the thesis will describe the methods for integrating (i) options analysis (ii) human reliability analysis (iii) dependent failure analysis for risk management in the short to long term.

Figure 2.27: Proposed risk model that can provide results for critical activities and considerations of long-term monitoring indication.

Chapter 3

Expert elicitation and aggregation for decommissioning

3.1 Preamble

This chapter presents the expert elicitation models for three different parts of the risk model: 'Options Analysis', 'Human Reliability Analysis' and 'Dependent Failure Analysis'. As each model analyses different components, the elicitation process differs slightly as well. In the case of 'Options Analysis' the result of interest is a score (0 - 100) or a percentage of success (0 - 100) and the elicitation scale would suit the numerical setting. In HRA, the result of interest is human error probability ($1e-5$ - 1) which is usually assumed to be distributed log-normally. Dependent failure analysis is usually based on established common cause failure models, thus the expert judgement is in the form of questionnaires and is elicited as separate coupling factor between joint CCF groups.

3.2 Options Analysis

The options analysis case study chosen is for a group of wells in the Cormorant field in the North Sea ([Lloyd's Register, 2019](#)). This section refers to Step 3: Well P&A of the decommissioning procedure in Figure 2.1. The wells are reviewed for their current well integrity in terms of the Lloyd's Register barrier standards (SIMTS-ST-002) and solutions are then proposed according to Offshore Installations and Wells Regulations 1996 (SI 1996/913) [Department for Business](#)

[Energy and Industrial Strategy UK \(2011\)](#) and the sections relevant to well decommissioning are 13, 15 and 16 which cover well integrity, design for decommissioning and materials. Some key requirements are summarised below:

1. Environmental plug - single cement barrier, typically a minimum of 100 ft of good cement, isolating any pressure-containing annuli. Rock to rock isolation is required, which implies that the milling of a section is required in order to establish contact in the rock on the outside of where the casing was (before the milling took place). Good cement is defined as cement having been verified in quantity and quality.
2. Environmental cap - single cement barrier, typically a minimum of 100 ft of good cement, isolating any annulus that contains oil-based fluids. Rock to rock isolation is not required.

The difference between an environmental plug and an environmental cap lies in the rock-to-rock isolation requirement, which is a full cross-sectional barrier extending towards the formation usually where the annulus material disqualifies as an annular barrier. This suggests that the section of the casing needs to be milled (removed), so that the cement establishes contact with the rock layer. This step is usually required if the cement quality in the annulus is poor, thus suggesting that leakage paths exist. Further details on verifying annular cement quality is expanded in Section [3.2.1 Options criteria](#).

Problem statement: The traditional methodology (see Figure [2.3](#)) involves the assessment of options against current knowledge of well status, in particular the integrity of the casing and liner cement with a reasonable chance of success elicited by the expert. The value of the chance of success is elicited based on an expert judgement, and usually corresponds to only a single value without traceability to how the expert obtains this number.

The proposed improved method (see Figure [2.4](#)) is systematic and still involves the assessment of options against current knowledge of well status. As a BBN is proposed to be used, the elicitation of the conditional probability tables is required. The difference therefore lies here: the elicitation of the conditional probability table requires the expert to consider a series of crucial and possible extreme scenarios that provides an indication of the chance of success (divided across 5 states). With the current knowledge of well status reflected in the BBN model, the model can compute the chance of success from the given observation and the earlier provided information on the indication of the chance of success. The elicitation procedure also considers the uncertainties (on the expert, and on the chance of success) to derive this particular chance of success so that the final chance of success can also be described in terms of a probability distribution with median,

mean, standard deviation values.

3.2.1 Options criteria

In order to understand the options of abandoning a well, a summary of well plugging and abandonment is discussed. In General, there are three phases to Well P&A. Phase 1 refers to reservoir decommissioning, where the primary and secondary permanent barriers are set to isolate all reservoirs' producing or injection zones. At this stage, the tubing is left in place, partly or fully retrieved. This phase is considered complete when the reservoir is fully isolated from the wellbore. Phase 2 refers to intermediate decommissioning, where the barriers are set to intermediate hydrocarbon or water -bearing permeable zones and potentially installing near-surface cement. It involves installing isolating liners, conducting section milling, retrieving sections of casings. Phase 3 refers to the removal of the wellhead and the conductors.

At each phase where there is a need to enter a well, a generic summary of steps to enter and cement a well is listed below:

1. Establish vessel on location. Perform dynamic positioning trials. Locate wellhead and survey.
2. Inspect wellhead.
3. Remove debris from well, if applicable.
4. Perform wellhead metrology.
5. Install Guide Cone to wellhead.
6. Install cementing system into wellbore.
7. Perform system / well pressure tests.
8. Perforate 10 3/4" casing into 'A' Annulus with lower 3 3/8" guns at 500ft BML (Below the Mud Line). Monitor for pressure and, if any, bleed off (max 40 gals).
9. Perform formation integrity test.
10. Perforate 10 3/4" casing into 'A' Annulus with 2" upper guns at 5ft BML.
11. Establish communication and circulate annulus clean, recovering the returned fluids to vessel storage tank. Circulate out the annular fluids until clean, flushing will continue until returns are visibly clean.

12. Pump dye pill to determine effective clean-up. Continue circulating to clean up if volume indicated by dye pill is less than 95% of actual volume and repeat dye pill.
13. Mix and circulate balanced cement plug into 10 3/4" casing and 'A' Annulus.
14. With 8 bbls cement left to pump, pressure the drop sub line and release the lower guns.
15. Displace cement out of the umbilical with 4 bbls seawater.
16. Deflate packers and circulate SWAT system clean of any cement returns.
17. Wait on cement.
18. Inflate upper packer and pressure test the cement in the 10 3/4" casing and the 'A' annulus. Pressure test plug.
19. If a satisfactory test is not obtained then attempt to circulate the annulus clean, perform another injectivity test and spot another cement plug. This process will continue until an acceptable test is obtained or until it becomes impractical to pump further cement.
20. Deflate the packer and recover the perforating system to the vessel.
21. Tag top of cement plug (expected depth 50 ft BML).
22. Recover guide cone from wellhead to vessel.
23. Sever casings 10ft BML.
24. Confirm wellhead is free. Examine rigging with ROV prior to lifting. Pick up and recover wellhead to surface.
25. Conduct ROV survey around wellhead and recover all well-related debris.

The following well scenarios would impact the option proposed for abandoning the well:

1. Minimum safe abandonment depth (MSAD) - this depth must be fulfilled by all plugs intended to permanently isolate the reservoir
2. Verification of cement - a key issue dictating the abandonment method. Records are often poorly kept. Where there is insufficient data (existing records or in-depth search) to verify cement integrity, other *in situ* methods for verification need to be undertaken and then the results of this verification is used to update the assessment of options. Some options are: inserting a tool to take ultrasonic images or installing new barriers which is verifiable

such as section milling or perforation and washing for remedial casing cement jobs. The verification is conducted in the (i) wellbore barriers (ii) annular barrier and in temporary well plugs (if any).

The guidelines (Lloyd’s Register barrier standards (SIMTS-ST-002) and Offshore Installations and Wells Regulations 1996 (SI 1996/913) ([Department for Business Energy and Industrial Strategy UK, 2011](#))) state that the **wellbore barrier** should be verified by an appropriate combination of the following:

1. Strength development of the cement slurry to be confirmed
2. Position of barrier to be verified by tagging, calculation or measurement to confirm depth of the cement plug (Example positions of such a barrier are identified in Figure 3.1)
3. Pressure test conducted should be ≥ 500 psi above the leak off pressure below the barrier (e.g into perforations or an open formation below the casing shoe), but not exceeding the casing strength minus wear allowance, or damage to the primary casing cement whichever is lower. Zero leak rate should be achieved at the stated pressure test condition.
4. Sonic logs from ultrasonic inspections can be used to evaluate casing integrity from echo amplitude and the travel time to provide images on the condition of the inside casing surface (e.g. pits and gouges) while travel-time and resonant-frequency analysis can provide information on casing thickness. Such an assessment is usually interpreted by an well log analysts.

The guidelines (Lloyd’s Register barrier standards (SIMTS-ST-002) and Offshore Installations and Wells Regulations 1996 (SI 1996/913) ([Department for Business Energy and Industrial Strategy UK, 2011](#))) state that the **annular barrier** should be verified by an appropriate combination of the following:

1. Records of cement operations - for example volume pumped, returns during cementing at different pressures, centralisations
2. Sufficient annular isolation through the original cement job. If the quantity of annular cement is to be based on differential pressure or monitoring volumes during the original cement job, then a longer cement column may be required to allow for uncertainty.
3. Casing pressure history

4. Modelling of well life-cycling loading
5. Logs - for example cement bond, temperature or sonic logs
6. Sampling of annular fluids

The guidelines (Lloyd's Register barrier standards (SIMTS-ST-002) and Offshore Installations and Wells Regulations 1996 (SI 1996/913) ([Department for Business Energy and Industrial Strategy UK, 2011](#))) state that the cement plug should be verified by an appropriate combination of the following:

1. A cement column should have a minimum of 100 ft of good cement to constitute a permanent barrier whether inside or outside the casing.
2. The internal cement plug should be adjacent to the annular good cement over an accumulative distance of 100 ft of cement length overlap.

Figure 3.1: Schematic of a PA Well (adapted from [Nichol and Kariyawasam \(2000\)](#)) with well barriers demarcated. Barriers 'B1', 'B2' and 'B3' correspond to the barriers to be analysed.

In a sample well from the report by [Lloyd's Register \(2019\)](#) on a well abandonment study of a 14,000 ft deep well, there were a number of crucial sections of the well in which the status of it was unknown. The current well status has the following information :

- The well is temporarily abandoned with a 10 ft cement plug situated at 10,494 ft, supported

by an inflatable bridge plug set in 2008. Report on this activity indicated that there was difficulty in passing through at a depth of 5452 ft. - *Obstructions in well?*

- At the 13-3/8" liner, old cementing reports indicated that the cementing job was performed in 1979, thus the quality of cement in the liner needs to be validated. - *Documentation on cement quality*
- At the 9-5/8" casing, there are conflicting reports on whether there is cement or not in the wellbore. This has a high impact on potential abandonment options. - *Documentation on cement quality*
- At Side-track 1, there is no clear evidence of abandonment in the well. - *Obstructions in well?*
- At Side-track 2, there is evidence that two plugs were set at 11,400 ft and 11,000 ft and that plugs have been pressure tested. - *Pressure test result?*
- At Side-track 3, there is evidence of plugs set, but no evidence of plugs being tested. - *Ultrasonic Inspection result*

Thus, some of the influencing factors indicated in italics above can be described graphically as in Figure 3.2.

The options for analysing a particular abandonment option are based on the existing integrity of casing and liner cement. The general principles applied to the options analysis process are based on the certainty of cement verification. This is usually based on reviewing the documents made when the well was set, which may include old documents that could be decades old. If there is uncertainty over cement quality, other *in situ* assessment methods are required, such as conducting an ultrasonic inspection or a pressure test. Location-specific factors, such as the potential to encounter shallow gas also influence the success of the proposed option. If a gas pocket is found at the depth at which perforation of the well casing is to take place, it will result in uncontrolled release of this gas, which is an undesirable consequence. The depths of interest relate to where the cement barriers are proposed to be located, i.e. along 'B1', 'B2' and 'B3' in Figure 3.1.

3.2.2 Score eliciting and aggregating

The Bayesian approach to aggregate expert estimates entails that the estimates concerning an unknown quantity (e.g. a HEP value or a probability of success) are used to update a prior belief

Figure 3.2: Influencing factors on the success of a well abandonment option which can be modelled in a BBN. The conditional probabilities of the influencing factors are proposed to be elicited by expert judgement. Zone A refers to the section of the casing where there is accumulation of gas, and where interaction with the casing is part of the proposed solution, such as sectional milling or perforation.

concerning that quantity. The underlying principle is that the quantity of interest, the probability of success, is distributed according to a normal distribution, with unknown parameters values. The expert opinion is then used to update the knowledge on the values of these parameters.

The score eliciting method proposed by [Podofilini and Dang \(2013\)](#) is used to elicit the conditional probabilities of the influencing factors on well abandonment. A simple example concerning two factors (see Figure 3.3) is used to describe the elicitation process. The node 'Presence of shallow gas in Zone A' has two discrete states: x_1 = 'Present' or x_2 = 'Not Present'. Zone A refers to the section of the casing where there is accumulation of gas, and where interaction with the casing is part of the proposed solution, such as to perform sectional milling (sectional casing removal) or perforating the casing (create holes) to establish a flow path. The node 'Ultrasonic inspection result' has three states : 'Good', 'Nominal' and 'Poor'.

In the case of presence of shallow gas, a 1999 drilling report ([Lloyd's Register, 2019](#)) indicated that there was a poor cement job with heavy losses at the 9 5/8" casing, coupled with uncontrolled releases of gases. This indicates shallow gas is likely to collect at the same depth in the future, thus 'Presence of shallow gas in Zone A' = 'Present'.

In 2012 an ultrasonic log inspection was conducted ([Lloyd's Register, 2019](#)). As the results rely on sound waves to generate a physical idea of the state of the formation behind the well, there is no certainty on whether there is shallow gas. The report provided an indicative probability that there is a 65-70% chance that the shallow gas is present behind the casing wall. Thus, 'Ultrasonic inspection result' = 'Nominal'. The uncertainty in the ultrasonic report likely arises due to the interference in the results from the multiple casings, and annulus cement in each casing.

Figure 3.3: Two factors influencing on the success of a well abandonment option which can be modelled in a BBN. The conditional probabilities of the influencing factors are proposed to be elicited by expert judgment. Zone A refers to the section of the casing where there is accumulation of gas, and where interaction with the casing is part of the proposed solution, such as sectional milling or perforation.

Table 3.1: Definition of the BBN output 'Success of well abandonment option'

State	State label	Reference value	probability	Probability range
1	Very high	1		(0.9,1)
2	High	0.8		(0.7,0.89)
3	Moderate	0.6		(0.5, 0.69)
4	Low	0.4		(0.1,0.49)
5	Very low	0.1		< 0.1

When dealing with discrete probability distributions, the Bayesian model can be written as:

$$\pi_j = k^{-1} L(E|j) \pi_j^0 \quad (3.1)$$

where $j = 1, 2, \dots, n$. π_j is the j -th element of the posterior probability distribution, $\pi = \pi_1, \pi_2, \dots, \pi_n$ of the variable of interest, x (e.g. the HEP). $\pi^0 = \pi_1^0, \pi_2^0, \dots, \pi_n^0$ is the prior distribution, updated in light of the evidence $E = i_1^*, i_2^*, \dots, i_N^*$, where N is the number of experts. Each element of the evident i_h^* represents the expert assessment that the i_h^* -th point in the scale applies to the assessment of the influencing factors on the HEP. The factor k normalises Equation 3.1,

over j to a probability distribution.

The likelihood term $L(E|j)$ is interpreted as the probability of evidence E given that the actual value of x is x_j over two elements:

- Matrix F , representing the inherent variability of the probability of success
- Matrix G , representing the confidence that the expert provides the correct probability of success

Similar to Table 2.20 in Chapter 2, Matrix F and G for the elicitation exercise are described below (see Tables 3.2 and 3.3). The difference is that a normal distribution is assumed instead of the lognormal distribution as the normal distribution better describes the reference probability range, which stems from 0.1 to 1. The lognormal distribution is used for HEP as each interval differs from the other by a factor of about 10, and the lognormal distribution describes better the probability range from 1 to 1e-4.

The well abandonment study (see Figure 3.9) shows a snippet of the report that the expert judgement is passed in terms of values of 0.3, 0.5, 0.7 (Lloyd's Register, 2019). The full table in the redacted report actually reports in terms of 0.2, 0.3, 0.5, 0.7, 0.8, which corresponds to five categories considered, thus five likelihood scales are considered (see Table 3.1).

Table 3.2: Elements of matrix F , where f_{ij} is the probability that the realisation of the probability of success is within interval i , given the realisation of the probability of the success is within interval j , given the median probability of success is x_j .

i	j				
	1	2	3	4	5
1	8.5e-1	1.7e-1	1.6e-3	3.8e-7	0
2	1.4e-1	6.7e-1	1.7e-1	1.7e-3	1.5e-9
3	1.1e-3	1.4e-1	6.9e-1	1.8e-1	4.8e-4
4	1.7e-7	9.6e-4	1.4e-1	7.9e-1	1.6e-1
5	6.2e-16	9.9e-10	3.2e-5	2.3e-2	8.4e-1

The element g_{ij} is the probability that the expert assesses $X = x_i$, when attempting to estimate x_j (i.e. when attempting to quantify probability of success of a well P&A event represented by x_j). For example, element g_{12} is the probability that the expert would assess the probability of success to be in the interval 1, when its realization is in interval 2. The elements of Matrix G are then modified to avoid too low probabilities (i.e. below 1e-2). It is not practical to suggest that expert estimates deviate by more than two intervals from the appropriate one, as indicated in Podofilini and Dang (2013). Therefore, elements with values below 1e-2 are set to 1e-2 as reported in Table 2.21.

Table 3.3: Elements of matrix G , g_{ij} = probability that the expert's assessment is x_i when attempting to estimate x_j - modified distribution tails with 1e-2 residuals.

i	j				
	1	2	3	4	5
1	7.7e-1	2.1e-1	1.0e-2	1.1e-2	1.0e-2
2	2.0e-1	5.8e-1	2.0e-1	1.0e-2	1.0e-2
3	1.0e-2	2.0e-1	5.8e-1	2.0e-1	1.0e-1
4	1.0e-2	1.0e-2	2.0e-1	5.8e-1	2.0e-1
5	1.0e-2	1.0e-2	1.0e-2	2.1e-1	7.7e-1

The factor labels and operationalisations may be considered too general ('Very Low', 'Very high'..): which experts may find difficult to specifically elicit a probability. To address this issue, [Podofillini and Dang \(2013\)](#) proposed an approach in which experts would be provided specific performance conditions, corresponding to for example human actions under a specified condition. These performance conditions are represented by the pattern of factor ratings under investigation. Continuing from the example above, this may be in the form of a specific well P&A failure event, in which the USIT result is 'Nominal' and the presence of shallow gas is 'No' (see [Table 3.4](#)). Once the experts have analysed the failure event and provided their estimates, the output of the approach in [Podofillini and Dang \(2013\)](#) is the probability distribution (continuous or discrete, depending on the case) of the HEP for the specific factor configuration under analysis. For example, for the scenario (See [Table 3.6](#), second last row) that there is no shallow gas present, nominal USIT result, the expert passes the judgement that the chance of success is at Level 2, which corresponds to a 'High' chance of success. This expert judgement of 'High' has a probability distribution as represented in the top right hand corner of [Figure 3.6](#). It is also highlighted that the combinations of the states of Shallow Gas, USIT Result and the 2 Well P&A Options (See [Table 3.6](#)) when inclusive of the 'Success' states is expanded as [Tables 3.6](#) and [3.7](#).

 Table 3.4: Single expert elicitation of the probability of success with respect to the influencing factors state combinations. The expert-assessed states take on values from 1 to 5 and their physical meaning can be interpreted in [Table 3.1](#).

Shallow gas	USIT Result	Well P&A Option	
		Set plug	Remediate
<i>Yes</i>	<i>Good</i>	3	4
<i>Yes</i>	<i>Nominal</i>	4	4
<i>Yes</i>	<i>Poor</i>	4	5
<i>No</i>	<i>Good</i>	1	1
<i>No</i>	<i>Nominal</i>	3	2
<i>No</i>	<i>Poor</i>	5	4

3.2.3 Supplementing the original options analysis model

The original options analysis model (see Figure 2.3) is a binary decision tree covering decision points at each stage of well status assessment. To incorporate the influencing factors on the binary decision tree, a section of the binary decision tree and the influence factors are modelled in a BBN.

Only two nodes from the binary decision tree and two influencing factors is included in the BBN model (see Figure 3.4). The two nodes from the binary decision tree are the 'Wellbore barrier verification' node and the 'Well P&A option'. Instead of Yes/No states at 'Wellbore barrier verification', the node takes on four states of Pass/Verified/Unverified/Fail. The 'Well P&A Option node' is made up of 2 solutions established from the binary decision tree.

Table 3.5: CPT entries in the node 'Well P&A option' of Figure 3.4

Wellbore verification	barrier	P	V	UV	F
Set plug		1	0	0	0
Remedial then plug		0	1	1	1

The CPT at the node 'Wellbore barrier verification' is set with equal prior probabilities of 0.25 per state. The CPT of Well P&A option is defined in a deterministic manner of a series of '1's and '0's. Where there is a slight uncertainty in the status of the wellbore barrier verification, the remedial option takes precedence as it is more conservative.

The node at 'Success' will be more complicated as it consists of more parent nodes and its has multiple-states in the parent nodes and its own node. From the expert judgement in Table 3.4 the generated CPT, with consideration of Matrix F (Inherent variability of the probability of success) and Matrix G (confidence that expert provides the correct probability of success) is reflected in Tables 3.6 and 3.7. The judgments are converted into probability distributions of the different probability ranges, (see Figure 3.5). In the single expert case, the peak of the probability distributions is the value assessed by the expert (Fig. 2 vs. Table 6). As presented in detail in Podofilini and Dang (2013), the uncertainty on the distributions combines the level of confidence in the expert estimates and the intrinsic variability of the success probability.

The 'Success %' node is a distribution of the elicited success levels across the five states (ranging from 'Very high' to 'Very low') and is calculated as a weighted sum of the distribution of the five different levels of success as explained in Chapter 2 (see Figure 2.21). The weights are the probability values from the prior 'Success' node. The distribution of each possible range of chance of success is based on the reference value of Table 3.1. There is an equation mechanism that can

Figure 3.4: BBN model comprising the two nodes from the binary decision tree and 2 influencing factors of the outcome of USIT results and Presence of shallow gas. The dotted cyan lines show the BBN nodes with respect to the original binary decision tree.

Table 3.6: CPT entries in the node 'Success' (Part 1 /2) of Figure 3.4. The CPT is generated from Table 3.4

USIT Result	Presence of shallow gas					
	Yes	No	Good	Nominal	Poor	
Well P&A Option	Set plug	Remedial then set plug	Set plug	Remedial then set plug	Set plug	Remedial then set plug
VH	0.0371	0.0099	0.0099	0.0099	0.0099	0.0108
H	0.2154	0.0364	0.0364	0.0364	0.0364	0.011
N	0.4497	0.2122	0.2122	0.2122	0.2122	0.0401
L	0.2586	0.488	0.488	0.488	0.488	0.2011
VL	0.0392	0.2535	0.2535	0.2535	0.2535	0.7369

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Figure 3.5: Conversion of the expert assessments (Table 3.4) in probability distributions based on a single expert. The expert judgement for 'Very low' is similar to 'Very high', except the State 5 would undertake the bulk of the distribution in decreasing order from States 4 to 1, i.e. the reverse of the judgement for 'Very high'.

be entered into the 'Success %' node to compute the weighted distribution based on the values of the weight from the previous parent node, 'Success'. The computing mechanism works in this manner: each state in the 'Success' node is a probability distribution therefore a median value of the expected density function of the probability of success can be obtained by the weighted sum of the individual density function of each probability of success level (see Table 3.8).

Table 3.7: CPT entries in the node 'Success' (Part 2 /2) of Figure 3.4.

Presence of shallow gas		No				
USIT Result		Good		Nominal		Poor
Well P&A Option		Set plug	Remedial then set plug	Set plug	Remedial then set plug	Set plug
						Remedial then set plug
VH		0.6662	0.6662	0.0371	0.252	0.0108
H		0.2693	0.2693	0.2154	0.455	0.011
N		0.4497	0.0448	0.0448	0.4497	0.238
L		0.01	0.01	0.2586	0.0451	0.2011
VL		0.0097	0.0097	0.0392	0.0099	0.737
						0.2535

Table 3.8: Summary of details used for obtaining the expected density function based on the Chance of Success elicited. The mean is based on reference probability value of the varying states; the standard deviation is assessed by judgement to be 0.1.

State (numeric)	State (description)	Reference probability value	Weights or Distribution from node	Distribution used is based on: $N \sim$ (Reference Prob. , 0.1)
1	Very high	1	1e-2	$N \sim (1, 0.1)$
2	High	0.8	3e-2	$N \sim (0.8, 0.1)$
3	Moderate	0.6	2.1e-1	$N \sim (0.6, 0.1)$
4	Low	0.4	4.9e-1	$N \sim (0.4, 0.1)$
5	Very low	0.1	2.5e-2	$N \sim (0.1, 0.1)$

3.2.4 Results

In the first section, the problem statement highlighted that in the traditional assessment of options, the value of the chance of success is directly elicited based on an expert judgement, and usually corresponds to only a single value without traceability to how the expert obtains this number.

The results of the proposed BBN method while including influence factors can be observed in two ways: the first is the 'Success %', which reflects the number most analysts are interested in - the median chance of success of a chosen well option. The second part demonstrates how the chance of success is arrived at.

The probability of success is a weighted sum across the multiple states of Success ranging from 'Very High' to 'Very Low'. Given the knowledge from the initial review that the wellbore barrier is on 'Unverified' status, and that the wellbore annulus needs to be remediated before a plug can be set, a survey of the well annulus is required. Assuming that the outcome of the ultrasonic inspection tool (USIT) result revealed nominal quality of the wellbore annulus and combined with the knowledge that there is no shallow gas present at the depth of interest, the 'success node' shows the distribution of the elicited varying levels of success (See Figure 3.6). The 'Success %' node calculates the estimated median probability of success. The median probability of success is 0.78 (See Figure 3.6 and 3.8). It can be noted that the state of 'H'/'High' takes on the bulk of the distribution, this suggests that it is likely that the median elicited probability of success would be in the range of 0.7 to 0.89 according to Table 3.1. This is usually the number that analysts are interested in.

The second part demonstrates how the chance of success is arrived at. The problem with the traditional elicitation method (see Figure 2.3) is that the value of the chance of success is elicited based on an expert judgement, and usually corresponds to only a single value without traceability to how the expert obtains this number.

One of the greatest benefits is the ability to track and trace how the expert arrives at the elicited chance of success (see Figure 3.9). In the past, the results are often just summarised within a table. With the BBN network, if there is presence of shallow gas, it is visible at once on what are the pertinent factors leading to the elicited chance of success. In this case, the pertinent factors are the outcome of an ultrasonic inspection and the presence of shallow gas.

The model is tested against another scenario where everything else remains the same, except for the presence of shallow gas. In the previous scenario, there is no presence of shallow gas. The

median chance of success for the 'remediate then plug' option dropped significantly from 0.78 to 0.41 (see Figure 3.8). If there is presence of shallow gas, the probability of success decreases to such that 'Low' state takes up the majority of the distribution of the elicited posterior probability (see Figure 3.8). The corresponding median probability of success is 0.41. This suggests that remediating the barrier may be impossible or, other methods need to be employed to increase the chance of success. Some examples are to (i) relocate the length of the cement plug, to other depths of the well where there is no shallow gas, while considering the Minimum Safe Abandonment Depth or (ii) to perforate at the location where shallow gas exists but with a more expensive and comprehensive option of chartering a drill rig in order to have a Blow-Out Preventor to mitigate the effects of uncontrolled release of gases.

A replication (in Matlab, see Figure 3.7) of the expected probability density of the probability of success is obtained from the weighing of each probability density function with the median in the distribution of $P(\text{Success}) = \text{Very High, High, Moderate, Low, Very Low}$ and error factor = 5. The graph range is shown to be same as the one elicited in the BBN software to demonstrate the similar shape and values obtained in both the BBN software and calculation by doing a weighted sum of the states of 'Success' node. The simulation in Matlab agrees with the result obtained in the BBN software used - both obtained 0.78.

The proposed improved method is systematic and still involves the assessment of options against current knowledge of well status. As a BBN is proposed to be used, the elicitation of the conditional probability tables is required. The difference therefore lies here: the elicitation of the conditional probability table requires the expert to consider a series of crucial and possible extreme scenarios that provides an indication of the chance of success (divided across 5 states). With the current knowledge of well status reflected in the BBN model, the model can compute the chance of success from the given observation and the earlier provided information on the indication of the chance of success. The elicitation procedure also considers the uncertainties (on the expert, and on the chance of success) to derive this particular chance of success so that the final chance of success can also be described in terms of a probability distribution with median, mean, standard deviation values.

3.2. OPTIONS ANALYSIS

Figure 3.6: Two influencing factors on the success of a well abandonment option which can be modelled in a BBN. The expected probability density of the probability of success is then obtained from the weighting of each probability density function with the median in the distribution of $P(\text{Success}) = \text{Very High, High, Moderate, Low, Very Low}$ and error factor = 5.

Figure 3.7: A replication (in Matlab) of the expected probability density of the probability of success that is obtained from the weighting of each probability density function with the median in the distribution of $P(\text{Success}) = \text{Very High, High, Moderate, Low, Very Low}$ and error factor = 5. The model is truncated at $x=1$ as that is the limit of probability values. The graph range is shown to be same as the one elicited in the BBN software to demonstrate the similar shape and values obtained in both the BBN software and calculation by doing a weighted sum of the states of the 'Success' node. The median value in the CDF (purple square) is 0.78 which agrees with the value in the BBN model in GeNie [BayesFusion \(2018\)](#).

Figure 3.8: Probability of success for a scenario where USIT result = 'Nominal' and shallow gas is present. The median probability of success decreases to 0.41.

VS

4. Selected Abandonment Method

The detailed decision trees, abandonment diagrams and other details are contained in the appendices.

The table below summarises the methods and chance of success for phase 1 abandonment of each well.

Well	Contingent 1	COS %	Contingent 2	COS %	Other options
CA06	Cement plug on DP	70	Remedial Casing Cement + cement plug on DP	30	N/A
CA16	Cement plug on DP	70	Remedial Casing Cement + cement plug on DP	30	No action even required (depends on further verification of existing plugs)
CA21	Cement plug on DP	30	Remedial Casing Cement + cement plug on DP	70	Coiled Tubing (unlikely)
CA23	Bullhead through tubing	50	Cement plug on DP	50	Remedial casing cement + plug on DP

Figure 3.9: The analyst is able to understand how the chance of success is derived at one glance, including the pertinent conditions to pay attention to. The bottom snapshot shows how results are presented in well plugging and abandonment options analysis reports. The area marked in dotted lines can be presented with more details with the BBN model in the same figure.

3.3 Human reliability analysis

With increasing interest in Human Reliability Analysis (HRA) in the offshore industry, this thesis sets out to propose an adaptation of Petro-HRA (Taylor, 2017), a recently developed method in the petroleum industry. Chapter 2 introduced the HRA process and a description of PSFs (see Section 2.4) in combination with a Bayesian elicitation and aggregation method (Podofillini and Dang, 2013). In Podofillini and Dang's method, the quantitative and qualitative scale of HEP is anchored to the initial calibration points for the experts mentioned in the ANTHENA method

([J. Forester et al., 2007](#), p.3-75).

The Petro-HRA method is adapted from the SPAR-H method ([Swain, 1987](#)). Decommissioning of offshore facilities includes multiple phases which can include the warm suspension phase, the cold suspension phases and the removal phase. Some examples of activities in the warm suspension phase are pipeline decontamination and sectional removal or well plugging and abandonment. Well plugging and abandonment (well P&A) involves multiple tasks, and an expert assessment of location-specific risks such as the reservoir profile, and presence of gas deposits from its drilling history. A Well P&A event involves operator interactions and is thus selected as a case study in the paper. The case study covers barrier performance, such as the performance of kick detection, and HRA of these barriers. This analysis also meets one aspect of the QRA framework's requirements in demonstrating how the performance of barriers changes with different conditions.

The thesis proposes to combine two methods (listed below) to conduct the HRA. This section briefly introduces the Petro-HRA method, and the expert elicitation method by [Podofilini and Dang \(2013\)](#). However, the reader is referred to the earlier section on well plugging and abandonment options analysis for details of the elicitation procedure. Only the PSFs of Petro-HRA (adapted from SPAR-H) is referenced. However the PSFs are not calculated from the proposed levels and multipliers from Petro-HRA. The PSFs are instead characterised by four ranked states: Misleading/Error-forcing, Poor, Nominal and Good together with the expert judgement elicitation aggregation approach by [Podofilini and Dang \(2013\)](#). The risk assessment is evaluated in a Bayesian Belief Network in order to capture dependencies (arising from the same event, or consideration of a temporal dependency) and the ability to compute a so-named hybrid BBN consisting of continuous and discrete probability distributions.

Problem statement: The existing HEP elicitation and aggregation method in SPAR-H (and Petro-HRA) is linear and additive in nature, thus the consideration of all eight PSFs is crucial to have a significant impact on the HEP. Dependencies are considered as a overall factor on the HEP depending on the assessed dependency level. In the elicitation method utilised in this model, the expert could directly elicit a 'very high' level of HEP (ranging from e-1 to 1) based on the assessed states of just three PSFs. The three PSFs are usually shortlisted as the most crucial ones. This is not possible in the SPAR-H computation method. Dependencies are also mathematically accounted for in the conditional probability tables, this is one of the highlights of modelling HRA using BBN.

The second problem is that with any increase in PSFs, the elicitation procedure increases exponentially. The elicitation of two PSFs/influencing factors in Section 3.1 on Options Analysis

was conducted for each scenario - this is feasible for two PSFs. With an increase in one more PSF, the elicitation burden increases such that it is too much expert input into every part of the conditional probability table. This section also identifies a method of linear interpolation among certain crucial points in the conditional probability table to ease the elicitation procedure.

3.3.1 Performance Shaping Factors

The event of plugging and abandonment (P&A) of a well has been chosen for the application of the proposed combination of HRA methods. The well P&A event is carried out by a multi-purpose tool called the Claxton SWAT tool, which consists of pressure packers and guns to conduct perforations of a multiple-annuli well casing to establish circulation paths, and subsequently cementation in order to plug a well permanently. A Hazard Identification Study (HAZID) on the use of the Claxton tool in the North Sea has been conducted by Lloyd's Register. It identified two high risk initiating events would be (i) failure to perforate casing and (ii) failure to plug with cement. The first high risk initiating event 'failure to perforate casing' is analysed in this paper.

In most cases the contributing factors leading to an incident are modelled by Fault Tree Analysis and through system reliability analysis. The same methodology has been utilised by identifying the components and function of the SWAT tool, and modelled using a combination of AND and OR gates. The technique of mapping a Fault Tree is demonstrated and discussed in [Bobbio et al. \(2001\)](#). The reliability values used in the model are obtained from OREDA. The barriers in place which affect which consequence could arise are modelled in a BBN, based on techniques discussed in [Bearfield and Marsh \(2005\)](#). The barriers identified are (i) Depth Monitoring and Control, (ii) Access to Stronger Charges, (iii) Pressure Monitor and (iv) Well Kill Function.

There are three HFEs modelled in the study: (1) (Failure to be at) Right Start Point/Depth which refers to the depth at which the tool is lowered in order to begin the perforation process. It has to be at the right depth or sufficiently deep so as to meet the height of cement required to pass Well P&A requirements. This HFE can be identified as part of the failure event leading to the Initiating Event (IE) of 'Failure of completion of Perforating casing using SWAT'. The second HFE is the (2) Failure for the operator to detect required drop in pressure. After perforation has succeeded, this implies that the casing has been successfully perforated to an acceptable size, so that the cement slurry can be squeezed into the well casing annulus and the formation. Thus a sufficiently large pressure drop must be observed, which indicates perforations of an acceptable size. The second HFE is part of the third barrier 'Barrier 3: Pressure Monitor'. The third HFE refers the failure of conducting (3) Well Kill Function in case of an uncontrolled release of

hydrocarbons. In this case, it refers to a process called ‘Bullheading’, which means the physical dumping of a heavy fluid into a well. The heavy fluid provides a hydrostatic head to contain the uncontrolled release of gas/fluids. The operator needs to calculate the optimum bullheading pressure, while considering surface pressure limitations of equipment, formation fracture pressure, and also prepare a chart of strokes pumped versus pumping pressure to aid in the monitoring of the process and make corrective actions such as slowing down or increasing the pump rate as necessary. This HFE is included as a part of ‘Barrier 4: Well Kill Function’.

Out of the nine PSFs available, only the most relevant are included in the model. This is due to the elicitation burden of the proposed method, where greater than three PSFs will make it too tedious for the expert to elicit the probabilities. Some of the PSFs can be common and thus influence multiple HFEs, so this is where modelling with a BBN allows this dependency to be captured. In the SPAR-H method, only the most relevant PSFs are used in the calculation; the emphasis is on using the most appropriate PSF. There is also a need to avoid double counting of PSFs for example, Time and Task Complexity. Time refers to the difference between available time and required time, and not the overall time taken. Usually a more complex task takes longer than less complex one, but this does not necessarily imply a longer time taken for a task equates automatically to less available time. Thus, the driving PSFs should be selected.

There are nine PSFs to be considered based on the Petro-HRA method (See Table 2.10). In addition to the HAZID session in 2011, there was a site survey in 2012 in which an acoustic tool was sent into the well to determine whether shallow gas was present in the well. If shallow gas had been present, the Claxton tool could not be used to plug and abandon the well. In 2014, there was a trial session in the port to become familiar with its operations as the tool was mostly used in the UK segment of the North Sea, and not in the Norwegian part of the North Sea.

Based on the opportunities provided by the trial in the port, it was determined that the PSF on ‘Teamwork’ should not be a performance driver. Likewise, the proposal of the trial and participation of the trial session in the port shows there is a positive aspect towards the PSF on Attitudes to Safety, Work and Management Support. Hence these two PSFs are dropped from being considered as negative performance drivers.

HFE1 refers to the task of determining the right depth at which the perforating tool should be lowered to a deep enough depth. This activity is dependent on the operator rightly observing the monitoring screen that displays the operational situation. Hence a proposed PSF that is a performance driver is Human-Machine Interface, defined as the quality of equipment controls, hardware, software, monitor layout, and the physical workstation layout where the operator/crew

receives information and carries out task (Taylor, 2017, p.75).

In the well profiles suitable for use with the Claxton tool, there ought to be a preliminary plug in place. One of the requirements is for the operator to calculate the theoretical top of this plug in order to verify the maximum depth of perforation. This information can be obtained from well records. Thus a proposed PSF based on this detail is the required experience to know which information to extract from well records in order to perform calculations. The definition in Petro-HRA refers to the number of times the operator has experienced the tasks/scenarios in question (Taylor, 2017, p.71).

The task occurs at the start of the operation and no perforation has been conducted yet. Hence it is relatively low-risk. Thus a PSF like a Threat Stress i.e. an event threatening to the operator's life or having severe consequences for the operators' self-esteem if they make an error (Taylor, 2017, p.69) is not a performance driver. The PSF Time, defined as the difference/margin between available and required time (Taylor, 2017, p.63), would also not be a performance driver, as this task occurs at the beginning of the operation, so sufficient time would have been allocated for this activity. The operators are monitoring from inside a drilling rig cabin, and thus there is no threat based on the definition of Physical Working Environment, which refers to accessibility, and working conditions such as a hard to reach place (Taylor, 2017, p.81).

The PSF Procedures is defined as a written document describing a series of decisions and actions steps to be performed by the operator to accomplish a goal safely and efficiently (Taylor, 2017, p.73). It can be used as a means to prepare for a task. From this perspective, this PSF is not a performance driver for the task of determining the right start depth. Since the HAZID process has identified that the correct depth needs to be determined, the procedures would not be lacking in determining this information. What is more crucial is thus whether the operator can extract the right information from old well reports.

HFE2, which is meant to determine if the perforation is successful based on the required drop in pressure, also depends on the operator correctly observing the monitoring screen. Thus, the PSF HMI is proposed as a performance driver.

The second PSF of interest is Time. HFE2 acts a detection state for monitoring pressure changes – there should be a required drop in pressure when perforation has been conducted. If pressure increases, it could indicate there is an uncontrolled release of hydrocarbons. If this step fails, it will impact HFE3, by reducing the available time in which the operator can rectify the situation.

The other PSFs of Threat Stress, Physical Working Condition, Task Complexity,

Experience/Training, and Procedures do not affect operator performance as much as the three PSFs identified, based on similar explanations mentioned while deriving the relevant PSFs for HFE1.

In HFE3, HMI remains a core PSF due to the reliance on monitoring screens in order to calculate the right amount of fluid to be ‘bullheaded’. The PSF Time is largely dependent on whether HFE2 successfully detected an anomalous operation condition. Since dependencies will be evaluated in the form of the probability of failure of HFE3 given HFE 2 has failed, this PSF is a crucial link to capture the failure probabilities which consider the temporal dependency. If HFE2 occurs, it implies that there is failure to detect the required drop in pressure arising from the perforation; this reduces the available time to respond to the anomaly. The third PSF of interest is Threat Stress, since at this stage; there is the risk of a blow-out, if the uncontrolled release of hydrocarbons is not well managed.

The other PSFs of Task Complexity, Experience/Training, Physical Working Condition, Procedures do not affect the operator performance as much as the three PSFs identified, based on similar explanations mentioned while deriving the relevant PSFs for HFE1. A summary of the PSFs, and how they relate to HFEs and overall risk model is summarised in Figure 3.10 and Table 3.9.

Figure 3.10: Human Failure Events (HFE) as part of barriers in the model. Note the dependencies existing between HFE from the performance shaping factors

Table 3.9: Summary of identified PSFs for the three possible Human Failure Events.

HFE no.	Description of HFE	Identified PSFs
1	Right starting point	HMI, Experience
2	Pressure Monitor	HMI, Time
3	Well kill function	HMI, Time, Threat Stress

3.3.2 Human Error Eliciting and Aggregating

Description of States of Human Failure Events

The qualitative scale used for the PSFs are referenced from [Podofilini et al. \(2014\)](#), in which the probability values ranges from Very Low to Very High in 5 ranked states. Each state corresponds to an order of magnitude of failure probability anchored to the initial calibration points for the experts mentioned in the ANTHENA method ([J. Forester et al., 2007](#), p. 3-75). This provides a scale of reference for the expert, and which indicates order of magnitude the HEP might lie.

Table 3.10: Definition of the BBN output 'HFE1', the qualitative impact scale with respect to failure probability values.

State	State label	Reference value μ_x	probability	Probability range
1	Very high	1		(3.2e-1,1)
2	High	1e-2		(3.2e-2,3.2e-1)
3	Moderate	1e-3		(3.2e-3, 3.2e-2)
4	Low	1e-4		(3.2e-4,3.2e-3)
5	Very low	1e-5		< 3.2e-4

The PSFs are characterised by four ranked states: Misleading/Error-forcing, Poor, Nominal and Good. In the case of HFE1, a total of $4 \times 4 \times 5 = 80$ conditional probabilities need to be

provided. The ‘4’ refers to the number of states in each parent node – the PSFs. The ‘5’ refers to the number of states in the child node – HFE. However, with Podofillini’s linear interpolation method, it reduces the elicitation burden significantly.

Elicitation of expert judgment

The model by Podofillini and Dang (2013) is one that ‘represents the human error probability as an inherently variable quantity’. This variability is a result of human performance, different type of tasks and other influencing factors. In the paper of Podofillini et al. (2018), the elicitation was carried out over a combination of negative performance conditions on a branch point of an event tree. The exercise carried out in this paper is similar, as the PSFs are selected based on how they drive a negative performance. This section discusses how HFE1 can be elicited with respect to the two parent nodes of ‘Experience/Training’ – PSF1 and ‘HMI’-PSF2. Based on the number of states of the parent and child nodes, the following table (see Table 3.11) needs to be filled with conditional probabilities.

Table 3.11: HEP elicited for HFE1 based on the two parent nodes of ‘Experience/Training’ – PSF1 and ‘HMI’-PSF2. For example, the expert assesses qualitatively that if PSF1 = Error-forcing & PSF2 = Misleading, the HEP should be ‘Very High’. The model will generate the corresponding probability distribution as seen in Figure 3.11.

<i>PSF2</i>	<i>PSF1</i>			
	Error-forcing	Poor	Nominal	Good
Misleading	Elicited HEP: (For <i>e.g.</i> <i>Very High</i>)	-	-	<i>High</i>
Poor	-	-	-	-
Nominal	-	-	<i>Nominal</i>	-
Good	<i>Nominal</i>	-	-	<i>Very Low</i>

The elicitation of the HEP also depends on the two matrices (Matrix F and G) which are used to provide the expert’s confidence in terms of his ability to assess the correct HEP or assess it to be one or more orders of magnitude off the correct HEP.

In terms of an expert elicitation of ‘Very High’ HEP, Figure 3.11 represents the corresponding probability distribution accordingly. After some of the elicitation is conducted, the bar charts are ‘shaped’ graphically to a normal curve which provides some form of graphing estimates . The so-called ‘mu’ and ‘sigma’ (curve fitting estimates) from this curve matching exercise are then put in a table similar to Table 3.11 and a linear interpolation (see Figure 3.12) is conducted (Podofillini et al., 2015) horizontally for the first and last row, and vertically for the first and last columns. The middle rows are interpolated horizontally. From the interpolated values of the ‘mu’ and ‘sigma’, the elicited HEP can be re-obtained from these graphing indices.

Figure 3.11: Elicited CPT based on expert judgement

Figure 3.12: Left figure: Probability distribution where the curving estimates 'mu' and 'sigma' are used to describe the distribution. These do not refer to the statistical information on the distribution. Right figure: Horizontal and vertical linear interpolation from the curving estimates of the elicitation procedure.

Figure 3.13: Expanded HRA model from Figure 3.10, which shows the multiple states in the PSFs and the HFE

Model input values

The end result for the node HFE1 would be a distribution of the elicited human error probability across the 5 levels of HEP, ranging from the states ‘Very High’ to ‘Very Low’. This represents the posterior probability distribution of the knowledge of the median HEP in light of experts. In most qualitative exercises, the median HEP is of the highest interest. In the same way as assessing the probability of success for the Well P&A event, the median value of the expected density function of the HEP is obtained by weighing the probability density function with the median and error factor 5. The probabilities expressed in percentages are the weights used for each corresponding distribution. A summary of the numerical details is found in Table 3.12. In the Agena software, the distribution can be entered as per each state of HFE1, HFE2 and HFE3 respectively (see Figure 3.14).

Table 3.12: Summary of details used for obtaining the expected density function based on the HEP elicited. The mean is based on the geometric mean of the varying states; the standard deviation is based on the error factor.

State (numeric)	State (description)	μ_x	Weights or Distribution from node	Distribution used is based on: LN $\sim$ ($\log(\mu_x)$, $\log(EF = 5/1.645)$)
1	Very high	1	3.31e-3	LN $\sim$ (0, 0.9784)
2	High	1e-1	4.64e-2	LN $\sim$ (-2.3026, 0.9784)
3	Moderate	1e-2	3.06e-1	LN $\sim$ (-4.6052, 0.9784)
4	Low	1e-3	5.02e-1	LN $\sim$ (-6.9078, 0.9784)
5	Very low	1e-4	1.42e-2	LN $\sim$ (-9.2103, 0.9784)

In dependent human reliability failure scenarios, the failure probability at one human failure event

Figure 3.14: The last column of Table 3.12 is used as input to obtain the posterior probability distribution of the knowledge of the median HEP in light of experts' judgement.

directly impacts the subsequent human failure event, such as the failure at HFE1 could result in less available time for action to be taken at HFE2.

These temporal dependencies are represented by time slices in a dynamic BBN, i.e. replication of the same BBN model, but with updates to the HFE1 in the time-slice of HFE2.

The main benefit to quantification in this manner is that conditional dependence is calculated (see Equation 3.2.

$$P(HEP) = P(HFE2 = Fail) \cdot P(HFE2 = Fail | HFE1 = Fail) \quad (3.2)$$

If conditional independence is assumed, then Equation 3.2 is adjusted to reflect the independence in Equation 3.3.

$$P(HEP) = P(HFE2 = Fail) \cdot P(HFE1 = Fail) \quad (3.3)$$

The conditional dependence $P(HFE2 = Fail | HFE1 = Fail)$ is calculated by setting the evidence at HFE1 to be 1 (Failure of HFE1 has happened). The evidence that has been input is propagated to the common nodes between HFE1 and HFE2 and thus updates the probability distribution at HFE2. A slight shift of the distribution can be observed as the states 'Moderate',

Figure 3.15: Modelling BBN in layers in order to capture dependent failures

‘Low’ and ‘Very Low’ are reduced, while there is an increase in the states ‘Very high’ and ‘High’. The shift of the probability distribution towards higher orders of magnitude of HEP at HFE2 thus represents the consideration of conditional dependence. The shift can be quantified as a median HEP value.

This also implies that the BBN is modelled in layers (see Figure 3.15). In order to calculate the HEP at HFE2 given that HFE1 has failed, the BBN layer for HFE2 has HFE1 reflected as failed. The update HEP is extracted and used to compute the overall HEP.

The CPT for HFE3 is in Appendix A.

3.3.3 Results

The problem statement in Section 3.3 highlighted that temporal dependencies are modelled based on an arbitrary scale which is not the most accurate way to account for dependencies. The second problem is that in a BBN, with an additional parent node, the elicitation burden on the child node increases exponentially. One way to work around this is to have expert(s) pass judgement on important/extreme scenarios in a CPT and interpolate the missing information from these

anchor points.

The result of the model can be looked at in terms of its result before consideration of conditional dependence and after considering of conditional dependence. The PSFs that make up HFE1, HFE2 and HFE3 have assigned levels (see Table 3.13). HFE1 and HFE2 only have two PSFs, with a common PSF - HMI. The results (1st column of Table 3.14) of the HEP at HFE1 (without conditional dependence) is $4.44\text{e-}3$, while that of HFE2 (without conditional dependence) is $8.49\text{e-}3$. In the elicitation of the CPTs, the expert deliberately assigned a greater importance to 'Time' factor than the 'Experience/Training' PSF. It can be observed that even though both PSFs are at 'Misleading' levels, the resulting HEP at HFE2 is greater than the HEP at HFE1. HFE3 is under the influence of 3 PSFs, one more than both HFE1 and HFE2, and with an additional PSF at the 'Misleading' level. The HEP at HFE3 (without conditional dependence) is $1.51\text{e-}2$, much higher than HFE2 and HFE1. This affirms that the CPT elicitation procedure can capture the nuances of one factor being more important than the other, and that the greater the number of negative PSFs, the greater the HEP. With respect to how accurate the value is, in SPAR-H (Swain, 1987), nominal HEP for a diagnosis category is at $1\text{e-}3$. The results of HFE1, HFE2 and HFE3 are greater than $1\text{e-}3$ as there is at least one PSF that is in a worse state than 'Nominal'.

The result of the model can also be looked at in terms of conditional dependence, which is the ability to consider dependent human reliability scenarios. At HFE1 (with conditional dependence), there is no conditional dependence to consider as that is the first HFE event. At HFE2, the conditional dependence considers if HFE1 has failed. The resulting HEP at HFE2 given that HFE1 has failed is $1.02\text{e-}2$, which is higher than if independent failure is considered at HFE2 ($8.49\text{e-}3$). At HFE3, the conditional dependence considers if HFE1 and HFE2 has failed. and the resulting HEP at HFE3 given that HFE2 and HFE1 has failed is $2.33\text{e-}2$. There is a 10% (HFE2) – 30% (HFE3) increase in the HEP for the accident sequence discussed here, which represents a substantial increase in the significance of the accident sequence, which would not have been discussed if conditional dependence has been ignored.

In the PHOENIX method (Ekanem, 2013), for a 2 time-slice calculation (i.e. HFE 2 with dependence on HFE1), the author also reported a 10% increase in the HEP obtained. In the Accident Sequence Evaluation Program (ASEP) method (Swain, 1987) the HEP for a dynamic task under moderately high stress is $5.00\text{e-}2$, and HFE3 (HEP = $2.33\text{e-}2$) which is a dynamic task under moderately high stress. The HEP from this modelling is slightly lower ($2.33\text{e-}2$ vs $5.00\text{e-}2$ but still fall within the ballpark of each other). In another study where the Success Likelihood

Index Model (SLIM) technique (a HRA method) is modelled in a BBN (Abrishami et al., 2020) in order to consider dependencies in the HRA, it is reported that the results modelling in a BBN (with consideration of dependencies) reflected a HEP value of 0.29, which is lower than the the HEP value of 0.34 (without consideration of dependencies), which also can be obtained through calculation by hand, based on equations outlined in the SLIM method. This suggests that the the equations may overestimate HEP because of the arbitrary scales used in the linear equations. The BBN is a more organic method of considering dependencies intrinsically which is embedded in the conditional probability table.

Thus, the results ascertain that the BBN model with temporal slices is able to capture temporal dependencies or conditional dependencies between HFEs. The BBN model is also able to reflect different extents of factor effects, such as two factors having the same negative state but one exerting a greater influence on the HEP as assessed by the expert, based on his experience. By comparison with other HRA models employed in a BBN (Ekanem (2013) and Abrishami et al. (2020)) the behaviour of the results agree with that obtained from this model - with dependent failures vs non-dependent failures, the difference ranges from 10% - 30%. At the same time, there are also scenarios that concurs with other BBN methods that the results generated from a BBN is lower than the HEP obtained from the linear additive methods worked through equations. The linear-interpolation method helps to reduce the elicitation burden, without compromising on the quality of the results.

The PSFs and the corresponding assessed levels are documented in Table 3.13.

Table 3.13: PSFs and the assessed levels.

HFE no.	Description of HFE	Identified PSFs and assessed levels
1	Right starting point	HMI = <i>Nominal</i> , Experience/Training = <i>Misleading</i>
2	Pressure monitor	HMI = <i>Nominal</i> , Time = <i>Misleading</i>
3	Well kill function	HMI = <i>Nominal</i> , Time = <i>Misleading</i> , Threat Stress = <i>Misleading</i>

The probabilities of the median HEPs with or without consideration of conditional dependence are summarised below:

Table 3.14: Posterior probabilities of HFE1 – 3 without and with the consideration of conditional dependence.

	No conditional dependence	With conditional dependence
i	Median $P(HFEi) = Failure$	Median $P(HFEi) = Failure$
HFE1	4.44e-3	4.44e-3
HFE2	8.49e-3	1.02e-2
HFE3	1.51e-2	2.33e-2

3.4 Dependent Failures Analysis

In offshore risk analysis, there is increasing attention towards modelling mechanisms that can capture dependencies in risk analysis. In 2017, the Bureau of Safety and Environmental Enforcement (BSEE) of US has issued a guideline ([Cross et al., 2017](#)) on how to include dependent failures in offshore risk analysis, in its overhaul move to turn offshore risk assessment in US from a checklist-based procedure to one that is goal-based. The proposed method of analysing dependencies references the strong development of dependency/common cause failures analysis in risk assessment in the nuclear industry. As the nuclear industry has long begun incorporating common cause failures in its analysis, there is sizeable quantity and quality relating to common cause failure data. This is not the case in the offshore industry.

However, a few researchers such as ([Guo et al., 2019](#)) have looked into utilising copula functions to define dependency among variables in a multivariate manner. The method can capture dependencies in greater detail but is more complex to implement. This paper aims to utilise the method of checklists, and categorical CCF to understand dependent failures. It is a step more advance than models like the Beta-factor CCF model. It also reduces assumptions made by the assessor as the factors are derived from answering checklist questions and is also less complex to implement.

Common Cause Failures if represented in a Fault Tree is also limited in terms of how dependencies can be propagated throughout the model. As such, the modelling technique proposed in this paper aims to cover how common cause failures can be modelled in a way such that results are updated (in light of evidence/observations) while considering dependencies among events, and how to model CCFs with limited information from databases.

The modelling technique is thus based on well-used/familiar risk analysis concepts, such as the Bow-tie risk model, and beta-factor common cause failure model, and adapting the methods from O'Connor's cause based methodology ([O'Connor, 2013](#)) for dependent failures (with data from a nuclear power plant common cause failure database), and SINTEF¹'s ([Hauge et al., 2015](#)) proposed methodology of using questionnaires to update a beta-parameter in the Beta-Factor model. The system is proposed to be modelled in a BBN due to its ease in representing dependencies between variables, and ability to adopt/map familiar risk analysis concepts in it.

Problem statement: There is increasing attention on CCF in terms of system reliability in offshore risk assessment. There are current methods which are simple to implement, or

¹Stiftelsen for industriell og teknisk forskning (Norwegian) for Foundation for Industrial and Technical Research)

comprehensive methods that are difficult to implement, and with features that are not meant to be used in CCF. The method proposed is an in-between solution, where it is one step more comprehensive than a CCF model that assumes a ratio of the equipment failure probability. The proposed method assumes a ratio of the independent failure probability in terms of CCF groups (such as environmental, material...) so that components can be linked across different CCF groups which is previously limited in a simpler CCF ratio model.

The other consideration on the decommissioning process is that the process takes place over a number of years. Ideally there should be a central model or documentation system that follows through the decommissioning process, so that data loss is minimal, and the judgement on the risk analysis process has reduced uncertainties as much as possible.

3.4.1 Common cause model parameters

Beta-Factor model

The CCF model proposed in this paper is the PDS ² (SINTEF) CCF model, which is an extension of the β -factor model (Hauge et al., 2015) whereby the parameter β represents the fraction of an item's failure that is a CCF. In the SINTEF PDS method CCF categories/causes have been divided into 3 groups namely (i) Design, (ii) Environmental Control (External and Internal) and (iii) Operation, maintenance and modifications which are further described in Table 3.15. In the PDS method, Operator Commission/Omission is included as part of Operation, Maintenance and Modifications.

Table 3.15: CCF categories and the respective examples to each category.

Design	Environmental control (external and internal)	Operation, maintenance and modifications
Component specification and manufacturing Material Selection	Climate and temperatures - Ice, snow, fog, rain, sea spray Variability in climatic conditions	Installation commonalities: procedures and routines Latent failures introduced during commissioning, installation and modifications
Complexity	Sand dirt hydrates and deposits	Maintenance commonalities- procedures and routines Management of change
Associated utility systems Software/Logic Prior Use	Corrosion and erosion	

The PDS method (Hauge et al., 2015) provides a mechanism to update a generic β -factor through

²Paalitelighet og tilgjengelighet av Datamaskinbaserte Sikringssystemer (Norwegian) for Reliability and Availability of Computerized Safety Systems)

a checklist of questions to obtain a facility-specific β -Factor. The answers to the questions are weighted according to the CCF categories (see Table 3.15), by proportion of occurrence based on a database frequency analysis and given a score according to the answer to the question. The score (see Table 3.16) proposed in the PDS method is based on a scaling method comparable to that used in NUREG/CR-6268 2007. The proposed scoring system consists of a weight and score system that addresses the problem of low sensitivity to changes in scores, which are found in methods utilising simple summation of scores arising from positive and/or negative answers.

Table 3.16: Example of checklist calculation with the score and weightage assigned to the CCF categories.

CCF category	Weight	Defence	Score	Modification Factor
Environmental control	45%			
Is system likely to operate always within the range of temperature, humidity, corrosion, dust, vibration, over which it has been tested, without the use of external environmental control?	6%	Has specific measures for control of the corrosive environment been implemented such as material choice, corrosion inhibitor on the Claxton tool?	0.1	0.006
Are all signals and power cables separate at all positions?	4%	Has physical measures for separating the signals and power cables been implemented?	1	0.04
...	...%	...	...	...
<i>Partial sum</i>	45%	-	-	1.3
Design control	20%	...	...	A
Operation, maintenance & modifications	35%	...	...	B
Total sum	100%		1.0	$1.3 + A + B$

Representing the β -Factor model in a BBN is tricky because of the difficulty in representing mutually exclusive states from the same parent node. [Fenton et al. \(2016\)](#) described a way to represent mutually exclusive states through the addition of a middle node between the parent and child node, and applying virtual evidence to the “control node” to work around this issue. Entering virtual observations (evidence) is similar to entering evidence. The main difference is that instead of observing a state of a node, a probability distribution is added over all states of the node.

In a Fault Tree analysis of a simple system of two pieces of equipment, the independent failure probabilities of each piece of equipment and a common cause failure have been demonstrated in

Figure 2.5 , based on sample values in Table 2.24 in Section 2.6. An equivalent representation is shown in Figure 3.16 with more expanded details to the BBN. In the additional nodes, the conditional probability tables (CPT) can be expressed based on the following deterministic way for the Control Node and the Equipment Nodes. The reader is referred to Table 3.17 (Fenton et al., 2016) for descriptions on how the CPTs are filled or. The software used for this analysis is GeNIe (BayesFusion, 2018).

Table 3.17: CPT of the control node.

	No cause	Fail				Not Fail			
	Independent cause	Fail		Not Failed		Fail		Not Failed	
	Common cause	Fail	Not Fail	Fail	Not Fail	Fail	Not Fail	Fail	Not Fail
Control node	No cause	0	0	0	1	0	0	0	0
	Independent	0	0	0	0	0	1	0	0
	CCF	0	0	0	0	0	0	1	0
	N/A	1	1	1	0	1	0	0	1

The Virtual Evidence node is established from the methods outlined in the Fenton paper (Fenton et al., 2016). In this particular case, the Virtual Evidence node is to be filled as outlined in Table 3.18 in order to obtain the desired posterior distribution at the child node, i.e. that Equipment 2/1's failure probability is propagated as a joint consideration of its independent and common cause failure probabilities. The details of the equations on how the Virtual Evidence node is derived can be found in (Fenton et al., 2011) and in Appendix 3 of (O'Connor, 2013).

Table 3.18: CPT of the virtual evidence node.

	No cause	Independent	CCF	NA
<i>TRUE</i>	$Q/2$	$1-(1-\beta) Q/2$	$(1-\beta Q)/2$	0
<i>FALSE</i>	1- <i>ABOVE</i>	1- <i>ABOVE</i>	1- <i>ABOVE</i>	1

3.4.2 Increasing the level of detail of CCF analysis in a BBN

This section discusses how the level of detail in a CCF analysis can be expanded from a CCF factor, to multiple CCF categories such as that found in the questionnaire - namely (i) Design, (ii) Environmental Control (External and Internal) and (iii) Operation, maintenance and modifications (as described in Table 3.15).

Figure 3.16: Fault tree represented in a BBN, with corresponding values from Equations 2.2 and 2.3 from Section 2.5.3

Representing a more detailed CCF analysis

The representation of an analysis in a BBN allows for the flexibility of representing dependencies, and this feature can be extended to expanding the common cause failure to the contributing components. This is practical for representing situations where a piece of equipment, such as a valve can have the same maintenance procedures, but is installed in different parts of a platform, and thus exposed to different environmental conditions. Thus the first step is to expand the ‘Common Cause’ node to three different CCF categories, reflected as the ‘Env’, ‘Maint’ and ‘Design’ sub-model (see Figure 3.17). This method is adapted from O’Connor (2013). The difference is that the numerical data (equipment failure rate and CCF parameters) in O’Connor’s model is based on a count analysis of a CCF database of nuclear power plants. The contribution of each CCF category (i.e. Env-1) to the failure rate of an item is based on expert judgment of a direct value between 0 and 1, multiplied to the CCF parameter.

In the method proposed in this thesis, the multiplicative factor (the contribution of each CCF category to the failure rate of an item) is initially derived from a backwards calculation based on known initial failure rates and its initial generic β -Parameters. Through the adapted SINTEF PDS questionnaires, the initial generic β -Parameter is updated, thus updating the contribution of each CCF category to the failure rate of an item. Initial failure rates/probabilities and generic β -Parameters are obtained from OREDA (SINTEF Technology and Society et al., 2002) and the PDS Handbook (SINTEF Technology and Society, 2010) respectively.

The sub-model has the same mechanism shown in Figure 3.16, with the exception that ‘Common Cause’ node now reflects one of the three CCF categories that contributes to the overall common cause failure. The sub-modal function is used to provide a neater representation as modelling a mutually exclusive event in a BBN requires additional Control and Virtual Evidence nodes which clutter the model. An expanded ‘Env’ sub-model is reflected in Figure 3.17.

The representation of a more detailed CCF analysis also warrants the need of additional nodes feeding into ‘Equipment 1’. These additional nodes are the contribution of the individual CCF category to the equipment of interest. The CPT for the node ‘Equipment 1’ is modelled from the NOISY-OR concept. A few researchers (O’Connor, 2013; Abimbola et al., 2016) have used this technique in BBN modelling to reduce the amount of work required for CPT elicitation. Using a NOISY-OR gate provides a result between those obtained from using an OR and AND gate.

Figure 3.17: The three CCF categories are shown in this model: ‘Env’, ‘Maint’ and ‘Design’. An expanded ‘Env’ sub-model is reflected here. The sub-models illustrate how the CCF mode in the ‘Env’ CCF category is linked to the child nodes of ‘Env1’ and ‘Env2’. This is the same mechanism as in the simplified β -factor common cause model in Figure 3.16.

NOISY-OR Gate

The NOISY-OR gate is a type of canonical gate to describe the relationships among variables and their common outcome (Neapolitan, 2004). An assumption relating to this gate is that each cause is sufficiently able to lead to the outcome in the absence of other causes. Also, the ability of each cause to lead to the outcome is independent of the presence of other causes. Neapolitan (Masegosa and Moral, 2013) also explained that using a NOISY-OR gate is based on the assumption that the mechanisms that inhibit the cause act independently of one another, i.e. $\overline{Design}$, $\overline{Env}$, $\overline{Maint}$ act independently from one another to, which can be seen by the individual ‘No-cause’ nodes in each of the CCF categories. Another benefit of using a NOISY-OR gate is the CPT elicitation varies linearly with the number of parent nodes. For example, Equipment 1 has three possible causes of failing (or three parent nodes) comprising of ‘Env’, ‘Maint’ and ‘Design’. Thus only 3 probabilities are required to fill the CPT.

The probability of Equipment 1 (shortened as E1 for equations (1) to (3)) failing when only one cause condition exists is described by Equations 3.4, 3.5 and 3.6 :

$$P(E1 = Fail | Env1, \overline{Maint1}, \overline{Design1}) = p_1 \quad (3.4)$$

$$P(E1 = Fail | \overline{Env1}, Maint1, \overline{Design1}) = p_2 \quad (3.5)$$

$$P(E1 = Fail | \overline{Env1}, \overline{Maint1}, Design1) = p_3 \quad (3.6)$$

When multiple causes are present, the probability of Equipment 1 failing is the union from each failure cause.

$$P(E1 = Fail | Env1, Maint1, \overline{Design1}) = 1 - (1 - p_1)(1 - p_2) \quad (3.7)$$

$$P(E1 = Fail | Env1, \overline{Maint1}, Design1) = 1 - (1 - p_1)(1 - p_3) \quad (3.8)$$

$$P(E1 = Fail | \overline{Env1}, Maint1, Design1) = 1 - (1 - p_2)(1 - p_3) \quad (3.9)$$

$$P(E1 = Fail|Env1, Maint1, Design1) = 1 - (1 - p_1)(1 - p_2)(1 - p_3) \quad (3.10)$$

Based on the above three probabilities from Equations 3.4, 3.5 and 3.6, the other CPTs relating to the other situation where the other CCF causes are present or not can be demonstrated in a CPT as in Table 3.19.

Table 3.19: CPT for 'Equipment 1' node. Numbers in brackets refer to equation numbers.

Design	Maintenance	Environment	State of Equipment 1	
			E1	$\overline{E1}$
Design1	Maint1	Env1	(3.10)	1-(3.10)
Design1	Maint1	$\overline{Env1}$	(3.9)	1-(3.9)
Design1	$\overline{Maint1}$	$\overline{Env1}$	(3.8)	1-(3.8)
$\overline{Design1}$	Maint1	Env1	(3.6)	1-(3.6)
$\overline{Design1}$	Maint1	$\overline{Env1}$	(3.7)	1-(3.7)
$\overline{Design1}$	Maint1	$\overline{Env1}$	(3.5)	1-(3.5)
$\overline{Design1}$	$\overline{Maint1}$	Env1	(3.4)	1-(3.4)
$\overline{Design1}$	$\overline{Maint1}$	$\overline{Env1}$	0	1

Setting baseline parameters for CCF modelling

The initial parameters for the detailed CCF model are obtained by working backwards from the database-given failure probability of Equipment 1, *i.e.* $Q = 0.1$, and that all CCF categories contribute equally to the failure of Equipment 1, *i.e.* $p_1 = p_2 = p_3$.

The joint probability distribution of the 4 nodes 'Equipment 1', 'Env1', 'Maint1', 'Design1' can be expressed by the multiplication of the marginal probabilities of 'Env1', 'Maint1' and 'Design1' to the conditional probabilities of Equipment 1 (see Table 3.19). As an example, the first column in Table 3.19 for the state of 'E1' where the conditional probability Equation 3.10 lies, Equation 3.10 should be multiplied by the marginal probabilities as defined in the heading of the same column. The sum of each conditional probability, multiplied by the combination of the marginal probabilities defined in each conditional probability's respective heading of Table 3.19 equates to the posterior probability of Equipment 1 = Q .

Since all CCF categories contribute equally at the stage of setting parameters, this implies that $p_1 = p_2 = p_3$. Thus Equation (3.11) which is obtained from the multiplication of marginal probabilities of 'Env1', 'Maint1' and 'Design1' to the conditional probabilities of Equipment 1 can be expanded to Equation (3.12). Equation (3.13) is a neater representation of the same expression.

$$P(\text{Design1})P(\text{Maint1})P(\text{Env1}) \cdot Eqn(3.10) + \dots + P(\overline{(\text{Design1})})P(\overline{(\text{Maint1})})P(\text{Env1}) \cdot Eqn(3.4) = Q \quad (3.11)$$

$$(1 - (1 - p)^3)p^3 + 3(1 - (1 - p)^2)p^2(1 - p) + 3(p^2(1 - p)^2) = Q \quad (3.12)$$

$$p^6 - 3p^4 + 3p^2 = Q \quad (3.13)$$

$$Q = 0.1, p = 0.18577 \quad (3.14)$$

Therefore Env1 $p_1 = \text{Maint1}$ $p_2 = \text{Design 1}$ $p_3 = 0.18577$.

Assuming that the database recommended a CCF β factor of 0.02 (usually based on equipment class), this implies that the value for CCF (Env1) = $0.02 \cdot 0.18577 = 0.003715$. The ‘independent’ failure of (Env1) is calculated as $(1 - 0.02) \cdot 0.18677 = 0.182055$.

After the questionnaire has been answered, the outcome of the survey revealed that the β factor for the Environment CCF category should be multiplied by the outcome of the survey, i.e. $1.3 \cdot 0.02$, yielding an updated CCF (Env 1) to $0.0260 \cdot 0.18577 = 0.00483$.

The independent probability remains the same at 0.182055. Thus, the new Env 1 failure is calculated as the sum of the independent and updated common cause failure = $0.182055 + 0.004833 = 0.186888$, an increase from 0.18677.

From this, p_1 thus changes from 0.18677 to 0.186888 and the CPT table (Table 3.19) for Equipment 1 will be adjusted accordingly as well. The system failure probability will also thus be updated from the outcome of the questionnaire conducted.

3.4.3 A case study on a Well P&A event using a Suspended Well Abandonment Tool (SWAT)

The purpose of the case study is to show the following:

1. Without considering CCF, the failure probabilities of components in a FTA is inaccurate (usually underestimated), and this extends to the frequencies in consequence analysis. The proposed CCF models can give insights to relationships between events that is previously not covered in CCF-ratio models.
2. Decommissioning takes place over a number of years, thus, ideally there should be a central model or documentation system that follows through the decommissioning process, so that data loss is minimal, and the judgement on the risk analysis process has reduced uncertainties as much as possible.

This section discusses the application of the proposed CCF analysis method to a well plugging and abandonment event using a SWAT by [Claxton \(2015\)](#). The activity was modelled based on a Bow-Tie modelling technique and mapped into a BBN to facilitate the study of dependencies. The CCF analysis is applied to the Electrical Control Panels and Pressure Monitoring Panels and components inside the SWAT tool, such as the packers, firing and shear pins.

The Claxton SWAT tool consists of pressure packers and guns to conduct perforation of a multiple-annuli well casing to establish circulation paths, and subsequently cementation in order to plug a well permanently. In most cases the contributing factors leading to an incident are modelled by Fault Tree Analysis and through system reliability analysis. The same methodology has been utilised by identifying the components and function of the SWAT tool, and modelled using a combination of AND and OR gates. The technique of mapping a Fault Tree is demonstrated and discussed in [Bobbio et al. \(2001\)](#). The reliability values used in the model are obtained from OREDA ([SINTEF Technology and Society et al., 2002](#)). The values are scaled such that the analysis leading to the initiating event, ‘Failure to perforate casing’ and respective consequences, are in terms of failure frequency ($year^{-1}$), one of the most commonly used metric for quantitative risk analysis. The CCF analysis is conducted on nodes of interest (or ‘Basic events’ in an FTA) which are represented as probabilities. The barriers in place that affect which consequence could arise are modelled in a BBN based on techniques discussed in [Bearfield and Marsh \(2005\)](#). The barriers identified are (i) Depth Monitoring and Control, (ii) Access to Stronger Charges, (iii) Pressure Monitor and (iv) Well Kill Function. Based on Figure 3.18, it

can be observed that dependencies between the contributing events to an initiating event and its safety barriers can be modelled as well.

Figure 3.18: Conceptual model with expanded CCF factors on the activity of Well P&A based on Initiating Event 1: Failure to perforate casing. “CCF2” represents the β -factor model used in traditional CCF analysis.

The decommissioning process takes place over a number of years. In the particular case of using the SWAT tool in the North Sea, the process started in 2011 before a successful P&A was conducted in 2014. Figure 3.19 shows the different work phases before the tool was deployed. It was assumed that at each stage below, there was an opportunity to update the CCF questionnaire/checklist, thus updating the CCF parameters at every state where new information can be used.

Figure 3.19: Decommissioning planning takes place over a number of years.

At the HAZOP phase in 2011, the following risk factors were identified: (i) High Pressure in the Annulus, (ii) Too low perforation depth and (iii) Uncertainty in casing strength, a critical knowledge for emergency bull heading operations. The High Pressure in the Annulus stems from a history of shallow gas during drilling, and that there is a history of gas flow at the depth 1157m, which could have accumulated in the position of the lower perforation point along the well. If there is presence of shallow gas, then this method of Well P&A cannot be used. These details set the investigative context for the site survey.

In the site survey in 2012, an acoustic tool was sent into the well, and no shallow gas was detected in the annulus, implying that the SWAT method by Claxton can be used. The well was pressure tested for casing integrity, and passed the pressure test, implying that bullheading operations can take place if needed. For the purpose of this thesis, it is also assumed that at this stage the first questionnaire was carried out, and a dependency between the Shear and Firing pins of the SWAT tool is identified. Conceptually the CCF model can be represented in Figure 3.20.

In the trial in 2014, the author had no access to information on the activity, but understood the rationale to be to optimize operational handling prior to the actual event. It is also hypothetically set that the CCFs have been updated based on a second round of questionnaire, and dependencies were identified between the Electrical Control and Pressure Monitor Panels. These panels are located in same location and are exposed to the same environmental conditions.

It is highlighted that a similar model set-up for this dependency created as per Figure 3.20 also applies to the first CCF analysed between the Packers, Shear and Firing Pins, except Electrical Controls 1 and 2 should be referred to Packers 1 and 2, while Pressure Monitor Panels 1 and 2 should be referred to Shear Pins and Firing Pins.

In the actual P&A event in 2014, it was reported that there was insufficient penetration capability, which amounted to an insufficient circulation rate. Thus, a re-perforation is required, and the tool was removed and re-lowered with stronger explosive charges. At the second perforation, a sufficient circulation rate was established and 200m of cement was successfully logged as a permanent well barrier.

The full questionnaire is in Appendix B. The values used in the BBN are summarised in Table 3.20.

Figure 3.20: CCF in terms of the environment modelled for the electrical and pressure monitoring panels. This model layout is also applicable to the CCF analysis between the shear and firing pins found inside the firing mechanism of the SWAT tool.

Table 3.20: Summary of values used in the BBN in Figure 3.22. These values are obtained from OREDA (SINTEF Technology and Society et al., 2002)

Node	Probability
Right Start Point	Calculated from HEP model
Pressure monitoring panel	1.17E-04
Electrical control panel	1.82E-02
Hydraulic Lines (Interface at control panel)	6.73E-04
Lower Packer	2.39E-03
Upper Packer	2.39E-03
Operating Piston	2.95E-04
Shear Pins	1.79E-03
Firing Pins	1.79E-03
Detonator	1.80E-03
Sufficiency of Charge	1.80E-03

3.4.4 Results

In this analysis, the results consequences ($year^{-1}$) is used to follow the the changes in the risk profile over the decommissioning process. The process took place over 4 years starting from the desktop study phase in 2011, a site survey in 2012, a trial in port in 2014 and the actual P&A event in 2014. In most cases of risk analysis, consequence analysis is a key component. The consequences have been identified from the HAZID session, which are (i) Safe State, (ii) Schedule Impact Level 1 (< 8 hours), (iii) Schedule Impact Level 2 (> 8 hours) and (iv) Blow out.

The base case refers to the scenario where there are original dependencies from the β -factor model that have not yet been looked at a detailed level, i.e. one resembling Figure 3.16. The result of 2012, where the site survey has been conducted, shows a decreased frequency of safe state, and an increase in the remaining consequences. In this model, there is a dependency in the Environmental category that has been identified between Packers and the Pins as these objects will be exposed to the same conditions inside the well.

For the results relating to the trial conducted in port in 2014, the model reflects an additional detailed CCF analysis extended to the Electrical and Pressure monitoring panels. With a greater detail of CCF analysis, the dependencies are captured and reflected in the increase in failure frequencies shown in Table 3.21. In the last column 'Rectified', it refers to re-looking the questionnaire and identify where improvements could be made in order to reduce the CCF factors. An example is to change the protective cover on the pressure and electrical panels after it has been used for a year.

Table 3.21: Summary of results in $year^{-1}$ with respect to the decommissioning phases in Figure 3.18. Rectified refers to when the CCF factors are improved such that the beta-factor parameters have been reduced

	Base	2012	2014	2014 (end)	Rectified
<i>Safestate</i>	9.96e-1	9.96e-1	9.96e-1	8.88e-1	9.96e-1
<i>Schedule1 < 1day</i>	1.99e-03	2.02e-03	2.10e-03	5.29e-02	1.93e-03
<i>Schedule2 > 1Day</i>	2.20e-04	2.24e-04	2.90e-04	7.20e-03	2.16e-04
<i>Blow – Out</i>	1.97e-03	1.97e-03	2.04e-03	5.21e-02	1.93e-03

In the case of 2014 for the actual well P&A event, since it was observed there was an insufficient amount of explosive charges, the model was updated to reflect that observation in the node 'Sufficiency of Charge'- $P(\text{Sufficiency of Charge} = \text{FAIL}) = 1$ (see Figure 3.22, bottom left) and the corresponding results show a much higher risk profile than when CCFs alone were analysed in the model.

Figure 3.21: Results of Table 3.21 represented in a graph for 3 of the 4 consequence categories. Safe state is not represented here. The plot marked in squares refers to ‘schedule <1 day’; triangle refers to ‘schedule 2 > 1 day’; ‘x’ refers to ‘blow-out’.

Figure 3.22: A section of the BBN model showing the nodes leading to the initiating event, ‘Failure to perforate casing’

A guidance ‘Guidance on calculating blowout rates and duration for use with environmental risk analysis’ published by the Norwegian Oil and Gas (Norwegian Oil and Gas Association, 2014) has an overview on blowout frequencies ranging $5.0 \times 10^{-4} \text{ year}^{-1}$ (Drilling Phase) to $4.9 \times 10^{-3} \text{ year}^{-1}$ (Production Phase). The blow out frequencies obtained from the Base case (1.97×10^{-3}) up to the Trial in the Port in 2014 (5.21×10^{-2}), fall within this range.

The above results aim to show that the model can capture the scenarios which deviates from the safe state, and thus it can help to portray the risk picture where there are unfavourable situations to analyse.

When the questionnaire is conducted again after reflecting the improvements made to reduce the failures stemming from common causes, i.e. changing procedures or maintenance activities, this action reduces the β parameter to its lowest possible for the Environment category (0.045). The consequences are reduced and there is an improvement to the overall risk results (See the last column of Table 3.21 and Figure 3.21).

One of the strengths of using BBN is the ability to reflect observations into the model to analysis what-ifs scenarios of interest. In mapping the CCFs to this level of detail, i.e. by separating it according to its CCF category, it is feasible to analyse what happens, if during an inspection, it is noted that there is an Environmental related factor present (such as increased salinity/sea spray) at the location where the Electrical Panel is located, and there is no knowledge of the environmental conditions at the Pressure Monitoring Panel (perhaps due to inaccessibility). This can be reflected in the BBN model but setting $P(Env - Elect1 = FAIL) = 1$ (see Figure 3.20, the node in top left corner).

The results demonstrated that the dependencies linked by the ‘Environment’ category between the Electrical and Pressure Panels are captured. As $P(Env - Elect1 = FAIL) = 1$ is updated in the model, the $P(PressureMonitoring1/2 = Fail)$ increased from 1.21e-3 (No evidence reflected) to 1.57e-3 (see Table 3.22).

Table 3.22: Summary of probabilities of nodes of interest from the reflection of observations in CCF categories. The last row referring to the initiating event is denoted in $year^{-1}$

	No evidence (2012)	$P(Env - Elect1 = FAIL) = 1$	$P(ENV = Fail) = 1$
Pressure Monitor Panel 1 / 2	1.21e-03	1.56e-03	2.06e-02
Barrier 2	6.49e-32	6.81e-3	2.57e-02
Electrical Control Panel 1	1.83e-02	8.96e-02	8.96e-02
Electrical Control Panel 2	1.83e-02	1.96e-02	8.96e-02
Perforation Failure (Initiating Event)	3.78e-02 $year^{-1}$	3.94e-02 $year^{-1}$	1.25e-01 $year^{-1}$

Assuming the inspection now identifies that the CCF of environment is observed at both Pressure and Electrical Panels, and thus $P(ENV = Fail) = 1$, the probabilities $P(PressureMonitoring1/2 = Fail)$ increased from 1.57e-3 to 2.06e-2 since it is now affirmative that the CCF is observed at both location. This confirmation is also reflected in the higher frequencies $year^{-1}$ of the consequences (see Table 3.23), as compared to when no evidence was reflected.

Table 3.23: Summary of results in $year^{-1}$ of consequences from the reflection of observations in CCF categories.

	No evidence (2012)	$P(Env - Elect1 = FAIL) = 1$	$P(ENV = Fail) = 1$
<i>SafeState</i>	9.96E-01	9.93E-01	9.76E-01
<i>Schedule1 < 1Day</i>	2.02E-03	4.81E-03	1.52E-02
<i>Schedule2 > 1Day</i>	2.24E-04	2.54E-04	2.68E-03
<i>Blow - Out</i>	1.97E-03	1.90E-03	6.04E-03

As the evidence $P(Env - Elect1 = FAIL) = 1$ and $P(ENV = Fail) = 1$ is updated in the

Figure 3.23: Results of parts of Table 3.23 represented here. The magnitude of the failure probabilities is linked to the extent of the perceived strength of dependencies, i.e. failure probability increases with the increased confidence of a common cause factor present. The plot marked in squares refers to ‘Pressure monitor panel 1/2’; diamond refers to ‘Electrical control panel 2’, and asterisk refers to ‘Barrier 2’. The plot marked in ‘x’ (orange) refers to ‘Perforation failure (initiating event) and should be read to the axis marked as year^{-1} ’.

model, the dependencies captured in the model also extend to other nodes (see Figure 3.23). The Pressure Monitor Panel node is linked to the Initiating Event – Perforation Failure (i.e. the failure to perforate the casing to allow a circulation path to be established). At the same time, Barrier 2 (Pressure Monitoring) also relies on the Pressure Monitor panel as a form of safety barrier. The failure probabilities of these nodes varied in accordance with the type of evidence reflected, i.e. with the evidence $P(\text{Env} - \text{Elect1} = \text{FAIL}) = 1$, the increase in failure probability is lesser than when $P(\text{ENV} = \text{Fail}) = 1$ is reflected, as $P(\text{Env} - \text{Elect1} = \text{FAIL}) = 1$ reflects that only such an observation is made based on environmental conditions at Electrical Panel 1, while $P(\text{ENV} = \text{Fail}) = 1$ implies that the environment conditions at both the Electrical Panel and Pressure Monitor have been observed. The model demonstrates that the magnitude of the failure probabilities is linked to the extent of the perceived strength of dependencies, i.e. failure probability increases with the increased confidence of a common cause factor present. If $P(\text{ENV} = \text{Fail}) = 1$, it implies that the environmental CCF group is present in both the Electrical Panel and Pressure Monitor. If $P(\text{Env} - \text{Elect1}) = 1$, it implies that the observer only sees a weather related corrosion at the Electrical Panel. While he has no information about the condition at the Pressure Panel, the failure probability at the Pressure Panel will now be increased because of the ENV-CCF between these 2 nodes.

3.5 Conclusion

The thesis covers three components of the decommissioning risk modelling: (i) Options Analysis (ii) Activity Risk Analysis and (iii) Long-term monitoring. This chapter covers Options Analysis (well plugging option) and Activity Risk Analysis (Human Reliability Analysis and Dependent Failure). A well plugging and abandonment event is used as case study as this is one of the initial work of decommissioning, and this also takes up a large part of the decommissioning budget.

The traditional methodology of options analysis involves the assessment of options against current knowledge of well status, in particular the integrity of casing and liner cement with a reasonable chance of success elicited by the expert. The value of the chance of success is elicited based on a expert judgement, and usually corresponds to only a single value without traceability to how the expert obtains this number. The proposed improved method of mapping an options analysis decision binary tree into a BBN is systematic, still involves the assessment of options against current knowledge of well status and allows the study of multiple influences on a junction of the binary decision tree. As a BBN is proposed to be used, the elicitation of the conditional probability tables is required. The difference between the traditional method therefore lies here: the elicitation of the conditional probability table requires the expert to consider a series of crucial and possible extreme scenarios that provides an indication of the chance of success (divided across 5 states). With the current knowledge of well status reflected in the BBN model, the model can compute the chance of success from the given observation and the earlier provided information on the indication of the chance of success. The elicitation procedure also considers the uncertainties (on the expert, and on the chance of success) to derive this particular chance of success so that the final chance of success can also be described in terms of a probability distribution with median, mean, standard deviation values. The model also demonstrates how the chance of success is arrived at in a graphical manner as the influence factors are visible in the BBN.

Diving into Activity Risk Analysis, in terms of Human Reliability Analysis, the existing HEP elicitation and aggregation method in SPAR-H (and Petro-HRA) is linear and additive in nature, thus the consideration of all eight PSFs is crucial to have a significant impact on the HEP. Dependencies are considered as a overall factor on the HEP depending on the assessed dependency level. In the elicitation method utilised in this model, the expert could directly elicit a ‘very high’ level of HEP (ranging from $e-1$ to 1) based on the assessed states of just three PSFs. The three PSFs are usually shortlisted as the most crucial ones. This is not possible in the SPAR-H computation method. Dependencies are also mathematically accounted for in the conditional

probability tables, this is one of the highlights of modelling HRA using BBN.

The second problem is that with any increase in PSFs, the elicitation procedure increases exponentially such that it is too much expert input into every part of the conditional probability table. This section also identified a method of linear interpolation among certain crucial points in the conditional probability table to ease the elicitation procedure. The results demonstrate that the interpolation method still manages to capture the dependencies and that the obtained HEP values agrees with other HRA-BBN models.

In the second part of Activity Risk Analysis, a CCF model is proposed to provide a higher level of detail amongst CCF groups/causes (Environment, Material and Design) to give insight to relationships between events that is not covered in existing simple CCF-ratio models, where the CCF probability is a ratio of the failure probability of the basic event. Also, decommissioning takes place over a number of years, thus, ideally there should be a central model or documentation system that follows through the decommissioning process, so that data loss is minimal, and thus the judgement on the risk analysis process has reduced uncertainties as much as possible. The model utilises data from questionnaires to update a parameter from a generic to a situation – specific one. The model allows the analysis of what-if scenarios through consequence analysis for relatively new methods of well plugging and abandonment so that further use of the risks of the method risk can be studied and an expert can assess if the method is suitable for other wells. By identifying which area needs improvement and then acting on that, can the risk then be lowered on the new well to be abandoned.

Chapter 4

BBN for Decommissioning Activities

4.1 Preamble

This chapter presents an extension of 'Dependent Failure Analysis' and 'Human Reliability Analysis' from the previous chapter into the form of a BBN model with dynamic considerations. Permanently abandoned wells dot most of the subsea environment. The nature of a well plugging and abandonment (Well P&A) run - usually the lowest-cost contractor engaged to plug several wells tapping the same reservoir makes it an ideal case study for incorporating failures based on common causes. The heavy use of operators during a cementing job also provides the case for analysis of human error in such tasks. The common cause failure model considers the subsea environment and the material of the casing. The dynamic BBN model considers fatigue accumulation in both the cement and casing structure. The model has not only captured the dependencies of multiple variables, but also projected it in a dynamic manner to provide a risk profile for the next decade where well integrity failure is likely to happen. A sensitive and diagnostic analysis is also proposed to validate the model.

4.2 Background

4.2.1 Well P&A Failures

The concept of permanently abandoning a well essentially consists of providing zonal isolation/barriers from the source (reservoir) to the undesirable leak location (which could refer to the seabed if the well is a subsea well). Most regulations require primary and secondary barriers

Figure 4.1: Schematic of a PA well (adapted from [Nichol and Kariyawasam \(2000\)](#)) with well barriers demarcated. Barriers 'B1', 'B2' and 'B3' correspond to the red nodes in the BBN model in Figure 4.4.

so cement plugs are set along the length of the well first at the production zone/ reservoir level, and subsequently at levels where there could be zones of interest, such as at a water zone in the subsea; and finally at the surface.

A number of analyses have been conducted on the leak paths of a permanently abandoned well. One study conducted by [Nichol and Kariyawasam \(2000\)](#) used Fault Tree Analysis to quantify the likelihood of a leak through leak paths of critical components of a permanently abandoned well, such as through a cemented plug at the producing zone, a cement plug at the secondary zone of the production casing and through the surface cement plug. At the secondary and surface plugs, leakages through the steel casing and the seal between casings are also considered. The model by [Nichol and Kariyawasam \(2000\)](#) is used as a base model for the analysis conducted in this paper. This model considers the failure of a PA Well through a combination of three cement plugs (see Figure (4.1), through the well casing or through the seals between casings (see Figure 3.3 of [Nichol and Kariyawasam \(2000\)](#) for illustration and Figure 3.4 of [Nichol and Kariyawasam \(2000\)](#) for leak paths mapped in a fault tree).

Saeed et al. (2018) investigated several parameters related to the failure of the cement plug in a wellbore, of which the two of interest are (i) the changes in wellbore pressure and (ii) the change in annulus pressure acting on top of the cement, which ultimately affects the fit of the cement with respect to the wellbore. If the fit is poor, leak paths exist. Saeed et al. (2018) also reported that radial stress has the highest sensitivity to annular fit. This implies that the presence of micro-annuli (because of volume shrinkage or improper centralisation) has a huge impact on contact stress (i.e. radial stress) compared to any other factor. Improper centralisation is a result of human error, so, analysing human error is crucial in an effective cementing job. Human error can be shaped by PSFs such as the procedures guiding the job, the complexity of the task, or the time pressure associated with the task.

Ahmed et al. (2015) further elaborated that the cementing in the well also has a role in supporting the casing, and in protecting the casing from corrosive formation fluids such as hydrogen sulphide and carbon dioxide. Thus other than the well bore pressure affecting the cement strength, other downhole parameters such as the concentration of formation gases can have an impact on the degradation of cement. In terms of what can be done pre-emptively to reduce well leak paths in the future, Ahmed et al. (2015)'s study highlighted that Q125 grade steel consistently higher corrosion resistance than T96 grade steels, thus this grade of steel should be utilised during the drilling phase.

The above would describe the CCF model due to environmental considerations. One other area of interest would be a CCF model that also influences human error, *i.e.* human reliability analysis. Well P&A jobs are mostly awarded as a contract of wells to be abandon for a platform, this could range from 1 to 40 wells. As the same crew and vessel will plug the wells of a reservoir, it is necessary to consider CCFs in well P&A tasks.

As such, the above sets the context for common cause failure analysis that the traditional model neglects to account for and hence results in an underestimated failure probability. The CCF section of the model is based on the work done in Chapter 3. This chapter builds upon the model by incorporating discrete time series analysis in a Dynamic BBN.

Problem statement: Well leaks are underestimated due to independent failures assumptions and poor regulatory oversight in some areas. The impact of oil leaks are multiple in nature. There are economic and environmental costs. Notably, well leaks usually do not appear in isolation. A literature study grouped wells that are decommissioned in the same time period and noted that over 40 - 80% of wells leak within the first decade of decommissioning (Boothroyd et al., 2016). The model proposed in this paper is able to consider dependent failures from common causes

which overcomes independent failure assumptions. The model also has a dynamic component that can provide insights on long-term well failures. Also there are no monitoring plans enforced for abandoned wells, thus the first observed leak is crucial. The model is able to update failure probabilities of the other wells with the same dependency as the well with the observed leak. The method complements industry-favoured methods of fault tree analysis, some facets of dependent failure and common cause failures which meets up-and-coming regulatory requirements.

4.2.2 Expert Judgment in Well P&A

In well abandonment methodology, an assessment of options are conducted and solutions proposed according to the current knowledge of well conditions, application of general principles (usually supported by guidelines) and consideration of lessons learnt in previous abandonment projects. The two crucial areas that determine whether a well would leak are based on the cement quality and the integrity of casing. As cement is used in many parts of the well, the cement quality in the annular space and in the well (as a plug) along different depths of the well is of interest. A review of a redacted well abandonment study by [Lloyd's Register \(2019\)](#) indicated that the abandonment option would have included a review of historical well logs to assess the condition of the annular well space. If there is uncertainty relating to the annular cement quality, remedial casing cement (section milling) would be put forth as an option to increase the quality of the annular seal. Thus, expert judgement on casing strength will be excluded since the strength of the casing is already considered or mitigated with section milling. It has also been reported in a literature review by [Boothroyd et al. \(2016\)](#) that the most important cause in determining wellbore failure rates was cemented casing. As such, the expert judgment is only applied to the nodes concerning the annular fit of the cement plug, and pressure build up in the well, over three ranked states of 'Severe', 'Moderate' and 'Low'. The same nodes will also extend to the accumulative effects of pressure build up over the time period of interest.

The second expert elicitation is in the human reliability nodes linked to operator action. The node for human error is ranked over five states of 'Very High', 'High', 'Moderate', 'Low' and 'Very Low', with the human error probabilities affected by performance shaping factors (PSFs) according to the method proposed by [Podofillini et al. \(2015\)](#). The PSFs are characterised by four ranked states: Misleading/Error-forcing, Poor, Nominal and Good together with the expert judgment elicitation aggregation approach by Podofillini et al [Podofillini and Dang \(2013\)](#). The risk assessment is evaluated in a Bayesian Belief Network in order to capture dependencies (arising from the same event) and the ability to compute a so-called Hybrid BBN consisting of continuous and discrete

probability distributions. Human Reliability Analysis is a detailed analysis in its own field - the expert judgment model allows the expert estimates to be aggregated and elicited formally and transparently. The approach by Podofillini et al [Podofillini and Dang \(2013\)](#) mathematically treats possible biases and inaccuracies in the expert estimates. In addition, the BBN model allows the following effects to be modelled: (1) Factor dominance (2) Error forcing effect (3) Dependency mapping, whereby the elicitation is used to provide a better estimate to the human error probability. The advantages of eliciting an expert judgment using Podofillini et al.'s method are that both uncertainty in an expert judgement and combined error forcing effects can be displayed. Combined error forcing effects refer to a scenario where a 'High' HEP should be indicated in a scenario where 2/3 of the PSFs are in an error-forcing state, in spite of the remaining PSF being in a success-forcing state. The reader is referred to [Podofillini and Dang \(2013\)](#) for more details.

4.3 Model development - BBN and Dynamic BBN

The model is developed as BBNs and dynamic BBNs and the theory behind the models can be referred to Chapter 2 Sections [2.3.3](#) and [2.3.4](#).

4.3.1 Data used in modelling

There are two types of data used to populate the probability tables of the BBN. The first type is considered objective information, usually collated statistically and obtained from databases such as OREDA ([SINTEF Technology and Society et al., 2002](#)). Such information is usually ideal for describing reliability values of equipment components. Such databases usually do not have information on scarce equipment, or equipment that is hardly studied due to a lack of access, or low prioritisation due to economic factors. Decommissioned equipment is usually not looked at again after the primary monitoring period. This scarcity of information introduces the need to exercise other kinds of judgment in the model, and expert elicitation on the transitional probability table relating to the accumulative fatigue in the well is chosen. The process of expert elicitation is based on methods by [Podofillini and Dang \(2013\)](#) that attempt to compensate for the disadvantages of expert elicitation.

Subjective information, also known as expert judgement or elicitation is used to fill such data gaps. There are numerous methods to aggregate expert opinions and these are widely used in quantitative risk analysis in consequence modelling in offshore risk analysis. Some examples are:

[Chang et al. \(2019\)](#) for a subsea wellhead fatigue failure analysis, [Guo et al. \(2019\)](#) for process risk analysis in a fractionator column and [Cai et al. \(2019b\)](#) for the analysis of the remaining useful life in subsea pipelines where fatigue is also pertinent factor. Expert judgment is also extensively used in human reliability analysis in nuclear PRA.

4.3.2 Methodology for estimating probability of leak through a P&A Well

The proposed methodology for the dynamic risk assessment of leaks through a PA well over a monitoring period is shown in Figure 4.2 and Figure 4.3. It includes the follow steps:

1. Defining the system

The first step is to define the context of the risk assessment. This step usually entails defining the boundary of analysis, *e.g.* the number of wells of interest and what types of well. Operational information is usually also required, such as the guidelines, codes and other legal requirements that are applicable to the plugging and abandonment of the well. At this stage, workshops are usually carried out to provide an initial identification of hazards of interest.

2. Development of the system reliability model

The skeleton of the model can be initiated with system reliability analysis to identify links of interest, in this case, the leak paths from where an overall leak through a PA well is realised (see Figure 4.4). Relevant parameters need to be identified as well, such as the failure probabilities of the basic events (termed as nodes in a BBN). The relationships between the parent and child nodes are mostly defined as OR and AND gates, thus the CPT are defined with respective '1's and '0's to mimic the respective gates ([Bobbio et al., 2001](#)). Other kinds of logic gates are used in the model as well, such as the NOISYOR gates from the nodes leading to the 'Top Event' - probability of leak of the PA well. The main benefit is that it significantly reduces the CPT elicitation burden. The results (leak probability) obtained is in between that derived from an OR and AND gate. NOISYOR gates have also been used to model leak probability of a PA well where there is uncertainty of data ([Babaleye et al., 2019](#)), in [O'Connor and Mosleh \(2016\)](#)'s common cause failure models and in [Cai et al. \(2014\)](#)'s BBN modelling for fault diagnosis of ground-source heat pump.

Some values used in the model are summarised below (see Table 4.1):

Figure 4.2: Framework of the proposed methodology.

3. Development of the dependent failure model

After the development of the skeletal model, a greater level of detail can be applied to the nodes that are identified to have common links. There are numerous common cause failure models. The β -Factor model is proposed to be used due to its ease of application, and the recommendation by a Norwegian SINTEF guideline (Hauge et al., 2015). The method of incorporating mutually exclusive nodes is documented in Fenton et al. (2016)'s work while the application of a common cause failure model in a BBN is highlighted by O'Connor and Mosleh (2016). The model used by O'Connor is an Alpha-Factor common cause model used in risk assessment of nuclear power plants; however, the model in this paper is adapted to a β -Factor model with supporting use in the offshore industry by Hauge et al. (2015). The common cause failures are often grouped by the context in which the dependencies exists. In this study, the subsea well conditions (*e.g.* temperature, pressure, presence of corrosive

Figure 4.3: Conceptual description of how the model is structured in terms of intra- and inter-time slices. Within the same time slice, the probability of leak of PA Wells (1,2,... i) belongs to the same dependency group. Within the same time slices, PA Well 2,... i is linked also by the same CCF groups and HRA as in PA Well 1. In the next time slice, the probability of leak of the PA wells is influenced by the condition of the said well in the previous time slice.

Figure 4.4: BBN model to determine the leak probability of a PA well constructed based on system reliability concepts. The nodes highlighted in red refer to the barriers that leak, while the nodes highlighted in yellow refer to nodes that are replicated with the transitional CPT in order to create Dynamic BBN.

Table 4.1: Prior probabilities/equations used for the nodes in the BBN. Estimates are from [SINTEF Technology and Society et al. \(2002\)](#) and [Babaleye et al. \(2019\)](#).

Event	Failure probabilities
Leak through PA Well	$NOISYOR(P(B1), P(B2), P(B3), leak = 0)$
B1, B2, or B3 Leak	Table (4.6)
Declining Annular Fit	Table (4.3)
Pressure Build Up	Table (4.4)
Cement Volume Shrink	$NOISYOR(P(EnvB1), P(MatB1), leak = 0)$
Human Error	Figure (3.13) and Fam et al. (2019c)
E2 Gate	$OR - Gate$
CCF	Figure (3.13), Fam et al. (2019b) and O'Connor (2013)
Leak through casing hanger	1.25e-2
Leak through surface casing	1.00e-3
Leak via 2 points	$OR - Gate$
Leak through casing hanger	1.05e-2
Leak via 3 points	$OR - Gate$
Leak through production casing	1.00e-3
Leak through 4 points	AND-Gate

gases) are one such dependency group. Questionnaire methods can be used to define the Beta-Factor parameters ([Hauge et al., 2015](#)) and ([Fam et al., 2019b](#)). In this paper, it is modelled with one other well (PA Well 2) belonging to the same dependency group as PA Well 1 (See Figure 4.3).

The sample CCF values are summarised below (see Table 4.2 and [Fam et al. \(2019b\)](#)) and are fed into the events of interest. An expanded CCF Environment group is shown in Figure 4.5. It can be seen that the Common Cause Failure node extends and interacts with the nodes 'Env B1', 'Env B2' and 'Env B3' which are linked to the respective 'Cement Vol Shrink' nodes at the different well zones. Different well zones refer to where the well barriers are located.

Figure 4.5: An detailed look at the nodes that provide information on the CCF group relating to the environment. The top nodes 'Env B1', 'Env B2' and 'Env B3' refers to cement volume shrinkage at the location of the three barriers 'B1', 'B2' and 'B3'.

Table 4.2: Prior probabilities/equations used for the nodes in the CCF section of the BBN

Event	Failure probabilities
Env/Mat Independent Failure	6.55e-2
Env/Mat CCF	1.65e-2
Env/Mat 'No Failure'	9.18e-1

4. Development of the HRA model

The HRA part (see Figure 3.13) of the model is to link operator dependent actions (such as poor cementing technique) across the wells conducted in a batch operation through established HRA models. The HRA model is also a part of the dependency analysis. There are multiple established HRA models used in the nuclear industry. The chosen model is by Podofilini et al. (2015) as it is adapted for use in a BBN. The HRA model developed in this thesis stems from the work in Chapter 3 of this thesis and Fam et al. (2019c), which also elaborates on the shortlisting of PSFs. The elicitation of conditional probability tables are found in Fam et al. (2019c) and in Podofilini et al. (2015). The performance shaping factors (Taylor, 2017) are reviewed and selected for use in a well PA context.

5. Development of the Dynamic BBN model

Dynamic BBN model is developed for the section of the model where there is interest in investigating the performance of barrier over time, in this case, the annular fit and the casing strength, which are represented as the nodes highlighted in yellow in Figure 4.4 - 'Declining Annular Fit' and 'Pressure Build-Up'. The transition CPTs represent the dynamic nature of the risk event over time with respect to the discrete-time Markov model. The transition CPTs are defined with expert judgment in a manner similar to the method proposed in Table 1 of [Chang et al. \(2019\)](#).

The three states in the nodes (i) Declining Annular Fit (ii) Pressure Build Up, are 'Severe', 'Moderate' and 'Low'. The definition of these measurable scales of varying severity are based on experiments (encased cemented plugs) conducted by [Saeed et al. \(2018\)](#) at varying conditions on temperature, presence of acidic gases and cement grade. In terms of the factor 'Declining Annular Fit', the density of microannuli (small pores in the cement plug) determines the severity of leak through the cement plug. The formation of microannuli can stem from the curing process based on the cement quality or the downhole conditions. Based on [Saeed et al. \(2018\)](#)'s report it has been identified that it is more likely the gradual deterioration of the cement plugs that leads to well leaks. Thus the density of microannuli can be linked to the downhole conditions in terms of acid gas variation. The experiments conducted in [Saeed et al. \(2018\)](#)'s reported that carbon dioxide showed the most damaging effect of all corrosive gases used in this study (carbon dioxide, hydrogen sulphide, methane gas and a mixture of these gases). The impact decreases in the following order: $CO_2 > \text{All gases} > H_2S > CH_4$. Since it is unlikely for pure CO_2 to be present in the formation, a combination of the concentration of all gases is used to reflect the labelled factors. Thus, for the factors "Declining Annular Fit", the state 'Severe' refers to "50% CO_2 and 50% 500 ppm H_2S with methane carrier"; 'Moderate' refers to "30% CO_2 and 70% 300 ppm H_2S with methane carrier" while 'Low' refers to "20% CO_2 and 80% 100 ppm H_2S with methane carrier".

The report highlighted the leaks at varying pressure differential between the formation and within the casing. Thus, for the factors "Pressure Build Up", the state 'Severe' refers to a pressure differential of > 1500 psi; 'Moderate' refers to > 500 psi and < 1500 psi, while 'Low' refers to < 500 psi.

The tables (see Tables 4.3, 4.4, 4.5, 4.6) are elicited from expert judgment and are presented below.

Table 4.3: Conditional Probability Table for the event 'Declining Annular Fit'

Cement Vol. Shrink	Human Error	Declining Annular Fit		
		Severe	Moderate	Low
<i>True</i>	<i>True</i>	1	0	0
<i>True</i>	<i>False</i>	0.8	0.2	0
<i>False</i>	<i>True</i>	0.8	0.2	0
<i>False</i>	<i>False</i>	0	0.01	0.99

Table 4.4: Conditional Probability Table for the event 'Pressure Build Up'.

Injection to nearby well	Borehole Pressure Build Up	Pressure Build Up		
		Severe	Moderate	Low
<i>True</i>	<i>True</i>	1	0	0
<i>True</i>	<i>False</i>	0.8	0.2	0
<i>False</i>	<i>True</i>	0.8	0.2	0
<i>False</i>	<i>False</i>	0	0.01	0.99

6. Predictive and diagnostic analysis

The nature of a BBN allows for a predictive analysis, such as a prediction of the leak failure probability in a forward-manner, from the nodes up to the top event of interest. Diagnostic analysis can also be conducted by reflecting observations in a particular well, in a particular time slice and the information can be propagated to the other nodes (through the defined dependencies), and ultimately update the leak failure.

7. Decision-making and preventive measures

With information on the most influencing factors, or the weakest link, preventive measures can be undertaken to improve the risk profile.

Table 4.5: Transition Conditional Probability Table for the event 'Declining Annular Fit' and 'Pressure Build Up' in a Dynamic BBN

Cement Vol. Shrink	Human Error	Declining Annular Fit (t-1)	Declining Annular Fit (t)		
			Severe	Moderate	Low
<i>True</i>	<i>True</i>	<i>Severe</i>	1	0	0
<i>True</i>	<i>True</i>	<i>Moderate</i>	0.9	0.1	0
<i>True</i>	<i>True</i>	<i>Low</i>	0.8	0.2	0
<i>True</i>	<i>False</i>	<i>Severe</i>	1	0	0
<i>True</i>	<i>False</i>	<i>Moderate</i>	0.8	0.2	0
<i>True</i>	<i>False</i>	<i>Low</i>	0.1	0.8	0.1
<i>False</i>	<i>True</i>	<i>Severe</i>	1	0	0
<i>False</i>	<i>True</i>	<i>Moderate</i>	0.8	0.2	0
<i>False</i>	<i>True</i>	<i>Low</i>	0.1	0.8	0.1
<i>False</i>	<i>False</i>	<i>Severe</i>	1	0	0
<i>False</i>	<i>False</i>	<i>Moderate</i>	0	1	0
<i>False</i>	<i>False</i>	<i>Low</i>	0	0	1

Table 4.6: Conditional Probability Table for the events 'B1 Leak through zone isolation plug', 'B2 Leak through lower plug' & 'B3 Leak through upper plug'

Declining Annular Fit	Pressure Build Up	B1, B2 or B3	
		<i>True</i>	<i>False</i>
<i>Severe</i>	<i>Severe</i>	1	0
<i>Severe</i>	<i>Moderate</i>	0.9	0.1
<i>Severe</i>	<i>Low</i>	0.8	0.2
<i>Moderate</i>	<i>Severe</i>	0.9	0.1
<i>Moderate</i>	<i>Moderate</i>	0.8	0.2
<i>Moderate</i>	<i>Low</i>	0.7	0.3
<i>Low</i>	<i>Severe</i>	0.8	0.2
<i>Low</i>	<i>Moderate</i>	0.7	0.3
<i>Low</i>	<i>Low</i>	0	1

4.4 Dynamic Failure Analysis

4.4.1 Model Development

The model consisting of the dependencies (Common Cause Failure Group - Maintenance, Common Cause Failure Group - Environment and Human Reliability Analysis on cementing operations), and NOISYOR gates, and the dynamic Bayesian Belief Network is built on AgenaRisk ([Agena Ltd, 2019](#)). The model also consists of 10 time slices, where each time slide represents one year. The time period of analysis is set as 10 years as a study by [Boothroyd et al. \(2016\)](#) highlighted that fugitive emissions of methane from abandoned, decommissioned wells specifically due to well integrity failure occurred within a decade of well decommissioning. The DBN aims to capture the accumulative effect of the decline in the barrier reliability of the cement seal (annular fit) and simultaneous build up of the pressure in the reservoir. Expert judgment is applied to derive the transition conditional probability table to illustrate the dynamic nature of the well PA failure. The results will be discussed in terms of (1) PA Well 1's failure across time, (2) Variations in PA Well 1's failure with observations of barrier failures in PA Well 1 (3) PA Well 2 failures given observations in PA Well 1, such as barriers failure or indeed observation of a leak in PA Well 1 has been observed.

4.4.2 Benefits of modelling with a BBN

The results of Equations 2.2 and 2.3 in Chapter 2 Section 2.3.2 show the (small) underestimation in the computation method of a basic event in a Fault Tree. In the BBN formulism, probabilistic dependence is included in the CPT. Additionally, the dependence can be carried forward to other affected nodes when there is a marginalised fault. This dependence allows the other factors/nodes linked by the same fault to have their failure probability adjusted accordingly. Concerning the computation of the cut-set importance, it is worth noting that a BBN may directly produce a more accurate measure of such an importance, *i.e.* being able to provide the posterior probability of each cut-set given the fault.

The following results highlight how dependent failures can be marginalised to update the overall risk profile of the system. The use of the NOISYOR gate in the BBN model (translated directly from a FTA model into a BBN) and the consideration of CCF Group 1 of the cement barrier and the Human Reliability Analysis (HRA) model yielded a top event - probability of leak through a PA well of 9.23e-3.

The subsequent model which is built with dependencies from the CCF Group 1 of the cement barrier, CCF Group 2 of the Pressure Build Up conditions and the Human Reliability Model also yielded a top event failure probability of 9.23e-3 as the failure probabilities of the Barriers B1, B2 and B3 are the same, except a common-failure factor has been added.

Differences between the results of the models are observed when the dependent failure of Barrier B1 are observed and propagated in the model as posterior probabilities. Marginalised dependent failures can be captured easily in modelling CCF with BBN. The results are summarised in (see Table 4.7):

Table 4.7: Summary of top event (TE) failure probabilities with or without dependencies modelled at t=0.

Model	TE = Fail	TE = Fail B1 = Fail
Regular FTA mapped in BBN 1	1.65e-4	1
BBN with CCF Group 1 and HRA	9.23e-3	6.07e-2
BBN with CCF Group 1,2 and HRA	9.23e-3	8.74e-2

With a dynamic BBN, it is possible to obtain the trend of the top event failure probabilities across the time period of interest, *i.e.* 10 years (see Figure 4.6). The model demonstrated that there is an increase in the failure of a PA well from 9.29e-3 in t=0 to 2.90e-1 in t=10. With the consideration of dependent failures in Barriers 1,2 3, the increase in the top event failure probability PA Well is captured. The maximum range of failure of a PA well is 1.59e-1 in t=0 to 6.90e-1 in t=10 with the consideration of failure of three barriers B1, B2 and B3. The greater the number of dependencies, the greater the increase in the top event failure probability with respect to the baseline case of no dependent failure observed. It can also be observed that the increase in the PA well failure probability follows a decreasing pattern, implying that the first dependent failure will result in the steepest increase in the risk profile, and the third subsequent dependent failures will also elevate the risk, albeit in smaller steps.

4.4.3 Sensitivity analysis for insights on dependencies captured from the same well across a time period

One way of analysing the impact of dependencies on the top event can be in terms of sensitive analyses based on the technique proposed by Coupé et al. (1999), which is that the relationship between individual parameter(s) and posterior probability (ies) can be described via a function. A posterior probability is a rational polynomial over the parameter under study (Equation 4.1):

Figure 4.6: Failure probabilities of PA Well 1 given that barrier failures are observed in PA Well 1. '+' refers to failure probabilities without dependent failures observed. 'o' refers to failure probabilities with Barrier 1 failure observed. '*' refers to failure probabilities with Barrier 1 and 2 failures observed. The square-shaped data points refer to failure probabilities with Barrier 1,2 and 3 failures observed.

$$P^{(\Theta=x)} = (V = v|e) = \frac{ax + b}{x + c} \quad (4.1)$$

Where Θ is the parameter under study and a , b , and c are real constants. $P^{(\Theta=x)} = (V = v|e)$ refers to the posterior probability of the value v for the variable V given the evidence e . The constants can be obtained by having three different values for Θ , computing the respective posterior probability in the BBN model, and then solving a system of multiple linear equations.

A sensitivity analysis is conducted on this model thus allowing for the observations of the effects of changing a network's parameter on one or more posterior probabilities of interest, which may provide a certain measure of confidence on the robustness of the model (Coupé et al., 1999).

The sensitivity analysis can be observed in terms of the width of the interval, and where on the probability scale of 0-1 that the intervals lies (Fam et al., 2019a). High sensitivity to a

parameter would indicate that the intervals are wider, as this means that a single change in the parameter would have a greater effect on that probability of interest. The position along the scale of the probability 0-1 would refer to whether the parameter ought to increase or decrease this probability. In the case of the sensitivity plots (see Figure 4.7), the plots from left to right represent the results of time slices $t=0$, $t=5$ and $t=10$. Within each vertical plot, the probability of interest, $P(\Theta=x)$, is the top event - the leak probability through the PA well. The parameters of interest are the failure probabilities of the Barriers B1, B2 and B3.

The bar graph labelled 'Prior' represents the sensitivity analysis for the top event - the leak probability through the PA well based on the initial information in the network. The subsequent bar graph labelled 'Given B1 failed' considers a dependent failure, *i.e.* the posterior failure probability of the top event (Leak through PA well) given that Barrier B1 has failed. The third bar graph noted as 'Given B1 and B2 failed' considers the posterior failure probability the top event (Leak through PA Well 1) given that both Barrier B1 and Barrier B2 has failed.

The left plot ($t=0$) shows the initial prior failure probability of Leak through PA Well 1 with an interval width of 0.082. With the consideration of the dependent failure of Barrier B1, the interval width decreases slightly to 0.083. With the consideration of dependent failures of Barrier B1, B2, the interval width decreases to 0.05. The decrease in the interval width is likely due to the reduced number of interactions from the 'free nodes' that the model now has. Each observation of failure 'locks' the node in a failure state and hence it cannot take any other state. The 'free' nodes which have no evidence reflected on them, maintain their flexibility to have a probability distribution among the their defined states. More importantly, with each failure observation, *i.e.* an increasing number of dependent failures, there is a shift towards higher probability values.

In the expert elicitation of the Pressure Build Up node which drives the dynamic analysis, the premise is that as the wells age up to a certain number of years (Boothroyd et al. (2016) noted that where well integrity failure occurred, it appeared within a decade of well decommissioning), the failure rates of the barriers would also increase due to intrinsic degradation of the barriers. It can be observed that at $t=5$, the interval width of the prior failure probability of Barrier B3 is higher than at $t=0$, with an interval width value of 0.146. There is also a substantial increase in the dependent failures with the consideration of the failure of Barrier B1 and the failure of Barriers B1 and B2. In the rightmost plot at $t=10$, the prior failure probability has the widest interval value of 0.177. The observations also indicate that the dependent failures across the time slices result in greater sensitivities in terms of the increase in interval width. It is noted that the interval width of Leak through PA Well 1 given that Barrier B1 has failed at $t=10$ is 0.162, as

compared to the other values of 0.138 ($t=5$) and 0.083 ($t=0$).

The results (see Figure (4.6)) indicate that failure probabilities increase as time progresses (up to a point), and as the number of dependent failures increases. The sensitivity plot (see Figure 4.7) agrees with the failure probability values at the respective time slices.

Figure 4.7: Sensitive analysis of Leak of PA Well 1 with no observed failures or observed failures in Barriers B1 and B2. The left plot refers to $t=0$, middle plot refers to $t=5$ and right plot refers to $t=10$.

4.4.4 Dependencies propagated from one well to another in a same time period

The model has the ability to consider the dependencies propagated from one well to another within the same time period (see Figure 4.3). This is useful for planning purposes in the event that when it is observed that one well in the vicinity has leaked, it is likely that the risk profile of other, similarly abandoned wells will be elevated, and pre-emptive action can be taken. The permanent abandonment of wells is usually run in batches by the same company, and same crew (representing a dependency in terms of human operator error). The proximity of each well, and its link to the same reservoir will indicate that the surrounding wells are exposed to the same conditions. Hence, if it is observed that Well 1 is leaking, perhaps from a poor annular fit of the cement plug, the reasons leading to this poor annular fit (such as cement failure due to cycles of extreme heat and pressure, or presence of corrosive gases) will likely impact the performance of the barriers in the other wells. The model is able to capture this dependency. With the dependent failure of Barrier 1 in Well 1, the leak probability of PA Well 2 (with dependent failure) at $t=0$ increases from $9.29\text{e-}3$ (Non-dependent failure) to $4.92\text{e-}2$. Over the time period of interest, the leak probability of PA Well 2 ranges from $4.92\text{e-}2$ at $t=0$ to $4.12\text{e-}1$ at $t=10$. The failure probability of Well 2 given Barrier 1 failure at Well 1 is lower than the failure probability of Well 1 given Barrier 1 failure at Well 1. The model describes the physical scenario that the greater the confidence of a failure, the higher the corresponding leak probability. There is confirmed observation of a Barrier

1 failure only at PA Well 1 and not at PA Well 2, thus the failure probability of PA Well 1 is $>$ PA Well 2. The overall trend of increasing dependent failures, will result in an increase in the leak probability of PA Well 2. However, the increase is to a lesser extent as compared to PA Well 1, where the barrier failure observations have been directly observed. However, the greater the number of dependent failures in Well 1, the smaller the differences between the dependent failure probabilities in PA Well 2 and Well 1. In summary, the dependency model is able to capture 2 nuances of dependent failures: (i) an initial elevated failure probability in PA Well 2 from the first dependent failure observed in the same common cause failure groups and (ii) an increase in the elevated dependent failure probability with an increase in dependent failures observed in the same common cause failure groups. Table (4.8) and Figure (4.8) summarise the results of Well 1 dependent failure versus Well 2 dependent failure.

Table 4.8: Summary of top event failure probabilities with or without dependent failures modelled at $t=0$, $t=10$ at Well 1 and its impact on neighbouring Well 2. Dependent failures are modelled at 'B1 Leak through zone isolation plug', 'B2 Leak through lower plug' & 'B3 Leak through upper plug'

Declining Annular Fit	PA Well 1		PA Well 2	
	t=0	t=10	t=0	t=10
Leak probability B1 at PA Well 1 = Fail	8.75e-2	5.30e-1	4.92e-2	4.12e-1
Leak probability B1, B2 at PA Well 1 = Fail	1.45e-1	6.70e-1	1.16e-1	5.93e-1
Leak probability B1, B2, B3 at PA Well 1 = Fail	1.59e-1	6.98e-1	1.26e-1	6.08e-1

Figure 4.8: Failure probabilities of PA Well 1 (Left) and Failure probabilities of PA Well 2 given that barrier failures are observed in PA Well 1 (right). '+' refers to failure probabilities without dependent failures observed. 'o' refers to failure probabilities with Barrier 1 failure observed. '*' refers to failure probabilities with Barrier 1 and 2 failures observed. The square-shaped data points refer to failure probabilities with Barrier 1,2 and 3 failures observed.

4.4.5 Well status in terms of annular fit and impact from Pressure Build Up

The transition probability table for both the 'Declining Annular Fit' and 'Pressure Build Up' are the same. However the distribution of the proportion of the states 'Severe', 'Moderate' and 'Low' varies between the two nodes. It is noted that the Pressure Build Up node reflects a greater proportion of 'Severe' and 'Moderate' states as time progresses. This difference is due to the different initial failure probabilities feeding into the respective nodes at Declining Annular Fit and Pressure Build Up. Both nodes have 2 parent nodes feeding failure probabilities into it, the failure probabilities of the parent nodes to Declining Annular Fit are 'Cement Vol Shrinkage' and 'Human Error' which are $9.99\text{e-}3$ and $7.40\text{e-}3$ respectively. The failure probabilities of the parent nodes to Pressure Build Up: '(Intrinsic) Pressure build up' and 'Injection to nearby wells' are $1.65\text{e-}2$ and $2.2\text{e-}2$ respectively. The failure probability in the 2 parent nodes differ by a factor of 10 (see Table 4.9).

Table 4.9: Summary of failure probabilities of parent nodes of Declining Annular Fit and Pressure Build Up

Declining Annular Fit		Pressure Build Up	
Cement Vol	Human error	Pressure build up	Injection to nearby wells
$9.99\text{e-}3$	$7.40\text{e-}3$	$1.65\text{e-}2$	$2.2\text{e-}2$

In a BBN model, it is possible to conduct a diagnostic analysis, which is a backward inference method, as opposed to the Fault Tree Analysis, which is a forward inference analysis. We are able to postulate that a leak has occurred and look back on these two factors (Annular Fit and Pressure Build Up) given that a Leak on PA Well 1 has occurred. It is also feasible to extend the backwards inference to PA Well 2 and its components, such as the Declining Annular Fit and Pressure Build Up node for PA Well 2. In the backward analysis in which failure of PA Well 1 has taken place, the nodes of Declining Annular Fit and Pressure Build Up reflect similar results in that, there is a greater proportion of the state 'Severe' in Pressure Build Up, as compared to Declining Annular Fit. It is obvious that Pressure Build Up has a greater impact on leak (see top right corner of Figure (4.9)) through a particular section of a PA Well, due to its higher initial probabilities.

Figure 4.9: Variation in the proportion of states 'Severe', 'Moderate' and 'Low' in the prior state for 'Declining Annular Fit in PA Well 1' (Top left), for 'Pressure build up in PA Well 1' (Top right) and the respective posterior results for 'Declining Annular Fit in PA Well 1' (Bottom left), for 'Pressure build up in PA Well 1' (Bottom right) .

The posterior distribution (see bottom halves of Figure (4.9) of states of 'Severe', 'Moderate' and 'Low' in Declining Annular Fit of PA Well 1, and in Pressure Build Up of PA Well 1 shows a steady, gradual increase in the 'Severe' state, and subsequently gradual decrease in the 'Low' state as time progresses over the 10 year period. The 'Moderate' state increases from time $t=0$ to $t=4$ before the increase plateaus and remains at that proportion (see Figure (4.9)).

Another interesting observation is that the behaviour of the nodes at PA Well 2 given that PA Well 1 has leaked showed that the Pressure Build Up still plays a greater role in contributing to the likelihood of the next well failing (PA Well 2) (bottom half of Figure (4.10)). The posterior distribution of the states 'Severe', 'Moderate' and 'Low' in Declining Annular Fit of PA Well 2, and in Pressure Build Up of PA Well 2 shows a less gradual increase (bottom half of Figure (4.10)). In general, the proportion of the state 'Severe' increases over the time period $t=0$ to $t=10$, and likewise the proportion of the state 'Low' decreases over the same time period. There are two crucial differences observed: which is that (i) the posterior distribution of Declining Annular Fit in PA Well 2 is much lesser than the posterior distribution of Pressure Build Up; and (ii) the increase in the state 'Severe' in Pressure Build Up has a visible lag before $t=2$ after which it increases, and plateaus much earlier time $t=5$ than the Pressure Build Up node in PA Well 1.

The lag in both the increment of the proportion of the state 'Severe' in Pressure Build Up and

generally lower proportion of the state 'Severe' in Declining Annular Fit is largely determined by when the accumulative build up in pressure begins to play a role. This only begins at $t=3$. At $t=2$, the slight increase is due to the dependencies mapped in terms of common cause failure groups (Environment and Material) and in the reservoir disturbance stemming from Injection to Nearby Well. The small increase in $t=2$ is from the smaller effect of dependent failure of PA Well 1. The increase at $t=3$ is due to the greater effect of accumulative build up in pressure carried forward from $t=2$ to $t=3$ at PA Well 2.

Figure 4.10: Variation in the proportion of states 'Severe', 'Moderate' and 'Low' in the prior state for 'Declining Annular Fit in PA Well 2' (Top left), for 'Pressure build up in PA Well 2' (Top right) and the respective posterior results for 'Declining Annular Fit in PA Well 2 | PA Well 1 failed' (Bottom left), for 'Pressure build up in PA Well 2 | PA Well 1 failed' (Bottom right) .

The dependent failure rates of PA Well 2 | PA Well 1 is plotted (see Figure (4.11)) and the difference between the independent failure probability and the dependent failure probability increases at each time step. This implies that the longer the wells have been abandoned, and if a barrier failure is observed in any of the group of wells, the greater the likelihood of the other wells failing. Even though the proportion of the 'Severe' states in Pressure Build up appears to stagnate or increases very slightly, the dependent failure probability of PA Well 2 does not. This is likely due to the NOISYOR gate of the Barriers 1, 2 and 3 that can propagate these small increases to a visible impact on the final top event probability.

Figure 4.11: Variation between the posterior failure probabilities of PA Well 2 given that PA Well 1 has failed (graph marked in 'o') with prior failure probabilities of PA Well 2 (without any dependent failure observed) (graph marked in '+').

4.5 Comparison of results with a case study

Nielsen and Jensen (2007) explained that the purpose of a BBN as a tool that 'gives estimates of certainties for events that are not directly observable or, observable at a high cost'. Thus the validation process is unique. In BBN models in which its structure is developed by data learning, a portion of the data can be set aside to validate the model. In this thesis, the

model is developed from system reliability techniques and modified with expert judgement on the paths of dependencies and fatigue accumulation. Kleemann et al. (2018) highlighted that 'expert judgement is the most often used method in the discretisation, model learning and validation processes of BBNs.' The expert judgement can be used over the results of a sensitive analysis (Marcot, 2012) or in contrasting modelling (Cai et al., 2019a). Sensitive analysis involves the analysis of covariation between input variables and output variable probability distributions and this has been covered in Section 4.4.3. Contrasting modelling involves determining incremental effects of selected inputs set to best, worst, or other specified values and Section 4.4.5 investigates the effect of a observed failure at PA Well 1 and its impact on the safety barriers in terms of its annular fit and pressure build up. The above sections, based on expert judgement provides insights on the dispersion of posterior probability value among different outcome states, a form on uncertainty analysis.

However, there is still on element of validation that can be carried out and this section attempts to compare the outcome of the proposed BBN model with a statistical study of permanently abandoned wells. Marcot (2012) noted that one more way of validating a BBN 'pertains to how well a BN model predicts or diagnoses some outcome, that is, the accuracy of model results'.

Boothroyd et al. (2016) conducted an analysis on emissions of methane from 103 wells aged between 8 to 80 years that were deemed to be properly abandoned. The proportion of wells leaking, according to the age of wells drilled, ranged from 40% to 82%. The posterior results of the model proposed in this thesis are comparable with the results: the failure probability of PA Well 1 from $t=0$ to $t=10$ ranges from 30% to 70% depending on the number of barriers observed to be compromised. The study also noted that the failure rate was 47% for wells drilled between 1940 and 1949, and 40% for wells most recently drilled 2000 - 2009 in the dataset. This implies that well integrity is a problem that occurs early on in the decommissioned life of a well (usually the first decade) and that the time period proposed in this study is sufficient for highlighting risky wells in order to take further action such as on re-mediating/reopening wells and strengthening the barriers.

Jackson (2014) noted that poor cementing or where the well has been damaged by acid corrosion were one of the most common causes of leaks, which strengthens the case for considering dependencies in well environment. The study also considered well location (geographical location and basin type) as one of three factors of study in an ANOVA analysis and determined basin type to be significant in its relation to well leaks, which supports the case for well bore environment being a important factor in assessing well leaks.

Well failure mechanisms are not studied in [Boothroyd et al. \(2016\)](#)'s analysis. However, the literature review in the paper recognised the numerous ways in which the wells can leak: (1) between the cement and surrounding rock formations; (2) between the casing and surrounding cement; (3) between the cement plug and casing or production tubing; (4) through the cement plug; (5) through the cement between the casing and rock formation; (6) across the cement outside the casing and then between the cement and the casing; and (7) along a sheared wellbore. Thus in order for a leak to be measured, it is assumed that the leak occurs through the possible leak paths. These leak paths have been modelled as common nodes in dependent failure analysis so if a leak is observed, it is assumed that a barrier has been compromised, and hence the comparison of the literature data is with the proposed model based on dependent failure.

In recent years, a well risk register (of wells in operation) has come about – operators need to manage such a register on the likelihood of a well barrier failing. Currently it is based on a traffic-light type of indication on the status of a well. Such registers ideally should contain information about where there is potential gas accumulation, as different casings have different burst pressures and thus gas accumulation along different lengths of the well have different risks. This is a starting point for deciding which type of failure would be most likely in a well of interest. The model proposed in this paper has provided further insights on the contribution of a declining well annular fit, and increasing pressure build up in a well.

4.6 Conclusion

The thesis covers three components of decommissioning risk modelling: (i) Options Analysis (ii) Activity Risk Analysis and (iii) Long-term monitoring. The work in Chapter 3 on Activity Risk Analysis serves as the base model, and in this chapter, a dynamic BBN together with the base model, is used to conduct long-term monitoring of a PA well.

Well leaks are underestimated due to independent failures assumptions and poor regulatory oversight in some areas. The impact of oil leaks are multiple in nature. There are economic and environmental costs. Notably, well leaks usually do not appear in isolation. A literature study grouped wells that are decommissioned in the same time period and noted that over 40 - 80% of wells leak within the first decade of decommissioning. The model proposed in this paper is able to consider dependent failures from common causes which overcomes independent failure assumptions. The model also has a dynamic component that can provide insights on long-term well failures. Also there are no monitoring plans enforced for abandoned wells, thus the first

observed leak is crucial. The model is able to update failure probabilities of the other wells with the same dependency as the well with the observed leak. The method complements industry-favoured methods of fault tree analysis, some facets of dependent failure and common cause failures which meets up-and-coming regulatory requirements. In conclusion, the model meets the following objectives (1) of capturing better estimates of a well PA event by incorporating dependencies, and meeting regulatory requirements by authorities; and (2) using the same model to provide long term monitoring of a group of wells linked by common dependencies. This model has not only captured the dependencies of multiple variables, but also projected it in a dynamic manner to provide a risk profile for the next decade where well integrity failure is likely to happen. The results of the sensitive analysis and backwards diagnostic analysis agree with a statistical study of 103 wells ([Boothroyd et al., 2016](#)). This affirms that well failure probabilities are underestimated if independent failure is assumed.

Chapter 5

Conclusion and Future Works

5.1 Preamble

Decommissioning projects are large in scope and involve multiple phases. Their large scope suggests that a prudent option analysis is crucial for a balancing act across the five categories commonly utilised in options analysis: Safety, Environmental, Technical, Societal and Cost. The involvement of multiple phases and its long-lasting impact (*i.e.* decommissioned solutions should last for perpetuity) provide the context for the interest in long-term monitoring.

5.2 Thesis summary

This thesis comprises three components to the risk modelling procedure : (i) options analysis for deciding which decommissioning option to employ (ii) the activity risk of the decided option taking into consideration human reliability analysis and dependent failures and (iii) the long-term monitoring of the decommissioned facility. A well plugging and abandonment event is used as case study as this is one of the initial stages of decommissioning, which also takes up a large part of the decommissioning budget.

5.2.1 Options analysis

The traditional methodology of options analysis involves the assessment of options against current knowledge of well status, in particular the integrity of casing and liner cement with a reasonable chance of success elicited by the expert. The value of the chance of success is elicited based on

a expert judgement, and usually corresponds to only a single value without traceability to how the expert obtains this number. The proposed improved method of mapping an options analysis decision binary tree into a BBN is systematic, still involves the assessment of options against current knowledge of well status and allows the study of multiple influences on a junction of the binary decision tree. As a BBN is proposed to be used, the elicitation of the conditional probability tables is required. The difference between the traditional and proposed method therefore lies here: the elicitation of the conditional probability table requires the expert to consider a series of crucial and possible extreme scenarios that provides an indication of the chance of success (divided across 5 states). With the current knowledge of well status reflected in the BBN model, the model can compute the chance of success from the given observation and the earlier provided information on the indication of the chance of success. The method proposed in the thesis allows uncertainties to be incorporated into the elicitation procedure. These uncertainties are (i) the inherent variability of the probability of success and (ii) the confidence that the experts provides the correct probability of success. The model is able to carry out a weighted sum of the probability across all possible intervals and with key values of indication of uncertainty - such as the median value, or the 5th or 95th percentile. The model also demonstrated how the chance of success is arrived at in a graphical manner as the influence factors are visible in the BBN. The example also looked at different local conditions, such as the impact of the presence of shallow gas. The model indicated that for a chosen option and given that there is no shallow gas, the median success probability is higher (0.78) vs the same option and given that there is shallow gas (0.41). In the traditional method, there is usually no clear indication on how the expert arrived at the elicited chance of success.

5.2.2 Activity Risk Analysis

After the option has been decided, risk analysis is conducted for the selected option. This part of the model focuses on adapting modelling components proposed to be added in by a draft offshore regulations guidelines by US. The approach shadows that of the nuclear industry and includes dependent failure analysis and Human Reliability Analysis. There are a number of common cause failure models and the one chosen is a PDS β -model. The PDS β -model is a questionnaire-based approached designed from a study by the same organisation on offshore operational data. The Human Reliability Analysis is conducted based on a modification of the Petro-HRA ([Taylor, 2017](#)) and [Podofilini and Dang \(2013\)](#)'s expert elicitation and linear interpolation to minimise the amount of judgement required. Likewise, with respect to the expert elicitation in option

analysis, uncertainty can be represented. In the nuclear industry, the log-normal distribution is used to describe the phenomena of human error probability. The same rigour can be applied by identifying the error factor to describe the distribution. HRA in traditional offshore risk analysis often only has a single input in human error probability.

In this chapter, the elicitation of three PSFs on a HEP demonstrated an exponential increase in the elicitation procedure as compared to two influencing factors in an options analysis. This section also identified a method of linear interpolation among certain crucial points in the conditional probability table to ease the elicitation procedure. The results demonstrate that the interpolation method still manages to capture the dependencies and that the obtained HEP values agrees with other HRA-BBN models.

In the second part of Activity Risk Analysis, a CCF model is proposed to provide a higher level of detail amongst CCF groups/causes (Environment, Material and Design) to give insight to relationships between events that is not covered in existing simple CCF-ratio models, where the CCF probability is a ratio of the failure probability of the basic event. Also, decommissioning takes place over a number of years, thus, ideally there should be a central model or documentation system that follows through the decommissioning process, so that data loss is minimal, and thus the judgement on the risk analysis process has reduced uncertainties as much as possible. The model utilises data from questionnaires to update a parameter from a generic to a situation – specific one. The model allows the analysis of what-if scenarios through consequence analysis for relatively new methods of well plugging and abandonment so that further risks of the method can be studied and an expert can assess if the method is suitable for other wells. By identifying which area needs improvement and then acting on that, the risk on the new well to be abandoned can be lowered.

5.2.3 Long-term Monitoring

The thesis covers three components of decommissioning risk modelling: (i) Options Analysis (ii) Activity Risk Analysis and (iii) Long-term monitoring. The work in Chapter 3 on Activity Risk Analysis serves as the base model, and in Chapter 4, a dynamic BBN together with the base model, is used to conduct long-term monitoring of a PA well.

The probability of a leak in a well is underestimated due to independent failures assumptions and poor regulatory oversight in some areas. The impact of oil leaks are multiple in nature. There are economic and environmental costs. Notably, well leaks usually do not appear in isolation. A

literature study grouped wells that are decommissioned in the same time period and noted that over 40 - 80% of wells leak within the first decade of decommissioning. The model proposed in this paper is able to consider dependent failures from common causes which overcomes independent failure assumptions. The two common cause failures are the (i) changes in wellbore pressure and the (ii) change in annulus pressure acting on top of the cement, which ultimately affects the fit of the cement with respect to the well bore. If the fit is poor, leak paths exist. One other area of interest would be a common cause failure model that also includes operator error, i.e. Human Reliability Analysis.

The model also has a dynamic component that can provide insights on long-term well failures. Since fatigue in cement is an accumulative process, dynamic BBN (discrete-time Markov model) modelling has been utilised to investigate the performance of barrier over time, in this case, the annular fit and the casing strength. This allows the projection of the well barrier failure rate to a decade, which is when a well would most likely fail, if it were to fail. Also there are no monitoring plans enforced for abandoned wells, thus the first observed leak is crucial. The model is able to update failure probabilities of the other wells with the same dependency as the well with the observed leak. The method complements industry-favoured methods of fault tree analysis, some facets of dependent failure and common cause failures which meets up-and-coming regulatory requirements.

In conclusion, the model meets the following objectives (1) to capture better estimates of a well PA event by incorporating dependencies, and meet regulatory requirements by authorities; and (2) to use the same model to provide long term monitoring of a group of wells linked by common dependencies. This model has not only captured the dependencies of multiple variables, but also projected it in a dynamic manner to provide a risk profile for the next decade where well integrity failure is likely to happen. The results of the sensitivity analysis and backwards diagnostic analysis agree with a statistical study of 103 wells. This affirms that well failure probabilities are under-estimated if independent failure is assumed.

5.3 Notable Contributions

A risk modelling method that combines and adapts methods from different and/or similar industries have been proposed. The method comprises the following modelling features: (i) multiple states in an node (ii) dependency analysis (iii) representation of uncertainties (iv) detailed HRA and (v) continuous temporal variables. The table below (Table 5.1) summarises features

of other methods used by other researches and adapted for use in the options analysis and well plugging and abandonment context. The first four rows represents the methods that have been adapted into this thesis, and their respective shortcomings. The last row is the method proposed in this thesis and plugs the gaps that the other methods have.

1. Applying an expert judgement process that can consider expert uncertainty and the inherent variability in the item to be elicited.

Expert judgment is a crucial part of the risk modelling process in the decommissioning field. Such judgment is utilised in options analysis, comparative assessments, human reliability analysis and discrete Markov chain time slices. Expert judgment is the primary input to the BBN. This is a delicate process as it should be comprehensive enough to avoid different types of biases, yet not be overly impractical. The method adapted from the combination of the linear interpolation method by [Podofilini et al. \(2015\)](#) and the Bayesian aggregation method by [Podofilini and Dang \(2013\)](#) can demonstrate dominance of one factor over others, or represent different uncertainties in relationships.

2. Modelling dependencies in terms of dependent failure (HFE2 Failure given HFE1 Failure) or CCF in terms of material, design or environmental causes.

Modelling dependency is also crucial in risk modelling. It has been noted that some figures for risks or failures are underestimated as these methods to derive the figures ignore dependencies between events. In the case of well plugging and abandonment, there are multiple dependent factors in the subsea well condition that impact the integrity of the cement or the casing. The modelling of dependencies yields results that corresponded to a statistical study of 103 decommissioned wells.

The model can also consider a concept that is similar to cascading failures. Cascading failures refer to a failure in an interconnected system, in which the failure of a part of the system can amend the failure probabilities and subsequently trigger the failure of the successive parts. Since there are no legal requirements for monitoring plans, the only time a well leak is known is when it is observed at the surface. From the information on the first observed leak, the model can update the failure probabilities of other wells that are plugged and abandoned in the same way, as the wells are linked by the dependencies in subsea conditions or human error.

3. Long-term monitoring

The model also has a dynamic component that can provide insights on long-term well

Table 5.1: Summary of hybrid risk assessment models. The first four rows represents the methods that have been adapted into this thesis, and their respective shortcomings. The last row is the method proposed in this thesis and plugs the gaps that the other methods have.

Model/Technique	Description	Authors	MSS	Dep.	Unc.	HRA	Con't	Temp.
							Var.	
Mapped FT into a BBN with dependency modelling (General Dependency Model).	The focus is on using a BBN to improve Common Cause Failure models typically used in reliability analysis. The proposed dependency model consists of three parameters for each failure cause, which relate to physical attributes of the system being modelled, i.e., cause condition probability, component fragility, and coupling factor strength.	O'Connor (2013) ; O'Connor and Mosleh (2016)	X	X	X			
Mapped FT and ET into Dynamic BBN	The temporal BBN is set up in a standard discrete self-linking transition CPTs. The transition CPTs are elicited by expert judgment.	Chang et al. (2019) ; Abaei et al. (2019)					X	X
Dynamic BBN for human factors modelling for offshore blowout	The temporal BBN is set up in a standard discrete self-linking transition CPTs. The transition CPTs and human factors are elicited by expert judgement.	Cai et al. (2013)				X		X
Expert-elicited probabilities in human reliability analysis	The analyst is only required to rate the performance in human factors, and the Human Error Probability (HEPs) are produced by the model. The performance factors and HEP are multi-state and can present the level of uncertainty.	Podofillini and Dang (2013)	X	X	X	X	X	
Proposed method in thesis	Options analysis based on expert elicitation from Podofillini and Dang (2013) . Maps FT and ET into Dynamic BBN. The temporal BBN is set up in a standard discrete self-linking transition CPTs. The transition CPTs are elicited by expert judgment. The model is adapted from the CCF model from O'Connor (2013) ; O'Connor and Mosleh (2016) .	Fam et al. (2019c,b) .	X	X	X	X	X	X

failures. Since fatigue in cement is an accumulative process, dynamic BBN (discrete-time Markov model) modelling has been utilised to investigate the performance of barrier over time, in this case, the annular fit and the casing strength. This allows the projection of the well barrier failure rate to a decade, which is when a well would most likely fail, if it were to fail. Also there are no monitoring plans enforced for abandoned wells, thus the first observed leak is crucial. The model is able to update failure probabilities of the other wells with the same dependency as the well with the observed leak. The method complements industry-favoured methods of fault tree analysis, some facets of dependent failure and common cause failures which meets up-and-coming regulatory requirements.

This thesis, is an industrial PhD thesis by nature, and aims to cover the topic with sufficient academic depth while not neglecting industrial application. The academic depth lies in the validation of a different technique to an old problem. This thesis highlighted the versatility of BBN models being maximised as literature review demonstrated that BBN models are often not maximised in terms of its modelling flexibility of multiple state systems, dependency, uncertainty representation, continuous variables and temporal state. Some features include demonstrating that expert judgement techniques (expert uncertainty and inherent variability) applied in the nuclear industry is also applicable to the offshore industry. Common cause failures was successfully expanded from equipment CCF models to one that considers environmental, material etc to improve PA well failure estimates. At the same time, the method complements industry-favoured methods of fault tree analysis (thus the industry should not be too resistant to implementing BBN models), as well as some facets of dependent failure and common cause failures which meets up-and-coming regulatory requirements.

5.4 Future Work

The modelling methodology can be improved in two major ways, one involving the specific parts of the model components, or the entire modelling approach. Some alternatives (Items 1,2,3) in the specific model components involve the Common Cause Failure components for different level of detailing, or the HRA models (the Petro-HRA and SPAR-H models identified in Literature Review are only two of the many HRA models). In terms of the overall model approach, future works can be undertaken by incorporating live feedback of evidence from sensors and/or to incorporate a physics-based model coupled with a data-based model. Once a substantial database is built, the model structure can be amended by incorporating insights from data learning to structure

the BBN model.

1. Extending the analysis to other phases of decommissioning

The next phase after well plugging and abandonment is equipment decommissioning. The subsequent large project phases would be the removal of the structure and assessing it for *in situ* decommissioning for Rigs-to-Reef projects or to be moved to a scrapyard. In these phases, structural reliability models can be incorporated into BBNs to analyse the risk of structural failure when sectioning the jackets. There is also a strong environmental consideration for Rigs-to-Reefs projects and the dynamic BBN section can project the study period to investigate the efficacy of the Rigs-to-Reefs project and its associated impact on increasing fishing opportunities.

2. Increasing dependencies in the analysis

The maximum number of dependencies considered in the model was three factors. The complexity of the model can be increased in terms of the number of nodes dependent on the common causes. The greater the dependent interactions, the greater the impact of the dependent failures.

3. HRA-specific influences

There are three areas that can be further investigated: (i) the impact of recovery mechanism for HFEs coupled by the same PSFs (ii) increasing the number of experts to investigate the changes in the uncertainty of result and (iii) overall operability of the model in terms of the ideal range of likelihood scales and its definition on the measurable scales to improve usability of the model across multiple experts.

In Chapter 3, linking HFE1 and HFE 2 through a common PSF allows for understanding dependent failures. However, it is also true that there can be recovery mechanisms that stops the dependent failure from propagating from HFE 1 to HFE2. The modelling mechanism is not explored in this thesis, but the same model is capable of reflecting recovery mechanisms. In Figure 3.15, modelling BBN in layers allow HFE2 to be represented as recovered by removing the observation that 'HFE1 = 1' in the second sub-model. In this way, HFE2 can be modelled as fully coupled to HFE1 (by reflecting HFE1 =1) or as recovered (by leaving HFE1 as unobserved). HFE1 can be modelled has failed without impacting HFE2 by only changing HFE1=1 in the first sub-model.

Though questionnaires were sent out, only one complete set of answers was received as some of the experts involved in the redacted well abandonment study have left Lloyd's Register.

The method proposed by [Podofilini and Dang \(2013\)](#) demonstrated the effect of having multiple experts (1, 2, 5, 10) having the same judgement or different judgement and this can provide insights on the extent the experts are able to reach consensus or if not, the impact of divergent assessments on the results. This is particularly useful as the offshore risk assessment process is consultative and workshop-based with heavy input from experts.

4. Consideration of data learning techniques for model input

As databases are beginning to be automatically updated, there is a possibility to make use of big data pertaining to an equipment's failure probability to update the BBN in light of updated data, or even with live monitoring data.

5. Coupling physics-based model with the existing data-based model

The method used in the thesis is largely data-based modelling. A more thorough modelling methodology would be to combine both data-based modelling and physics-based modelling.

The thesis investigated the degradation of cement barriers in PA Wells. The degradation of cement barriers can exist as general fatigue degradation as well as corrosion (high temperature and pressure). These information is modelled as part of a data-model where the factors of existing temperature and pressure are modelled as a Common-Cause Failure (CCF)- Environment node. Current nodes in the BBN exists as failure probabilities obtained from database.

For a more specific CCF model, a physics component can be built in by considering structural fatigue models as an input. For example crack length in cement can be modelled, and the crack length can be translated to a remaining useful life value or a barrier failure probability, instead of using cement failure probabilities from databases.

5.5 Final Comments

Decommissioning projects are large in scope and involve multiple phases. Project management in this area is niche due to regulatory requirements surrounding operational safety, comparative assessments of the most suitable decommissioning option and consideration of the impact of *in situ* options. The proposed risk assessment method attempts to address the issues of expert elicitation and underestimation of risks from independent failure analysis, and also to provide a dynamic component to solutions with long-lasting impacts.

Well abandonment data is disjointed in nature due to political and geographical boundaries which

regulate the management and sharing of offshore information. Even then, no monitoring plans are set for decommissioned wells until the first leak occurs. However, research funding allocated to well failures ([Nichol and Kariyawasam, 2000](#); [Saeed et al., 2018](#); [Ahmed et al., 2015](#)) indicates there is a trend to understand well failures better. In the context of this paper, it has been shown that the proposed model has met both objectives of capturing better estimates of a well PA event as part of regulatory requirements and that the same model can be used to provide long term monitoring of a group of wells linked by common dependencies.

In terms of future work, as the model has been developed in a plug-and-play modular manner, it can be extended to other complex considerations in a well leak event, such as the environmental modelling of leaks. The combined analysis of leak probability and the extent of environmental impact or other significant consequential impact will be useful for policy-makers to make a sound and economic decisions on post decommissioning monitoring requirements or to review well decommissioning guidelines.

Appendix A

Full conditional probabilities elicited for HFE3

A.1 Conditional probabilities for 3 parent node elicitation

The CPT is based on 3 parent nodes of ‘HMI’ – PSF1, ‘Time’-PSF2 and ‘Threat Stress’ – PSF3 in Figure [3.13](#).

HMI	Misleading															
Time	Error Forcing				Inadequate				Nominal				Good			
Threat Stress	Error Forcing	Inadeq uate	Nomi nal	Good	Error Forcing	Inadeq uate	Nomi nal	Good	Error Forcing	Inadeq uate	Nomi nal	Good	Error Forcing	Inadeq uate	Nomi nal	Good
Very high	0.6957	0.5806 08	0.375 614	0.236 665	0.580608	0.3751 36	0.225 192	0.129 836	0.375614	0.2251 92	0.122 152	0.060 952	0.236665	0.1298 36	0.060 952	0.024 33
High	0.2506	0.3934 22	0.511 198	0.501 163	0.393422	0.5229 21	0.532 336	0.453 403	0.511198	0.5323 36	0.465 308	0.350 997	0.501163	0.4534 03	0.350 997	0.231 042
Moderate	0.0338	0.0258 06	0.109 478	0.236 665	0.025806	0.0993 61	0.225 192	0.353 074	0.109478	0.2251 92	0.356 1	0.450 736	0.236665	0.3530 74	0.450 736	0.489 256
Low	0.0099	0.0001 64	0.003 69	0.024 922	0.000164	0.0025 73	0.017 048	0.061 313	0.00369	0.0170 48	0.054 749	0.129 072	0.024922	0.0613 13	0.129 072	0.231 042
Very Low	0.0099	1.01E-07	1.96 E-05	0.000 585	1.01E-07	9.09E-06	0.000 231	0.002 374	1.96E-05	0.0002 31	0.001 691	0.008 242	0.000585	0.0023 74	0.008 242	0.024 33

HMI																				
Poor																				
Time																				
Threat Stress	Error Forcing					Inadequate					Nominal					Good				
	Error Forcing	Inadeq uate	Nomi nal	Goo d	Error Forcing	Inadeq uate	Nomi nal	Goo d	Error Forcing	Inadeq uate	Nomi nal	Goo d	Error Forcing	Inadeq uate	Nomi nal	Goo d				
Very high	0.6565 41	0.5210 42	0.3757 33	0.236 665	0.5210 42	0.3257 55	0.1612 94	0.060 952	0.3737 33	0.1612 94	0.0457 02	0.008 242	0.236 665	0.0609 52	0.0082 42	0.000 585				
High	0.3100 4	0.4057 46	0.4799 33	0.501 163	0.4057 46	0.4942 16	0.4767 56	0.350 997	0.4799 33	0.4767 56	0.3109 34	0.129 072	0.501 163	0.3509 97	0.1290 72	0.024 922				
Moderate	0.0326 48	0.0704 6	0.1374 33	0.236 665	0.0704 6	0.1672 02	0.3142 47	0.450 736	0.1374 33	0.3142 47	0.4717 29	0.450 736	0.236 665	0.4507 36	0.4507 36	0.236 665				
Low	0.0007 67	0.0027 28	0.0087 76	0.024 922	0.0027 28	0.0126 15	0.0461 89	0.129 072	0.0087 76	0.0461 89	0.1595 94	0.350 997	0.024 922	0.1290 72	0.3509 97	0.501 163				
Very Low	4.01E-06	2.36E-05	0.0001 25	0.000 585	2.36E-05	0.0002 12	0.0015 14	0.008 242	0.0001 25	0.0015 14	0.0120 41	0.060 952	0.000 585	0.0082 42	0.0609 52	0.236 665				

Nominal																				
Time		Error Forcing					Inadequate					Nominal					Good			
Threat Stress	Error Forcing	Inadeq uate	Nomi nal	Goo d	Error Forcing	Inadeq uate	Nomi nal	Goo d	Error Forcing	Inadeq uate	Nomi nal	Goo d	Error Forcing	Inadeq uate	Nomi nal	Goo d	Error Forcing	Inadeq uate	Nomi nal	Goo d
Very high	0.4475 86	0.2366 65	0.0907 56	0.024 33	0.2366 65	0.1027 18	0.0336 51	0.008 242	0.0907 56	0.0336 51	0.0099 85	0.002 374	0.0243 3	0.0082 42	0.0023 74	0.000 585				
High	0.4475 86	0.5011 63	0.4069 87	0.231 042	0.5011 63	0.4237 64	0.2704 79	0.129 072	0.4069 87	0.2704 79	0.1438 54	0.061 313	0.2310 42	0.1290 72	0.0613 13	0.024 922				
Mode rate	0.0998 1	0.2366 65	0.4069 87	0.489 256	0.2366 65	0.3898 73	0.4848 16	0.450 736	0.4069 87	0.4848 16	0.4621 55	0.353 074	0.4892 56	0.4507 36	0.3530 74	0.236 665				
Low	0.0049 63	0.0249 22	0.0907 56	0.231 042	0.0249 22	0.0799 86	0.1937 8	0.350 997	0.0907 56	0.1937 8	0.3311 07	0.453 403	0.2310 42	0.3509 97	0.4534 03	0.501 163				
Very Low	5.5E-05	0.0005 85	0.0045 13	0.024 33	0.0005 85	0.0086 59	0.0172 72	0.060 952	0.0045 13	0.0172 72	0.0528 98	0.129 836	0.0243 3	0.0609 52	0.1298 36	0.236 665				

HMI	Good															
Time	Error Forcing				Inadequate				Nominal				Good			
Threat Stress	Error Forcing	Inadeq uate	Nomi nal	Go o d	Error Forcing	Inadeq uate	Nomi nal	Go o d	Error Forcing	Inadeq uate	Nomi nal	Go o d	Error Forcing	Inadeq uate	Nomi nal	Go o d
Very high	0.2366 65	0.1298 36	0.0609 52	0.024 33	0.0609 52	0.0204 13	0.0048 43	0.000 759	0.0082 42	0.0011 59	7.25E-05	1.45E-06	0.0005 85	1.99E-05	1.01E-07	2.23E-11
High	0.5011 63	0.4534 03	0.3509 97	0.231 042	0.3509 97	0.2266 96	0.1135 16	0.041 738	0.1290 72	0.0481 97	0.0105 74	0.001 084	0.0249 22	0.0036 9	0.0001 64	9.34E-07
Mode rate	0.2366 65	0.3530 74	0.4507 36	0.489 256	0.4507 36	0.5057 81	0.4761 72	0.360 99	0.4507 36	0.3587 73	0.2101 22	0.078 387	0.2366 65	0.1094 78	0.0258 06	0.001 87
Low	0.0249 22	0.0613 13	0.1290 72	0.231 042	0.1290 72	0.2266 96	0.3574 49	0.491 296	0.3509 97	0.4779 35	0.5691 08	0.548 716	0.5011 63	0.5111 98	0.3934 22	0.179 051
Very Low	0.0005 85	0.0023 74	0.0082 42	0.024 33	0.0082 42	0.0204 13	0.0480 2	0.105 216	0.0609 52	0.1139 37	0.2101 22	0.371 812	0.2366 65	0.3756 14	0.5806 08	0.819 078

Appendix B

Questionnaire for PDS β -model

Design properties (incl Location)
Environmental Control (internal and external)
Operation, Maintenance and modifications

Selected questions from IEC 61508 Annex D

CCF Category	Weight	Relevance	Defence	Efficiency Score	Mod. Factor
Environment Control	45%				
Is system likely to operate always within the range of temperature, humidity, corrosion, dust, vibration, over which it has been tested, without the use of external environmental control?	6%	Y	Has specific measures for control of the corrosive environment been implemented such as material choice, corrosion inhibitor on the Claxton tool	0.1	0.006
Are all signals and power cables separate at all positions?	4%	Y	Has physical measures for separating the signals and power cables been implemented?	1	0.04
Has the system been tested for immunity to all relevant environmental influences (for eg. Temperature,Vibration, Shock, Humidity) to an appropriate level as specified in recognised standards?	4%	Y	Has specific measures for simulating the well conditions been documented in order to test/verify the system has been tested for immunity to environmental influences?	1	0.04
		Y	Is there a physical or electronic access to well logging information from its operation time and can be accessed to understand the well conditions?		
Results of initial well logging details are logged into a maintenance system, and is accessible.	9%		If well has history of shallow gas, is there a procedure of sending a analytical tool to assess if shallow gas is present?	3	0.27
Has it been verified that the well classification is suitable for the Claxton tool?	11%	Y	The Claxton tool can only be done on well classified as Category 2 (presence of deep set permanent cement plugs in place)	3	0.33
Has Bullheading operations successfully killed well, with tool in it, and tool operable thereafter?	11%	Y	Has the process of killing well via a direct influx of fluid into the well been used in similarly classed wells when shallow gas has emerged before?	3	0.33
Subtotal modification factor for 'Environmental Control'	45%				1.016
Design Control	20% ...				
		Y	Has the design been reviewed with the purpose of revealing common vulnerabilities, associated with sizing, material selection, location and so on, and are defences implemented to reduce common vulnerabilities (separation, diversity)	1	0.05
Valves within the same equipment group are of the same type (make, manufacturer, material selection, etc)	5%				
Response times (max/min) are critical for the successful performance of the valves.	5%	Y	Have design reviews been carried out with the purpose of identifying possible design constraints in view of response time requirements?	0.1	0.005
Failure of common utility systems, such as accumulators, hydraulic-, or pneumatic systems can result in valves failing to close.	5%	Y	Has it been confirmed that the associated utility systems have sufficient capacity, and are procedures in place to ensure that as well as the individual valve actuators?	0.1	0.005
		Y	Has it been verified by analyses (and possibly testing) that there is sufficient actuator force to close the valve under all foreseeable process conditions and/or has extra sizing/ dimensioning of actuator, etc. been implemented to ensure that the valve will function under all foreseeable process conditions?	1	0.05
Inadequate actuator force can cause the valve not to close upon particular process conditions, such as e.g. low pressures.	5%				
Subtotal modification factor for 'Design Control'	20%				0.11

Operation, maintenance & modifications		35% ...	...	...	...
The valves are periodically tested and maintained according to a predefined maintenance program	Y	3%	Are test- and maintenance procedures readily available, made familiar among the maintenance personnel, and are they kept continuously updated throughout the operational phase?	0.5	0.015
As above	Y	3%	Are there routines/procedures in place to periodically review and if necessary adjust the frequency of functional testing for the valves in light of registered failure history and experienced failure causes?	3	0.09
As above	Y	3%	Do the maintenance personnel always check for similar failures on other valves, if a failure is revealed during testing or operation?	0.5	0.015
Results from periodic testing and maintenance are logged into some kind of electronic (or written) maintenance system.	Y	5%	Have the maintenance operators been given particular training with respect to understanding the valves functionality, critical failure modes and registering maintenance notifications in order to give a good description of e.g. failure cause, detection method and failure modes?	1	0.05
As above	Y	5%	Are maintenance notifications regularly gone through in order to reveal repeating valve failures, to compare results for all relevant valves across the facility, and to initiate and perform root cause analysis in order to identify measures to remove these failure causes?	1	0.05
In case of a valve failure during testing or operation it may be a relevant measure to run the valve again until it functions	Y	5%	If a valve has to be run several times to function satisfactorily (e.g. close fast enough), are then additional measure (lubrication, cleaning, finding the root cause) always put in place in order to prevent this from happening again?	1	0.05
Wrong tuning of bleed off valve and/or weaknesses in the bleed-off that the bleed-off arrangement is correctly tuned arrangement / control block may result in valve failing to close or closing too slow.	Y	5%	Are operational measures implemented to ensure that the bleed-off arrangement is correctly tuned and (if relevant) periodically calibrated towards required closing times?	1	0.05
Adding new valves or valve modifications, including changes to valve performance requirements may become relevant during the operational phase	Y	5%	Are there procedures for independent checks after valve modifications, valve adjustments and adjustments of closing/opening time?	1	0.05
Subtotal modification factor for 'Operation, maintenance & modifications'		20%			0.2
Aggregated modification factor					1.326

Bibliography

Mohammad Mahdi Abaei, Rouzbeh Abbassi, Vikram Garaniya, Ehsan Arzaghi, and Ahmad Bahoo Toroody. A dynamic human reliability model for marine and offshore operations in harsh environments. *Ocean Engineering*, 173(December 2018):90–97, 2019. ISSN 00298018. doi: 10.1016/j.oceaneng.2018.12.032.

Majeed Abimbola, Faisal Khan, and Nima Khakzad. Risk-based safety analysis of well integrity operations. *Safety Science*, 84:149–160, 2016. ISSN 18791042. doi: 10.1016/j.ssci.2015.12.009. URL <http://dx.doi.org/10.1016/j.ssci.2015.12.009>.

Shokoufeh Abrishami, Nima Khakzad, Seyed Mahmoud Hosseini, and Pieter van Gelder. BN-SLIM: A Bayesian Network methodology for human reliability assessment based on Success Likelihood Index Method (SLIM). *Reliability Engineering & System Safety*, 193(July 2019): 106647, 2020. ISSN 09518320. doi: 10.1016/j.res.2019.106647. URL <https://doi.org/10.1016/j.res.2019.106647>.

Agena Ltd. AgenaRisk software package, 2019. URL www.agenarisk.com.

Alan Agresti. *Categorical Data Analysis*. John Wiley & Sons, Hoboken, New Jersey, 2002. ISBN 0471360937.

Ramadan Ahmed, Subhash Shah, Subhash Shah, Shokrollah Hassani, Omotayo Omosebi, Rida Elgaddafi, Himanshu Maheshwari, Aman Srivastava, Jueun Hwang, Mounraj Sharma, Sagar Tale, and Jiwon Jeon. Effect of H₂S and CO₂ in High- Pressure High-Temperature (HPHT) Wells on Tubulars and Cement BSEE Project # E12PC00035. Technical report, The University of Oklahoma, 2015.

Ahmed O. Babaleye, Rafet Emek Kurt, and Faisal Khan. Safety analysis of plugging and abandonment of oil and gas wells in uncertain conditions with limited data. *Reliability*

- Engineering and System Safety*, 188(August 2018):133–141, 2019. ISSN 09518320. doi: 10.1016/j.res.2019.03.027. URL <https://doi.org/10.1016/j.res.2019.03.027>.
- BayesFusion. GeNie, 2018. URL <http://www.bayesfusion.com/>.
- George Bearfield and William Marsh. Generalising event trees using bayesian networks with a case study of train derailment. *Computer Safety, Reliability, and Security*, pages 52–66, 2005. ISSN 1748-006X, 1748-0078. doi: 10.1243/1748006XJRR131. URL <http://www.springerlink.com/index/B4CR2RQC9KPKD50H.pdf>.
- Jyoti Bhandari, Rouzbeh Abbassi, Vikram Garaniya, and Faisal Khan. Risk analysis of deepwater drilling operations using Bayesian network. *Journal of Loss Prevention in the Process Industries*, 38:11–23, 2015. ISSN 09504230. doi: 10.1016/j.jlp.2015.08.004. URL <http://dx.doi.org/10.1016/j.jlp.2015.08.004>.
- A. Bobbio, L. Portinale, M. Minichino, and E. Ciancamerla. Improving the analysis of dependable systems by mapping Fault Trees into Bayesian Networks. *Reliability Engineering and System Safety*, 71(3):249–260, 2001. ISSN 09518320. doi: 10.1016/S0951-8320(00)00077-6.
- I. M. Boothroyd, S. Almond, S. M. Qassim, F. Worrall, and R. J. Davies. Fugitive emissions of methane from abandoned, decommissioned oil and gas wells. *Science of the Total Environment*, 547:461–469, 2016. ISSN 18791026. doi: 10.1016/j.scitotenv.2015.12.096. URL <http://dx.doi.org/10.1016/j.scitotenv.2015.12.096>.
- B Cai, Y Liu, Y Zhang, Q Fan, Z Liu, and X Tian. A Dynamic Bayesian networks modeling of human factors on offshore blowouts. *Journal of Loss Prevention in the Process Industries*, Vol. 26:pp. 639—649, 2013.
- Baoping Cai, Yonghong Liu, Qian Fan, Yunwei Zhang, Zengkai Liu, Shilin Yu, and Renjie Ji. Multi-source information fusion based fault diagnosis of ground-source heat pump using Bayesian network. *Applied Energy*, 114:1–9, 2014. ISSN 03062619. doi: 10.1016/j.apenergy.2013.09.043. URL <http://dx.doi.org/10.1016/j.apenergy.2013.09.043>.
- Baoping Cai, Xiangdi Kong, Yonghong Liu, Jing Lin, Xiaobing Yuan, Hongqi Xu, and Renjie Ji. Application of Bayesian Networks in Reliability Evaluation. *IEEE Transactions on Industrial Informatics*, 15(4):2146–2157, 2019a. ISSN 15513203. doi: 10.1109/TII.2018.2858281.
- Baoping Cai, Xiaoyan Shao, Yonghong Liu, Xiangdi Kong, Haifeng Wang, Hongqi Xu, and Weifeng Ge. Remaining useful life estimation of structure systems under the influence of

- multiple causes: Subsea pipelines as a case study. *IEEE Transactions on Industrial Electronics*, 0046(c):1–1, 2019b. ISSN 0278-0046. doi: 10.1109/tie.2019.2931491.
- Yuanjiang Chang, Xiangfei Wu, Changshuai Zhang, Guoming Chen, Xiuquan Liu, Jiayi Li, Baoping Cai, and Liangbin Xu. Dynamic Bayesian networks based approach for risk analysis of subsea wellhead fatigue failure during service life. *Reliability Engineering and System Safety*, 188(June 2018):454–462, 2019. ISSN 09518320. doi: 10.1016/j.ress.2019.03.040.
- Claxton. The Claxton SWATTM - Suspended Well Abandonment Tool operational (Paragon - B391) (1), 2015.
- V.M.H. Coupé, N. Peek, J. Ottenkamp, and J.D.F. Habbema. Using sensitivity analysis for efficient quantification of a belief network. *Artificial Intelligence in Medicine*, 17(3):223–247, 1999. doi: 10.1016/S0933-3657(99)00024-X. URL <http://www.scopus.com/inward/record.url?eid=2-s2.0-0032586121&partnerID=40&md5=9aa753a1f95acc4832ad291c44f12fb3>.
- Robert Cross, Robert Youngblood, Ronald Boring, Gordon Bower, Bruce Reistle, Kurt Vedros, and Andrew Wolford. Probabilistic Risk Assessment Procedures Guide for Offshore Applications (DRAFT) JSC-BSEE-NA-24402-02. Technical report, NASA Johnson Space Center (JSC) and Idaho National Laboratory (INL), 2017. URL https://www.bsee.gov/sites/bsee.gov/files/ProbalisticRiskAssessment{%}28PRA{%}29/bsee{_}pra{_}procedures{_}guide{_}-{_}10-26-17.pdf.
- Department for Business Energy and Industrial Strategy UK. Decommissioning of Offshore Oil and Gas Installations and Pipelines under the Petroleum Act 1998. Technical Report March, Aberdeen, 2011. URL https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/69754/Guidance{_}Notes{_}v6{_}07.01.2013.pdf.
- DNV GL. World Offshore Accident Database, 2017. URL <https://www.dnvgl.com/services/world-offshore-accident-database-woad-1747>.
- Nsimah Joseph Ekanem. *A model-based human reliability analysis methodology (PHOENIX Method)*. PhD thesis, University of Maryland, 2013.
- Fairfield Fagus Limited. Osprey Field Subsea Infrastructure Comparative Assessment. Technical report, 2017. URL https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/668411/Osprey{_}Final{_}DP.pdf.

M L Fam, D Konovessis, L S Ong, and H K Tan. A review of offshore decommissioning regulations in five countries – Strengths and weaknesses. *Ocean Engineering*, 160(April):244–263, 2018a. ISSN 0029-8018. doi: 10.1016/j.oceaneng.2018.04.001. URL <https://doi.org/10.1016/j.oceaneng.2018.04.001>.

Mei Ling Fam, Hoon Kiang Tan, Dimitrios Konovessis, and Lin Seng Ong. A review of offshore decommissioning Regulations in three countries - strengths and weaknesses. In *ASME 2017 36th International Conference on Ocean, Offshore and Arctic Engineering*, pages 1–14, 2017.

Mei Ling Fam, Xuhong He, Patrik Hilber, Lin Seng Ong, Dimitrios Konovessis, and Hoon Kiang Tan. Data learning and expert judgment in a Bayesian Belief Network for offshore decommissioning risk assessment. In *Proceedings of the 28th International European Safety and Reliability Conference (ESREL 2018), Trondheim, Norway, 17-21 June 2018*, pages 297–405. Taylor & Francis Group, 2018b.

Mei Ling Fam, Xuhong He, Konovessis Dimitrios, Lin Seng Ong, and Hoon Kiang Tan. Validation of a Bayesian Belief Network (BBN) Model of an Offshore Decommissioning Operation Introduction to Bayesian Belief Networks. In *The 29th International Ocean and Polar Engineering Conference, 16-21 June, Honolulu, Hawaii, USA*, number i, pages 1351–1360. International Society of Offshore and Polar Engineers, 2019a.

Mei Ling Fam, Dimitrios Konovessis, Xuhong He, Lin Seng Ong, and Hoon Kiang Tan. Analysing dependent failures in a Bayesian belief network. In *Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE*, volume 3, pages 1–10. ASME, 2019b. ISBN 9780791858783. doi: 10.1115/OMAE2019-95853.

Mei Ling Fam, Dimitris Konovessis, Xuhong He, Lin Seng Ong, and Hoon Kiang Tan. (in press) Bayesian aggregation methods of expert judgement to incorporate human error probabilities for offshore decommissioning risk assessment. In Michael Beer Zio and Enrico, editors, *Proceedings of the 29th European Safety and Reliability Conference.*, pages 1–10. Research Publishing, Singapore, 2019c.

Norman Fenton, Martin Neil, and David Lagnado. Modelling mutually exclusive causes in Bayesian networks. In *IEEE*, pages 1–11, 2011. doi: 10.1111/cogs.12004. URL https://www.eecs.qmul.ac.uk/~norman/papers/mutual{}_IEEE{}_format{}_version.pdf.

Norman Fenton, Martin Neil, David Lagnado, William Marsh, Barbaros Yet, and Anthony Constantinou. How to model mutually exclusive events based on independent causal pathways

- in Bayesian network models. *Knowledge-Based Systems*, 113:39–50, 2016. ISSN 09507051. doi: 10.1016/j.knosys.2016.09.012.
- Government of the United Kingdom. Energy Act 2016: Chapter 20, 2016. URL http://www.legislation.gov.uk/ukpga/2016/20/pdfs/ukpga_{_}20160020_{_}en.pdf.
- Chuanqi Guo, Faisal Khan, and Syed Imtiaz. Risk assessment of process system considering dependencies. *Journal of Loss Prevention in the Process Industries*, 55(June):204–212, 2018. ISSN 09504230. doi: 10.1016/j.jlp.2018.06.014. URL <https://doi.org/10.1016/j.jlp.2018.06.014>.
- Chuanqi Guo, Faisal Khan, and Syed Imtiaz. Copula-based Bayesian network model for process system risk assessment. *Process Safety and Environmental Protection*, 123:317–326, 2019. ISSN 09575820. doi: 10.1016/j.psep.2019.01.022. URL <https://doi.org/10.1016/j.psep.2019.01.022>.
- Stein Hauge, Åsa Snilstveit Hoem, Per Hokstad, Solfrid Håbrekke, and Mary Ann Lundteigen. Common Cause Failures in Safety Instrumented Systems : Beta-factors and equipment specific checklists based on operational experience. Technical report, Trondheim, 2015.
- Health and Safety Executive (HSE) (UK). Safety Case Assessment Initial Review - Dismantlement of an Installation Safety Case, 2015. URL <http://www.hse.gov.uk/osdr/safety-cases/dismantlement-safety-cases.htm>.
- J. Forester, A. Kolaczowski, S. Cooper, D. Bley, and E. Lois. *ATHEANA User 's Guide Final Report*, (NUREG-1880). 2007. ISBN 1800553684.
- R. B. Jackson. The integrity of oil and gas wells. *Proceedings of the National Academy of Sciences*, 111(30):10902–10903, 2014. ISSN 0027-8424. doi: 10.1073/pnas.1410786111.
- Dolly Jørgensen. OSPAR’s exclusion of rigs-to-reefs in the North Sea. *Ocean and Coastal Management*, 58:57–61, 2012. ISSN 09645691. doi: 10.1016/j.ocecoaman.2011.12.012. URL <http://dx.doi.org/10.1016/j.ocecoaman.2011.12.012>.
- Sohag Kabir and Yiannis Papadopoulos. Applications of Bayesian networks and Petri nets in safety, reliability, and risk assessments: A review. *Safety Science*, 115(April 2018):154–175, 2019. ISSN 18791042. doi: 10.1016/j.ssci.2019.02.009.
- Janina Kleemann, Enrico Celio, and Christine Fürst. Reprint of "Validation approaches of an expert-based Bayesian Belief Network in northern Ghana, West Africa". *Ecological Modelling*,

- 371:101–118, 2018. ISSN 03043800. doi: 10.1016/j.ecolmodel.2017.12.021. URL <http://dx.doi.org/10.1016/j.ecolmodel.2017.12.021>.
- Zengkai Liu, Yonghong Liu, Baoping Cai, Dawei Zhang, and Chao Zheng. Dynamic Bayesian network modeling of reliability of subsea blowout preventer stack in presence of common cause failures. *Journal of Loss Prevention in the Process Industries*, 38:58–66, 2015. ISSN 09504230. doi: 10.1016/j.jlp.2015.09.001. URL <http://dx.doi.org/10.1016/j.jlp.2015.09.001>.
- Lloyd’s Register. Redacted Well Abandonment Study. Technical report, Aberdeen, 2019.
- Bruce G. Marcot. Metrics for evaluating performance and uncertainty of Bayesian network models. *Ecological Modelling*, 230:50–62, 2012. ISSN 03043800. doi: 10.1016/j.ecolmodel.2012.01.013. URL <http://dx.doi.org/10.1016/j.ecolmodel.2012.01.013>.
- Andrés R. Masegosa and Serafin Moral. An interactive approach for Bayesian network learning using domain/expert knowledge. *International Journal of Approximate Reasoning*, 54(8): 1168–1181, 2013. ISSN 0888613X. doi: 10.1016/j.ijar.2013.03.009. URL <http://dx.doi.org/10.1016/j.ijar.2013.03.009>.
- L. Mkrtchyan, L. Podofilini, and V.N. Dang. Bayesian belief networks for human reliability analysis: A review of applications and gaps. *Reliability Engineering & System Safety*, 139:1–16, 2015. ISSN 09518320. doi: 10.1016/j.ress.2015.02.006. URL <http://linkinghub.elsevier.com/retrieve/pii/S0951832015000514>.
- Richard E. Neapolitan. *Learning Bayesian networks*. Prentice Hall, 2004.
- JR Nichol and SN Kariyawasam. Risk assessment of temporarily abandoned or shut-in wells. Contract No. 1435-01-99-RP-3995. Technical Report 1435, 2000. URL <http://www.mms.gov/tarprojects/329/329AA.pdf>.
- Thomas Dyhre Nielsen and Finn Verner Jensen. *Bayesian Network and Decision Graph*. 2007. ISBN 9780387682815. doi: 10.1007/978-0-387-68282-2.
- Norwegian Climate and Pollution Agency. Decommissioning of offshore installations, 2011. ISSN 00222410. URL <http://www.npd.no/en/Publications/Reports/Decommissioning-of-offshore-installations/>.
- Norwegian Oil and Gas Association. Guidance on calculating blowout rates and duration for use in environmental risk analyses, 2014. URL <https://www.norskoljeoggass.no/contentassets/d6c1d516cc4945358fea471a8610becf/guidance-blowoutrates-with-supp-report.pdf>.

Norwegian Petroleum Directorate. Act 29 November 1996 No. 72 relating to petroleum activities, 1996. URL <http://www.npd.no/en/Regulations/Acts/Petroleum-activities-act/{#}5-4>.

Andrew O'Connor and Ali Mosleh. A general cause based methodology for analysis of common cause and dependent failures in system risk and reliability assessments. *Reliability Engineering and System Safety*, 145:341–350, 2016. ISSN 09518320. doi: 10.1016/j.ress.2015.06.007. URL <http://dx.doi.org/10.1016/j.ress.2015.06.007>.

Andrew N O'Connor. *A general caused based methodology for analysis of dependent failures in system risk and reliability assessments*. Phd thesis, University of Maryland, 2013.

Oil & Gas Authority UK. Decommissioning Delivery Programme Contents, 2016. URL <https://www.ogauthority.co.uk/media/2720/decommissioning{ }delivery{ }programme.pdf>.

Oil & Gas UK. Guidelines for Comparative Assessment in Decommissioning Programmes. Technical Report 1, 2015. URL <https://oilandgasuk.co.uk/product/en038/>.

Petter Osmudsen and Ragnar Tveteras. Decommissioning of petroleum installations - major policy issues. *Energy Policy*, 31(970911):1579–1588, 2003. doi: PiiS0301-4215(02)00224-0.

Petroleum Institute of Thailand. Draft Thailand Decommissioning Guidelines for Upstream Installations, 2008. URL [DraftThailandDecommissioningGuidelinesforUpstreamInstallations-Final](#).

PETRONAS. Decommissioning Safety: Dana and D30 Decommissioning Project. In *SPE Workshop : Process Safety and Technical Risk Assessment*, number December, 2017.

L. Podofillini and V. N. Dang. A Bayesian approach to treat expert-elicited probabilities in human reliability analysis model construction. *Reliability Engineering and System Safety*, 117:52–64, 2013. ISSN 09518320. doi: 10.1016/j.ress.2013.03.015.

L Podofillini, L Mkrtchyan, and V N Dang. Aggregating expert-elicited error probabilities to build HRA models. In *Safety and Reliability: Methodology and Applications*, pages 1083–1091, London, 2015. Taylor & Francis Group. ISBN 9781138026810.

L Podofillini, D Pandya, F Emert, A J Lomax, and V N Dang. Bayesian aggregation of expert judgment data for quantification of human failure probabilities for radiotherapy. pages 501–508, 2018.

- Luca Podofillini, Vinh Dang, Enrico Zio, Piero Baraldi, and Massimo Librizzi. Using expert models in human reliability analysis-a dependence assessment method based on fuzzy logic. *Risk Analysis*, 30(8):1277–1297, 2010. ISSN 02724332. doi: 10.1111/j.1539-6924.2010.01425.x.
- Luca Podofillini, Lusine Mkrtchyan, and Vinh N Dang. Quantification of Bayesian Belief Net Relationships for HRA from Operational Event Analyses. *Probabilistic Safety Assessment and Management PSAM 12, June 2014, Honolulu, Hawaii*, (June), 2014.
- Willy Røed, Ali Mosleh, Jan Erik Vinnem, and Terje Aven. On the use of the hybrid causal logic method in offshore risk analysis. *Reliability Engineering and System Safety*, 94(2):445–455, 2009. ISSN 09518320. doi: 10.1016/j.ress.2008.04.003.
- R.W. Saaty. The Analytical Hierarchy Process- What and Why it is Used. *Mathematical Modelling*, 9(3):161–176, 1987.
- Salehi Saeed, Ramadan Ahmed, Catalin Teodoriu, Chinedum Peter Zeakacha, Harshkumar Patel, George Kwatia, Shawgi Ahmed, and Mustafa Al-ramadan. Studying “Fitness for Service” of the Sealing Assemblies and Cement System in Shallow Well Designs by Conducting Scaled Laboratory Testing, Leakage Modelling and Risk Assessment. BSEE Project #E17PC00005. Technical Report October, The University of Oklahoma, 2018.
- SINTEF Technology and Society. *Reliability Data for Safety Instrumented Systems PDS Data Handbook*. SINTEF, Trondheim, 2010.
- SINTEF Technology and Society, Norges teknisk-naturvitenskapelige universitet, and DNV GL. *OREDA - Offshore and onshore reliability data handbook*. OREDA Participants, Trondheim, 2002. ISBN 82-14-02705-5.
- Stortinget (Norwegian Government). Recommendation of the energy and environment committee on the disposal of disused pipelines and cables on the Norwegian Continental Shelf. Report no. no. 47 (1999 -2000) Disponering av utrangerte rørledninger og kabler på norsk kontinentalsokkel. St.meld., 2000. URL <https://www.stortinget.no/no/Saker-og-publikasjoner/Saker/Sak/?p=20500>.
- Geir-Ove Strand and Mary Ann Lundteigen. Human factors modelling in offshore drilling operations. *Journal of Loss Prevention in the Process Industries*, 43:654–667, 2016. ISSN 09504230. doi: 10.1016/j.jlp.2016.06.013. URL <http://linkinghub.elsevier.com/retrieve/pii/S0950423016301668>.

A.D. Swain and H.E. Guttman. *Handbook of Human Reliability Analysis with Emphasis on Nuclear Power Plant Applications (NUREG/CR-1278)*. Number August. US Nuclear Regulatory Commission, Washington, DC, 1983.

Alan D Swain. Accident Sequence Evaluation Program Human Reliability Analysis Procedure. Technical report, 1987.

Claire Taylor. *The Petro-HRA Guideline*. Institute for Energy Technology, Halden, 2017. ISBN 9788270179015.

The American Society of Mechanical Engineers. ASME Standard for Probabilistic Risk Assessment for Nuclear Power Plant Applications. Technical report, The American Society of Mechanical Engineers, New York, 2013. URL <https://www.nrc.gov/docs/ML0037/ML003733342.pdf>.

United States Department of the Interior. ACCIDENT INVESTIGATION REPORT - G01241. 2007.

J. E. Vinnem, J. Seljelid, S. Haugen, S. Sklet, and T. Aven. Generalized methodology for operational risk analysis of offshore installations. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 223(1):87–97, 2009. ISSN 1748006X. doi: 10.1243/1748006XJRR109.

J. E. Vinnem, R. Bye, B. A. Gran, T. Kongsvik, O. M. Nyheim, E. H. Okstad, J. Seljelid, and J. Vatn. Risk modelling of maintenance work on major process equipment on offshore petroleum installations. *Journal of Loss Prevention in the Process Industries*, 25(2):274–292, 2012. ISSN 09504230. doi: 10.1016/j.jlp.2011.11.001. URL <http://dx.doi.org/10.1016/j.jlp.2011.11.001>.