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Activity-based Modelling for Operational Decision-support

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Reliability, Availability, Maintainability and Safety (RAMS)
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Supervisor: Stein Haugen, IPK

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Preface

This Master Thesis is written in culmination of the International Master Program in Reliability, Availability, Maintainability and Safety (MSc. RAMS) within the Production and Quality Engineering Department (IPK) at the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. This work has been performed during the spring of 2015 in continuation of the project thesis written in the autumn of 2014.

This report is prepared in collaboration with the Modelling Instantaneous Risk for Major Accident Prevention (MIRMAP) project, financed by the Norwegian Research Council, coordinated by NTNU and supported by Statoil and Gassco as industrial partners.

The intended reader for this report should have practical experience in areas related to risk and operations in the oil and gas industry and/or education equivalent to that gained in the course TPK 5160 - Risk Analysis at NTNU. In addition, certain basic knowledge on Bayesian Belief Networks is required to understand the models discussed in this report.

Trondheim, 2015-06-17

Nathaniel John Edwin

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Firstly, my supervisor, Professor Stein Haugen for his time, patience and invaluable guidance which was very vital in the execution of this work.

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A special thank you to Stein Hauge from SINTEF Technology and Society, Safety Research for his inputs on critical aspects of the master thesis. I would also like to thank my other colleagues at SINTEF Technology and Society, Safety Research, in particular Lars Bodsberg, for giving me the opportunity to work closely with the department through 2014. This experience was vital in kindling my interest in the field of risk analysis.

Special mention to the faculty of the RAMS study group at NTNU, without whom this master thesis would never be complete.

Last but not the least, a heartfelt thank you to my family and friends who supported me throughout the past years and especially during my study at NTNU.

N.J.E

Summary and Conclusions

The recent plunge in oil and gas prices has led to most players in the industry cutting capital investments and squeezing operational costs. In such a business setting, increasing production while improving safety performance is a challenge. The Norwegian Petroleum Safety Authority, over the years, has emphasized the importance and relevance of using risk analysis as decision support during all phases of the lifecycle of a facility. The traditional Quantitative Risk Analysis is useful for developing safe design, but during operations its relevance is limited. Therefore the focus has been to develop suitable risk analysis tools to support decisions on a day-to-day operational context.

Existing operational risk analysis methods are broadly grouped into two categories – first which provides an updated average risk level and the second a dynamic real-time risk level. The latter has been the area of focus in the recent past and most industry players have developed their own proprietary tools for the same. These are typically software solutions that support integrated management of safety critical information through visualization solutions and better data management. They provide a coarse qualitative overview of the current conditions on a facility, but do not provide any quantitative decision support. An interpretative literature review of existing methods in operational risk analysis from the oil and gas industry reveals that much is left to be done to gain insight into short-term changes in risk levels, also known as risk transients. The few existing methods that provide quantitative real-time operational decision support are limited in coverage and applicability.

To bridge this gap, activity-based modelling is suggested as an approach to measure these transient risk levels in operations. The basic unit of the activity-based operational risk analysis framework is a Risk Influencing Factor (RIF). To support systematic RIF identification for work activities, a hierarchical tree breakdown of an activity is suggested, to support understanding of the relevant hazards, hazardous events, accident scenarios and controls in place for a particular activity. One of the key takeaways from this study is the need to distinguish between risk increasing 'activities' and 'conditions'.

To develop a suitable method to model degradation in barrier condition due to risk increasing activities, a set of existing and relevant models from literature are reviewed. Various features from each of these models are adapted to develop the suggested method. As activities are characterized by

the interaction of technical, operational and organizational factors – Bayesian Belief Networks (BBNs) are the best available method to reasonably model these factors and their interrelationships. The developed model quantifies barrier condition on a scale from A to F and formally treats uncertainty in RIF measurements and interaction effects between RIFs. The interaction modelling method suggested is an advancement from the original adapted technique from the literature.

To demonstrate the applicability of the model, the BBN is implemented in software and two case scenarios are simulated. The simulations highlight the importance of accurately modelling interaction effects between factors. Using sensitivity analysis, risk reducing measures can be easily identified.

Discussions on the model's relevance and applicability, highlights the need to develop an extended risk model for it to be relevant to decision-makers. This involves understanding and mathematically accounting for synergies and interactions not only between individual factors, but also between individual activities themselves. A coarse idea to integrate this into a unified full-fledged risk model is introduced and identified as an area of further work. Furthermore, if an alternate BBN structure is required to better represent the real-world, this can be done while retaining the mathematical concepts such as uncertainties, interactions etc. as discussed in the thesis.

Contents

Abbreviations

ALARP: As Low as Reasonably Practicable

BBN: Bayesian Belief Network

BDV: Blowdown Valve

BF: Barrier Function

CDF: Cumulative Distribution Function

CPT: Conditional Probability Table

DAG: Directed Acyclic Graph

ESV: Emergency Shutdown Valve

FMECA: Failure Mode Effect and Criticality Analysis

GeNIe: Graphical Network Interface

HAZOP: Hazard and Operability study

HAZID: Hazard Identification

HC: Hydrocarbon

HCL: Hybrid Causal Logic

HSE: Health Safety and Environment

HVAC: Heating Ventilation and Air Conditioning

IO: Integrated Operations

IOCenter: Center for Integrated Operations in the Petroleum Industry

MIRMAP: Modelling Instantaneous Risk for Major Accident Prevention

I-Risk: Integrated Risk

NCS: Norwegian Continental Shelf

ORA: Operational Risk Analysis

ORIM: Organisational Risk Influence Model

PDF: Probability Distribution Function

PFP: Passive Fire Protection

PSAN: Petroleum Safety Authority, Norway

PSV: Process Safety Valve

QRA: Quantitative Risk Analysis

RIF: Risk Influencing Factor

SJA: Safe Job Analysis

VBA: Visual Basic for Applications

WO: Work Order

WP: Work Permit

Chapter 1

Introduction

1.1 Background

Risk analysis forms a part of the basis for managing risk - it provides insight into the enterprise and helps identify knowledge gaps (PSAN, 2014). In the oil and gas industry, there has been constant emphasis to promote the use of risk analysis for decision-making in both strategic and operational decision contexts (Vinnem, 2013). This also happens to be one of the main focus areas for the Petroleum Safety Authority Norway (PSAN) in 2015 (PSAN, 2015). Quantitative Risk Analysis (QRA) is widely used in the oil and gas industry to support strategic decisions and has proved to be satisfactory in aiding development of safe design for a facility as a whole. On the other hand, to support operational decisions, most analyses are qualitative and are weakly linked to the risk of the facility.

PSAN (n.d.) points out that maintenance, modification and related simultaneous activities contribute to a significant increase in risk levels in operations. Therefore, the use of risk analysis for operational decision making is taking increased significance. There is a clear need to expand the current realms of operational risk analysis - from qualitative studies addressing a problem with limited scope, to analysis that help reflect the actual risk condition of a facility based on ongoing operational activities.

Over the past decade there have been significant advances in modelling the impact of human, technical and organizational factors on risk not only within the oil and gas sector, but also the nuclear and space sectors to provide better decision-support in operations.

Within safety research in Norway, the Organizational Risk Influence Modelling (ORIM) project (Øien, 2001) was one of the first efforts to make QRAs more dynamic by charting how organizational factors estimated through risk indicators could influence failure modes. The limitation of the ORIM was that it did not extend existing QRAs to shed light on failure causes. This was followed by the Barrier and Operational Risk Analysis (BORA) project (Aven et al., 2006) that shifted focus to barrier and operative issues where a basic risk influence modelling framework was setup. The modelling framework so established was very similar to that in the nuclear industry (Vatn, 2013). This was followed by the OTS project (Sklet et al., 2010) which focussed on how human and organizational factors affect barrier performance. Soon after, the RiskOMT method (Vinnem et al., 2012) built upon the work from both the BORA and OTS projects. It presents a comprehensive approach to Risk Influence Factor (RIF) modelling which was also successfully tested in a case study (Gran et al., 2012). One of the major limitations with the RiskOMT method is its complexity and the tedious work required to extend existing QRAs to fit in with the modelling framework. More recently, Scandinavian research institute SINTEF, in collaboration with the Centre of Integrated Operations in the Petroleum Industry (IOCenter) has conceptualized the Risk Barometer (Hauge et al., 2014). It is a tool that relates the status of the safety barriers to the instantaneous risk level on the installation.

Meanwhile, due to continued focus and attention on risk and barrier management from the PSAN, there have been a number of internally driven projects by oil and gas operators themselves - ConocoPhillips (Etterlid, 2013) and Statoil (Refsdal, 2011) to name a few, who have developed integrated software solutions to promote better management of safety critical information and thereby reduce their operational risk. These developments and more are reflected upon in detail through a structured review in Chapter 2.

Across other industries there have been a number of projects aimed at modelling human and organizational factors for major accident prevention. The SPAR-H human reliability analysis method (Gertman et al., 2005) was developed for use within the US nuclear sector and is now being extended for use in oil and gas industry (PetroHRA) (SINTEF, 2013). The I-Risk (Integrated Risk) method models the probability of major hazard occurrence weighted by human and organizational factors (Le Coze et al., 2003). The SoTeRiA project presents an integrated methodology for socio-technical risk analysis to incorporate the effect of both social and technical failure mechanisms in risk assessment (Mohaghegh et al., 2009). Although not directly relevant to the research problem at hand, these methods provide a cross-domain understanding of human and organizational factors in operational risk analysis.

In spite of all the industry research effort in recent times, none has been able to develop a comprehensive and scalable solution for implementation within the oil and gas sector for real-time, risk-based operational decision support. Most of the quantitative operational risk analysis methods are either too tedious to run on a regular basis or incomplete in being able to completely represent reality. This master thesis presents a step forward in this direction. The objective is to promote better management of frontline work activity and related operational risk to integrate with planning processes. Providing an understanding of key risk drivers in operations provides decision makers with relevant information to proactively manage and mitigate risk.

1.2 Objectives

The main objectives of this Master's thesis are:

1. Review literature on operational risk analysis and to report the same and document existing solutions/methods that model activities to express operational risk.
2. Describe the concept of Risk Influencing Factors (RIFs) for work activities and suggest an approach to systematically identify relevant RIFs for the same.
3. Build on already existing methods and models in literature, to suggest a suitable method to quantify the impact of work activities on barrier condition.
4. Test the suggested method, identify shortcomings, areas of potential improvement and avenues for further work.

1.3 Limitations

The scope of this thesis is limited to activity planning and execution for hazardous chemical industries on land. This is because the MIRMAP project focuses on a land based gas processing facility as a case. The results are likely to be applicable for other purposes as well with minor modifications (e.g. offshore installations). However, these have not been considered and strictly differentiated between in this study.

Decision-making in reality is a trade-off between various economic and safety aspects. Due to limitations in time and knowledge base, this thesis does not focus on the economic aspects of risk and decision-making.

Health Safety and Environment (HSE) issues with regard to work related accidents (occupational safety) are very critical and are of paramount importance in hazardous chemical industries. However these are not explicitly addressed in this thesis. That said, the importance of HSE must not be considered less or forgotten.

Data availability and collection is often a challenge because due to current reporting practices it is available across multiple sources and in various formats. The challenges in data collection and management are not explicitly reflected on in this presentation. It is assumed that all relevant information is readily available in the required format for use.

1.4 Approach

The master thesis begins with a qualitative review of existing literature and methods for operational risk analysis in the industry. The literature review documented in Chapter 2, is an interpretative review of the 'state-of-the-art' in operational risk analysis within the oil and gas industry. This provides the background knowledge built upon to address the research problem. Over the course of the spring of 2015, the author has been an observer at the MIRMAP project meetings to gain perspective on developments and challenges discussed by the project group.

With the theoretical background knowledge from the literature review and exposure to practical challenges during the project meetings, a method to quantify barrier condition based on ongoing activities is suggested, tested and critically analysed. An outline of this approach is illustrated in Figure 1.1.

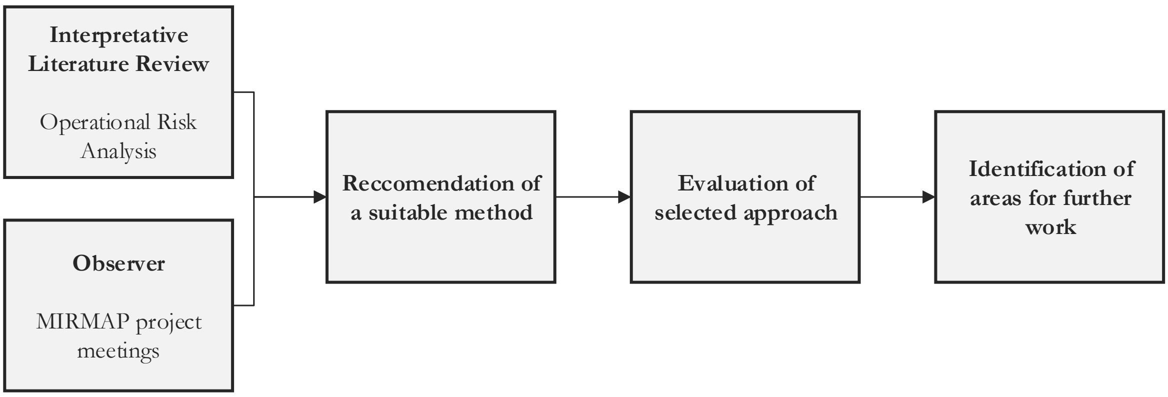


Figure 1.1 Adopted research approach

1.5 Structure of the Report

The remainder of this report is organized as follows:

Chapter 2 documents the interpretative literature review on operational risk analysis. A classification scheme for operational risk analysis is suggested and existing methods/tools in the oil and gas industry are reported.

Chapter 3 highlights the importance of measuring transient risk levels in operations and suggests activity based modelling as an approach to achieve this. An idea for an activity based model from the MIRMAP project group is presented, discussed and critically reviewed.

Chapter 4 defines RIFs for work activities and a structured method to identify these is suggested. The work permit form, which is often underutilized, is identified as an important source for information on RIFs for work activities.

Chapter 5 builds on existing methods for operational risk analysis from literature and suggests using Bayesian Belief Networks (BBNs) to quantify the effect of work activity RIFs on barrier condition.

Chapter 6 implements the BBN model for a selected work activity in software. The validity and relevance of the results are discussed along with the implications, limitations and shortcomings of the model.

Chapter 7 presents conclusions from the work and gives recommendations for future work.

Chapter 2

Managing Risk in Operations

Rausand (2011) defines risk management as a continuous management process with the objective to identify, analyse, and assess potential hazards in a system or an activity, and to identify and introduce risk control measures to eliminate or reduce potential harm to people, the environment or other assets. Risk analysis is an important part of the risk management process which provides input to risk evaluation.

The results from a risk analysis can be expressed in a variety of formats depending on the context of the problem, techniques adopted, etc. The risk analyses involve a variety of quantitative and qualitative methods, each with their own format of results. These features are also characteristic of operational risk analyses. This chapter elaborates on operational risk analyses. Existing methods and models for managing operational risk as developed/in-use in the industry are reported.

2.1 Risk and Risk Analysis

2.1.1 Types of Risk

Yang and Haugen (2014) classify risk into different categories. *Site-specific risk* is the 'normal' risk level averaged over a year. *Activity risk* is the risk level associated with performing a certain activity and *period risk* is the expression of risk over a short period of time.
With similar intention, DNVGL (2014) broadly divides risk into two – (1) a *"basic risk level"* or the inherent risk level which is a product of the engineering phase where safety studies are performed to ensure safe design and that all risks are as low as reasonably practicable (ALARP). (2) a *"variable risk level"* driven by technical and operational conditions, activity levels, etc. The former corresponds to a site-specific risk level and the latter to the activity and period risk levels. The variable short-term changes to the risk are also termed as risk transients by Vinnem et al. (2003).

To provide effective decision support, these risk types must be correctly identified, measured and differentiated between, using suitable risk analysis.

2.1.2 Risk Analysis in Literature

Vatn and Haugen (2012) differentiate between different types of risk analyses performed in the oil and gas industry - strategic risk analysis and the operative risk analysis.

Strategic risk analyses provide decision support to the development of safe design and operating procedures. They focus on technical aspects and only limited operational input is used (e.g. number of visits of offshore supply vessels, number of crane lifts, etc.). Examples of strategic risk analyses are the Quantitative Risk Analyses (QRA) or Total Risk Analyses (TRA) conducted in the Norwegian Oil and Gas industry. The QRA provides a 'normal' risk level averaged over a year (Vinnem et al., 2003) which is a measure of the site specific risk.

On the other hand *operative risk analysis* is applied to a limited problem area. For example, for an activity to be performed, to support specific decisions with limited scope, etc. The safe job analyses (SJA) performed before safety critical work is conducted, is an example of an operative risk analysis. Therefore operative risk analysis typically covers aspects of activity risk alone.

An *operational risk analysis* (ORA) is different from the operative risk analysis as defined by Vatn and Haugen (2012) in that, it reflects changes in the risk level in two ways -: (as introduced in Section 2.1.1. Also see Figure 2.1)

a. A change in the base (normal) risk level of the facility due to long-term/permanent changes. These could be due to updates to regulations, activity levels, technical solutions adopted, etc.
b. Short-term high risk intervals within a generally low risk environment. This occurs due to regular operational activity. It is these short-term changes that contribute to the average base risk level in (a).

The operative risk analysis (Vatn and Haugen, 2012) qualitatively addresses aspects of only item (b) and is therefore only a subset of operational risk analyses. Section 2.1.3 elaborates further on operational risk analysis (ORA).

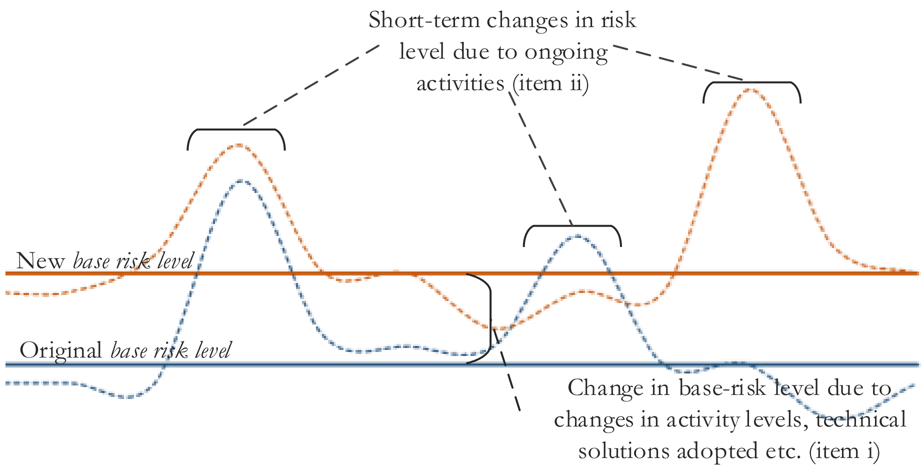


Figure 2.1 Components of the changing risk level

2.1.3 Operational Risk Analysis

Operational risk is characterized by the interaction of people with the plant (Lehmann and Neill, 2013). This interaction could be on a daily basis through activities or over a larger time scale due to changes in technical solutions adopted and activity levels at the plant. With this in mind, ORA is defined as *a family of systematic methods (both qualitative and quantitative) that provide insight into the changing risk level in operations, due to long term changes such as measures taken, technology used, changing regulations, etc. or short term transients due to ongoing operational activities.*

To cover all aspects of the changing risk levels as suggested by the definition above and elaborated in Section 2.1.2, ORAs are broadly classified into three categories. This classification is illustrated in Figure 2.2.

- Category 1: Reflect changes in base (average) risk level
- Category 2: Measure risk transients (short-term increases in risk levels) in real-time
- Category 3: A combination of categories 1 and 2, providing an updated measure of the average risk level by real-time measurement of risk transients.

Category 1:
Updating the base risk level would mean to update the site-specific risk and will therefore utilize the existing QRA. This can be done in two ways:

1.1 *Updating the QRA* by modifying relevant analyses, assumptions, etc. to account for major changes in technical solutions adopted, regulations, etc.

1.2 *Extending the QRA* to account for certain technical/organizational factors that are not explicitly modelled in the existing QRA.

By being able to update the results from the QRA, focus areas for risk reducing measures and potential areas for operational improvement can be identified. All documented methods that suggest updating/extending the QRA can only be achieved at infrequent intervals (typically greater than one year).

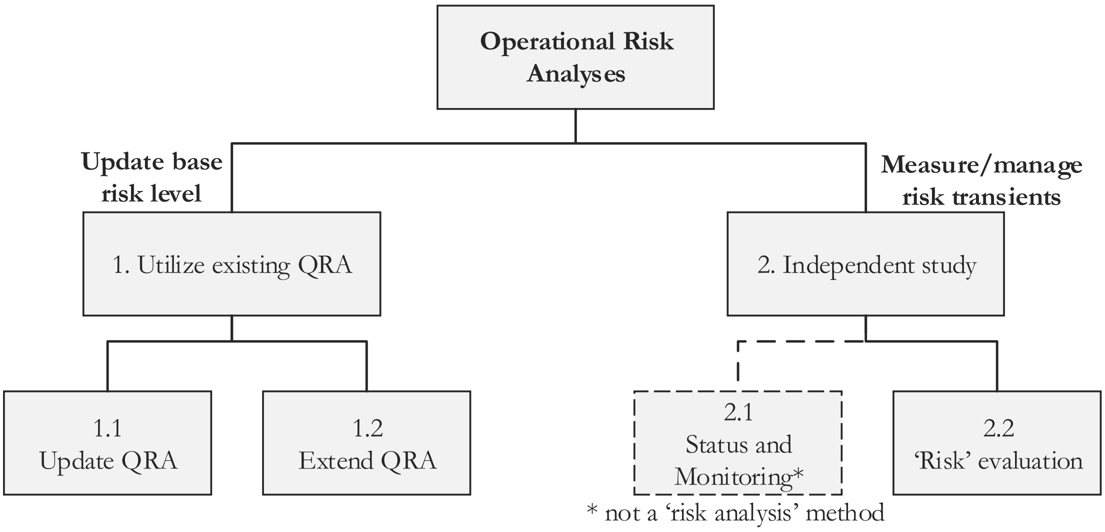


Figure 2.2 Suggested classification scheme for Operational Risk Analyses

Category 2:

Measuring/monitoring risk transients can also be achieved in two ways:

2.1 Through status and monitoring tools and techniques that promote integrated management of safety critical information (status of barriers, deviations, ongoing activities, etc.) through better visualization and/or data management and reporting. The visualization of planned jobs in combination with other safety hazards on a geographical representation of the installation, improves the decision-maker's ability to address safety hazards (Skjerve et al., 2013).

2.2. Through explicit risk evaluation methods where the activity/period risk levels are calculated based on the current operational climate (ongoing and planned activities, current deviations etc.)

Effective management of risk transients in operations can support decisions with regard to Work Permit (WP) planning and approval, activity level management etc.

Category 3:

This category is included only for the sake of completeness and being irrelevant for oil and gas industries, is omitted from Figure 2.2. Category 3 ORAs reflect changes in the average risk level due to changing operational conditions in real-time. The living risk analysis (Vinnem and Haugen, 2012) in the nuclear industry falls in this category. The Probabilistic Risk Analyses (PRA) methods in the nuclear industry have a detailed focus on the modelling initiating events, using fault trees and therefore real-time updation is possible.

On the contrary, the QRA in the oil and gas industry focusses primarily on the reactive side of the bow-tie (i.e. consequence modelling). Furthermore, in order to simplify the risk analyses models, not all barriers are included in the QRA (Johansen and Rausand, 2015). This makes updating the oil and gas QRA in real-time impossible.

Remark: The classification scheme presented here is only a suggestion. It must be acknowledged that "Status and Monitoring" and "Risk Evaluation Methods" (2.1 and 2.2) are not completely mutually exclusive categories. For example, if a tool identifies and monitors parameters based on the risk analysis, it would fall in both categories. Hence this classification must be treated with caution.

2.1.4 Literature Review: Current Industry Practice

The oil and gas industry boasts of a variety of methods and tools in both realms of ORA illustrated in Figure 2.2. This section presents results of a literature review of current practice in ORA in the oil and gas industry.

Information for the literature review in this chapter is obtained mainly through internet searches supplemented by information that is known to be of potential interest. The predominant material source is Google Scholar and the One Petro database. The documented literature is found mainly through searches using the following terms:

- Dynamic risk
- Operational risk
- Instantaneous risk
- Cumulative risk

Using these search terms in engines such as Google Scholar, most of the hits were related to financial risk. Therefore the search terms were supplemented with terms such as "oil and gas", "hazardous industries" and other related terms. It is also important to note that as operational risk analysis is a new topic of interest in the oil and gas sector, most of the relevant reviewed literature date 2011 or later.

Utilize the Existing QRA

i. Update the QRA

Periodic intervals for QRA updates are either set by individual companies/regulators or performed on an on-demand basis (due to changes in technical solutions used, modifications made, changes in operational assumptions, etc.).

For example, regulatory based examples of QRA updating are – (i) Statoil recommends the need for QRA updating every three years (Vinnem, 2014). (ii) The UK Safety Case Regulations (HSE, 2005) sets very rigid requirements for updating of the QRA.

It can be argued that regulatory based updating of the QRA to get new risk numbers need not add any value because they need not necessarily contribute to promoting directed and effective risk reducing measures in operations.

ii. Extending the QRA

The QRA in the oil and gas industry is very coarse (Johansen and Rausand, 2015). A detailed study on a QRA by Vinnem and Haugen (2012) reveal that the actual number of barriers represented both explicitly and implicitly in the QRA are very low. There are a number of methods that have suggested extending the QRA to account for these shortfalls.

For example, the RiskOMT method (Vinnem et al., 2012) models the influence of operational and organizational factors on the leak frequency. However, it has limitations in being able to represent a true working environment (Vinnem, 2013) and cannot be used for daily updates (Nyheim, 2014).

Other recent methods reviewed in literature include the absolute risk approach in the Risk Barometer (Hauge et al., 2014) and the BORA method (Aven et al., 2006).

Independent Methods

i. Risk Evaluation

These methods provide information on activity/period risk.

E.g. The relative risk approach in the Risk Barometer (Hauge et al., 2014) relate the status of safety barriers with the current risk level in a particular area of the installation at a particular time instant. Procient by Petrotechnics (Lehmann and Neill, 2013) also falls into this category of methods – however the authors do not provide information on implementation procedures/methods.

ii. Status and Monitoring

In the recent past there have been a number of operators who have developed their own proprietary solutions to effectively monitor and communicate safety critical information.

These solutions do not say anything explicitly about the risk but the claim is that effective visualization and presentation of safety critical information promotes better risk monitoring and management.

E.g. ConocoPhillips (Etterlid, 2013) has developed iSee which provides a visualization interface for all risk related data – barrier analyses, work permit system, barrier breaches and deviation information.

A complete listing of independent methods developed/in use in the industry is presented in Table 2.1. A recent trend in the industry is the use of barrier panels by oil and gas operators (Item 10 in Table 2.1). These panels provide integrated visualization of status information from dedicated condition monitoring, maintenance and control systems to provide live follow-up for barrier maintenance in operations (Øien et al., 2015).

2.1.5 ORA Method Selection

Section 2.1.3 has suggested a broad classification for ORA. To summarize, criteria that justify the need for a specific category of operational risk analysis are presented here.

Utilizing the QRA by either updating or extending it might be useful in operations:

i. If technical solutions established during design undergo significant changes.
ii. To quantify the effects of operational and organizational factors on the risk level and prioritize areas of improvement.
iii. To satisfy internal company or regulatory requirements.

Independent analyses may utilize the QRA as an information source but is not fully integrated/built into the QRA. These methods promote better management of risk transients and can prove useful in operations:

i. To visualize/quantify interactions between various activities at a site/installation.
ii. To integrate with planning and execution of regular activities.
iii. To understand the effects of an impaired barrier on the overall risk level to help make a judgement on the tolerability of the situation.

For example, iSee by ConocoPhillips (Etterlid, 2013) does not aim to quantify the effect of risk transients in operations but through an integrated software solution promotes better management of safety critical information (ongoing work permits, deviations and breaches) – Category 2 - "Status and Monitoring" method.

Table 2.1 List of Operational Risk Analyses methods developed/in-use in the industry

S.No	Tool Name	Developers	Reference	Type	Status information overlaid on installation plot plans	Barrier Condition monitoring	Provides information about the risk	Integrates with planning	Implementation details provided
1	Risk Barometer	SINTEF	(Hauge et al., 2014)	Risk Based	-	✓	✓	-	✓
2	Procient	Petrotechnics	(Lehmann and Neill, 2013)	Risk Based	✓	✓	✓	✓	-
3	Total Risk	Shell UK	(Schellings, 2013)	Status and Monitoring	✓	-	✓	-	✓
4	Cumulative Risk Assessment	British Gas	(Cassidy et al., 2011)	Status and Monitoring	-	✓	-	-	✓
5	Safety Barriers Integrity Management System	Petrobras	(Neto et al., 2014)	Status and Monitoring	-	✓	-	-	✓
6	IOMap	IFE	Braseth & Sarchar, 2012	Status and Monitoring	✓	-	-	✓	✓
7	iSee	Conoco Phillips	(Etterlid, 2013)	Status and Monitoring	✓	✓	-	-	-
8	TIMP	Statoil	(Refsdal, 2011)	Status and Monitoring	-	✓	-	✓	-
9	Kårstø Risk Management Tool	Statoil	(Vinnem and Haugen, 2012)	Risk Based	-	-	✓	-	-
10	Barrier Panels	Misc.	(Øien et al., 2015)	Status and Monitoring	-	✓	-	-	-

✓	Available	-	Not available

Through an interpretative literature review, this chapter has suggested a classification scheme of Operational Risk Analyses and presented a summary of available solutions in the oil and gas industry. The study reveals that most operators promote the use of Category 2 - status and monitoring solutions. None of the tools reviewed provided a real-time risk measure apart from items 1, 2 and 9. However, these are limited with regards to approach, methodology and coverage, respectively. This is discussed in further detail in Section 3.2.2.

In light of these findings, an alternative approach to risk quantification is activity-based modelling, discussed further in Chapter 3.

Chapter 3

Activity Based Modelling

This chapter introduces activity based modelling as an approach to measure risk transients. Section 3.1 begins with defining risk transients and identifying key contributors to risk transients in operations. Thereafter, Section 3.2 introduces an idea towards measuring these transients using activity based modelling.

3.1 Risk Transients

3.1.1 Definition

The term 'transient' is defined as that which lasts for only a short time. With this interpretation, risk transients are defined by Vinnem et al. (2003) as short-term increases in risk due to short duration activities (ranging from one hour up to several days).

If the emphasis were on a longer time duration – for instance, months to years, the focus would need to be much broader that just short-duration activities. For example, weakening in the structural integrity of equipment due to corrosion. Such long-term variations are reasonably accounted for in the design QRA. It is re-emphasized that the term risk transients is only associated with short-duration activities.

3.1.2 Major Accident Risk Transients

PSAN (2013) highlights, that from 1996-2004 more than eighty percent of the total major accident risk on the NCS could be accounted for by HC leaks. As long as hydrocarbon containment is intact, it can be argued that the plant has significantly reduced risk levels. As described by Sklet et al. (2005), five barrier functions are considered relevant with regard to prevention of major accidents. These are illustrated using a barrier grid in Figure 3.1. (Wagnild et al., 2015).

Certain barriers like "containment"/"prevent HC leak" are always active, while others are dormant until demanded. When there are ongoing activities, they might influence the likelihood of these barriers functioning satisfactorily and therefore the risk level might increase considerably (Vinnem et al., 2003). These short-duration activities that introduce risk transients could be typical work activities such as maintenance work on HC equipment, construction of scaffolding, installation/removal of equipment, etc.

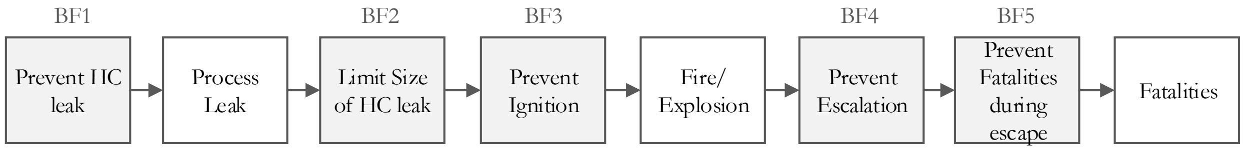


Figure 3.1 Barrier Grid (Wagnild et al., 2015)

3.1.3 Activities and Risk Transients

Ongoing activities represent interaction of people with the plant and this is a component of operational risk. This interaction is illustrated by (Mohaghegh and Mosleh, 2009) in Figure 3.2.

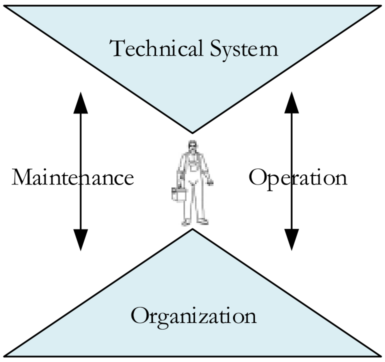


Figure 3.2 Interaction of people with the plant during maintenance and operations (Mohaghegh and Mosleh, 2009)

In current practice, the status of barriers are managed in isolation from the ongoing work and related risk (Mackay, 2013). However, it is important to note that barrier impairments exist alongside ongoing work and is sometimes caused by the ongoing work itself. The measurement of risk transients should therefore aim to quantify operational risk as a function of this interaction of people with the plant. This interaction is characterized by factors related to the technical system as well as human and organizational factors that result in barrier degradation and/or weakening. Activities that might have an influence on the performance of each barrier function from Figure 3.1 is listed in Table 3.1.

The classification in Table 3.1 reported from Wagnild et al. (2015) is made without any scientific arguments or justification. There are a number of flaws within this classification. For example, certain activities such as "inhibit gas detectors" impairs not only "Reduce size of leak" (BF2) but also the "Prevent Ignition" (BF3) barrier. This is because ignition may occur at different points along the event sequence. Modelling the event sequence is a challenge as it is dependent on the operation mode and other associated factors (Vinnem et al., 2004). Furthermore, activities relating to maintenance/work on process safety valves (PSVs) are also missing from the classification. PSVs are an important barrier system for preventing overpressure and resulting leaks which is missing from the classification scheme. There is a clear need to verify, improve and expand on the suggested classification.

Table 3.1 Predefined activity categories for onshore facilities that influence major accident potential (Wagnild et al., 2015)

Predefined Activity Category	Barrier Affected	Sub Category
Activities that might lead to leakage	BF1	Normal operation (manual)
		Preparation – HC activity
		Resetting - HC activity
		Critical Lifting Activity
Activities that influence leakage duration given leakage	BF2	Inhibiting gas detectors
		Locking of ESV
		Locking of BSV
Activities affecting probability of ignition given leakage	BF3	Hot work Class A
		Hot work Class B
		Digging
		Blasting
		Car Traffic
		De-isolation of equipment
		Temporary equipment use
Activities affecting probability of escalation given ignited leakage	BF4	Removal of PFP
		Inhibiting fire detectors
		Inhibiting fire water
Activities affecting duration of leakage, ignition and escalation	BF2, BF3, BF4	Scaffolding
		Work on HVAC

3.1.4 Relevance of analysing risk transients

The importance of effectively managing risk transients in operations is understood from the following two examples.

Example 1

Comparing the Piper Alpha and the Brent Alpha accidents – example adapted from Vinnem et al. (2003)

The same sequence of events transpired for both platforms (a limited gas explosion followed by fire), except that for the Piper Alpha, the fire water system was out of service while for the Brent Alpha it functioned as required. This highlights that maintenance work (e.g. taking the fire water system out of service) represents a temporary increase in risk levels. See Figure 3.3.

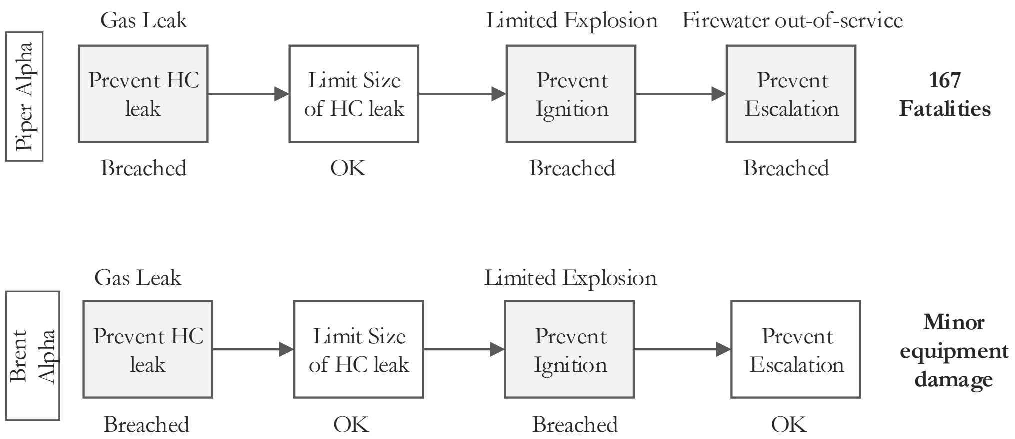


Figure 3.3 Example 1: Piper Alpha accident compared with the Brent Alpha incident

Example 2

Collapse of semi-submersible platform Petrobras P-36 (Oil Rig Disasters, n.d.)

In 2001, the semi-submersible platform Petrobras P-36, sank off the coast of Brazil. A loss of containment incident turned disastrous due to (i) a delay in the activation of the drainage pump (ii) An ignition source causing a gas cloud to ignite and (iii) on-going maintenance on both sea water pumps which rendered them out of service. See Figure 3.4.

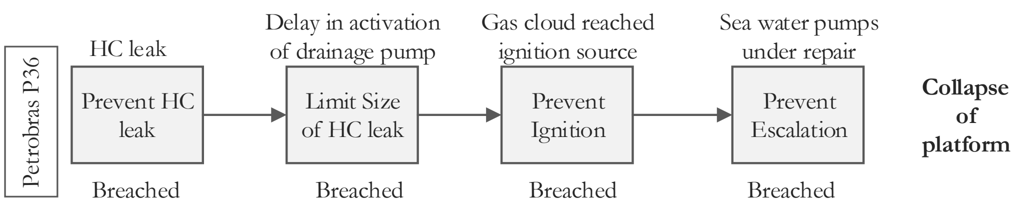


Figure 3.4 Example 2: Petrobras P-36 major accident

The sequence of events in the two examples illustrates how simultaneous impairment/degradation of barrier functions - although individually seemingly unrelated, can together lead to a major accident.

3.2 Activity Based Modelling

Section 3.1 has highlighted how activities have a significant impact on the risk level in operations. To be able to quantify and understand the relationship between activities and the risk level, activity-based modelling is the path forward.

3.2.1 Objectives

The operational risk analysis must be able to promote risk understanding on avoiding a risk developing into an actual accident. Adopting activity based modelling to achieve this provides the following advantages:

a) Promotes measurement of instantaneous risk levels rather than average values
b) Integrates seamlessly with planning and identifies risk at an early stage
c) Suggests risk reducing measures which can provide near immediate risk reduction.
d) Promotes awareness of ongoing activities and identifies potential conflicts
e) Supports decisions with regard to permissible tasks and related activity levels
f) Provides updated information on the status of barriers in operation

3.2.2 Current Modelling Approaches

None of the existing methods and tools studied in Chapter 2 explicitly deal with activity based modelling to measure risk transients. The three risk based tools - the Risk Barometer (Hauge et al., 2014), Procient (Lehmann and Neill, 2013) and the Kårstø Risk Management Tool (Vinnem and Haugen, 2012) have limitations with regard to approach, methodology and coverage respectively. The Risk Barometer (Hauge et al., 2014) addresses mainly breaches/deviations of safety critical functions, Procient (Lehmann and Neill, 2013) claims to provide a risk level based on ongoing activity levels but does not specify the algorithm/method to do so and the Kårstø Risk Management Tool (Vinnem and Haugen, 2012), is limited to quantifying the effect of only manual intervention, hot work, vehicle traffic and manning levels and is therefore not very comprehensive.

The only activity that the current QRA explicitly addresses is the risk associated with helicopter landing or take-off, (Vinnem et al., 2003). In addition, number of well operations and number of supply vessel visits are also examples of the limited operational input used in the QRA. However, a similar approach is not followed for modelling other operations and activities as a part of the QRA. Instead, other quantitative studies such as Hazard Identification (HAZID), Safe Job Analysis (SJA) etc. are used.
The limitation of these existing approaches clearly identifies the need for a new approach to activity-based modelling.

3.2.3 New modelling approach

Brautaset et al. (2014) suggest developing the activity based risk model along the lines of Kahneman (2011) concept of slow thinking – fast thinking. Kahneman (2011) divides human decision making into two areas.

i. System 1: Fast Processing – Assess situation - make immediate decisions
ii. System 2: Slow Processing – Assess situation – Seek new/missing information and make decisions

Figure 3.5a reported by Brautaset et al. (2014) shows initial thoughts in this direction for decision making - *"If the risk level is low and the uncertainty is limited, this should be easily and quickly recognizable, to avoid spending unnecessary time on low risk situations. On the other hand, if the risk level is high, or the uncertainty is high, this should trigger reflection rather than automatic actions."* Unfortunately Brautaset et al. (2014) in their presentation fail to explain what is meant by "uncertainty"- *"...uncertainty associated with the situation should be reflected in the information that is provided. If a decision is made on highly uncertain information, the decision makers should know about this…"*

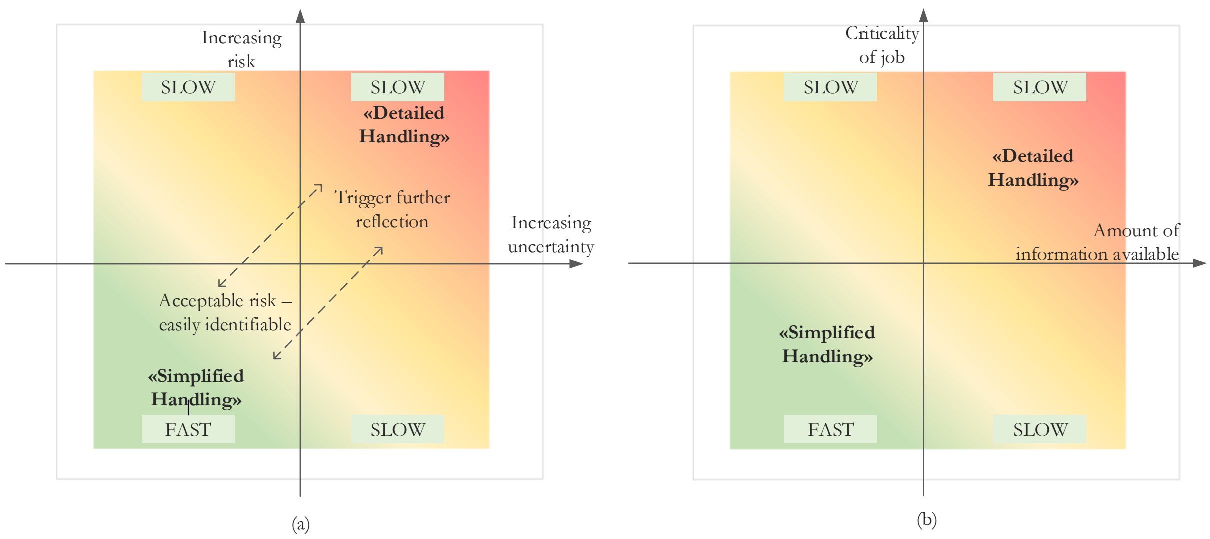


Figure 3.5 Principle behind modelling approach. (a)- Brautaset et al. (2014) (b) – Revised outlook

Is uncertainty here expressed by probability? Or is uncertainty related to the amount of information available? It is difficult to interpret the intentions of this figure without being explicit on the meaning of uncertainty. If the belief of Brautaset et al. (2014) is that there exists a "true risk" which cannot be uncovered due to weaknesses in the strength of knowledge, this illustration might be relevant.

However there are many who are critical about this belief of an underlying "true risk" because risk itself is the uncertainty of outcome, actions and events (Unit, 2002).

There is a need to be more explicit on the interpretation of Figure 3.5a. It is said that any activity that needs to be executed (Table 3.1) is processed by one of two systems. To decide which system is assigned to a particular activity, two broad criteria are specified:

1. Criticality of job (~expected risk involved = *fn*(production risk, major accident risk))
   This is measured by calculating activity risk and period risk (i.e. measuring risk transients). Furthermore, the focus must be on leak prevention (Haugen, 2014) and therefore the model based on the barrier grid (Figure 3.1) is relevant. In addition to risk considerations, the simultaneity of multiple activities and possible dependencies between them are also taken into consideration.

2. Amount of information available (~ uncertainty surrounding the activity)
   Uncertainty ("strength of knowledge") about the activity must be acknowledged. As time progresses, information about the activity increases (i.e. uncertainty reduces).

Based on this understanding, the figure from Brautaset et al. (2014) is re-specified (Figure 3.5b). Kahneman (2011) however warns of a significant limitation within this frame of thinking. It needs to be ensured that the size of system 2 never gets too small ("overconfidence" in decision treatment) or too large ("paralysis by analysis") in comparison to system 1.

Based on this understanding, the figure from Brautaset et al. (2014) is re-specified (Figure 3.5b). Kahneman (2011) however warns of a significant limitation within this frame of thinking. It needs to be ensured that the size of system 2 never gets too small ("overconfidence" in decision treatment) or too large ("paralysis by analysis") in comparison to system 1.

3.2.4 Suggested Approach

In alignment with the ideas presented in Section 3.2.3, an approach to activity based modelling from Wagnild et al. (2015) is presented in this section. In Figure 3.6, a flowchart is used to present the outline of the methodology. It provides a simple and logical structure that can sequentially describe the steps of the method.

The method is broadly divided into three stages:

In Stage 1 all activities to be executed are sorted into "low" and "high" risk categories. This is performed based on Risk Influencing Factors (RIF) and simultaneity factor evaluations, to measure the inherent risk of an activity and study if there are any conflicts between activities in time, space and risk.

In Stage 2, the "low" risk activities are continuously monitored in for any updates/changes.

In Stage 3, "high" risk activities are subjected to further detailed evaluation.

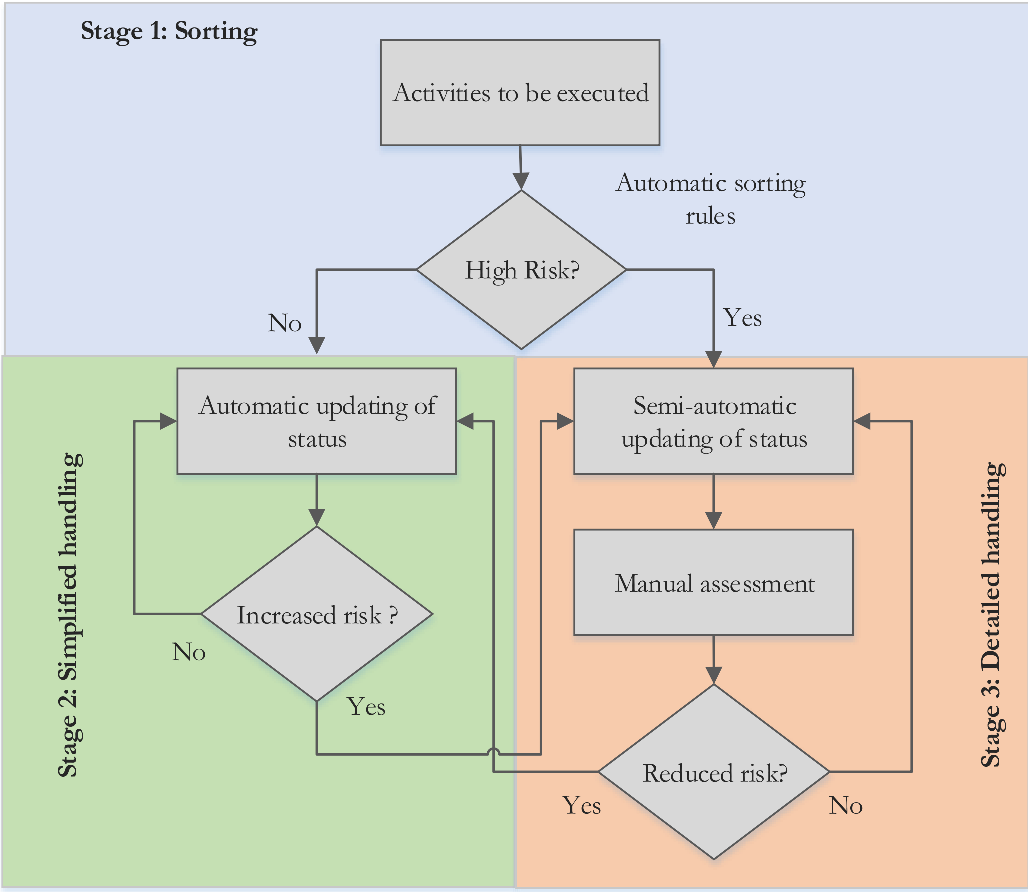


Figure 3.6 Outline of method for activity based modelling of risk (Wagnild et al., 2015)

Wagnild et al. (2015) report that "Stage 2-Simplified handling" will operate very similar to the "Stage 1-Sorting". Therefore, there is no significant advantage of splitting Stage 1 and Stage 2. A simplified representation of the method is shown in Figure 3.7. This has just two distinct stages – The first stage evaluates <u>all</u> activities, and only a select set of activities that have high risk potential are evaluated in "Stage 3–Detailed handling". Further development of the re-specified model in Figure 3.7 incorporates the following steps

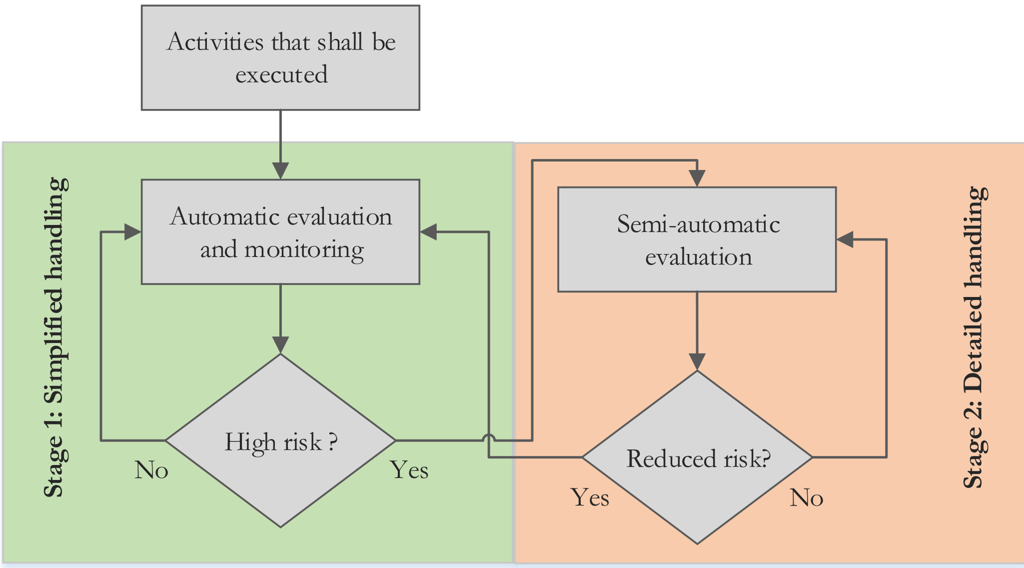


Figure 3.7 Simplified model representation

For simplified handling:

1. Develop a methodology for identification of a representative set of RIFs for each activity from Table 3.1. This RIF structure must provide a basis for risk evaluation per activity.
2. Develop a method to quantify the effect of simultaneous activities that together represent an increased level of risk. The main challenge here is how to deal with aggregation of risk information.
3.

For detailed handling:

4. Establish a method to integrate information from the QRA and other information sources (e.g. barrier analyses, expert judgements etc.) to reflect the risk based on actual plant condition.
5. Establish a framework for result reporting – top risk contributors and possible risk reducing measures.

This thesis focuses only on Item 1: RIF identification to model barrier condition due to activities that represent an increased risk potential.

Chapter 4

Risk Influencing Factors

The basic unit of the activity-based modelling framework is a Risk Influencing Factor (RIF). Most literature on risk influence modelling focus on RIF identification for specific event/accident types. An alternate approach is needed for work activities. This chapter presents a summary on principles for RIF identification from literature and builds on this, to specify a recommended process to RIF identification for work activities.

4.1 Theory

4.1.1 Definition

In literature, a Risk Influencing Factor (RIF) is defined as an aspect (event/condition) of a system or an activity that affects the risk level of this system/activity (Øien, 2001). Rausand (2011) defines a RIF as "a relatively stable condition that influences the risk". These definitions are unclear in specifying what actually constitutes a RIF. To clear this confusion Vatn (2013) defines RIFs in connection with the QRA and clarifies that a RIF is a factor or condition that influences the risk and are of three types (i) RIFs that equal a QRA parameter (ii) RIFs which influence a QRA parameter (iii) RIFs which do not explicitly influence a QRA parameter.
(A QRA Parameter is a condition that affects risk and is included as a single factor in the QRA risk model. These could typically be basic events in the fault trees of the QRA, e.g. availability of gas detection, probability of ignition, etc.)

However, as discussed in Section 3.2.2, existing QRA techniques do not focus on activity based modelling and hence the definitions from Vatn (2013) are not directly relevant. Nevertheless, the key takeaway from Vatn (2013) is that RIFs must be connected to an underlying risk model (directly or indirectly). This risk model would provide a basis to quantification of risk transients in operations.

As pointed out by Section 3.1.2, barrier degradation is sometimes caused by the ongoing work itself and in this context a RIF is defined as, "*an aspect of an activity that contributes to risk transients*". Where it is recalled from Section 3.1.1 that risk transients refer to short duration increases in risk caused by activities ranging from a few hours to a few days.

4.1.2 Classification

A RIF may either be classified as technical, operational or organizational (Haugen et al., 2012). To be able to adequately identify RIFs, a deeper understanding of various RIF types is necessary.

Technical Factors

Technical factors include systems or processes which have been implemented to prevent or reduce the impact of an event or prevent it from occurring (Haugen et al., 2012). This definition must not be confused or limited to cover only technical barrier systems. Technical factors are more inclusive and cover a wider set of factors that must include not only the technical system, but also characteristics of the same. That is, not only equipment, hardware and software aspects (Johansen and Rausand, 2015), but also equipment design, condition, process complexity, etc.

Operational Factors

Operational factors refer to aspects related to safety critical operations such as maintenance and inspection (Haugen et al., 2012). They include human and task-related factors.

Human factors are not to be confused with the human errors of slips, lapses, mistakes and violations (Vinnem et al., 2012); (Rausand, 2011). They can instead be considered as aspects that influence the probability of human errors. These include factors that influence the successful completion of an activity such as competence, workload, fatigue, etc. Task related factors are specific aspects of the activity itself such as task complexity, time pressure, tools required, spare part availability, etc.

Organizational Factors

Organizational factors are structural or managerial aspects that influence the risk (Haugen et al., 2012). These factors shape the culture of safety amongst the employees in an organization and may be either active or dormant (Reason, 1997). They also include administrative issues which are governing aspects that help ensure smooth execution of activities. Examples of organizational factors are supervision, leadership, communication, change management, procedures, task documentation, etc.

Remark 1: Sometimes it might be difficult to clearly distinguish between operational and organizational factors. For example, "task documentation" which is an organizational factor is also an important operational element, which defines the scope of the activity under consideration. It is important to be aware that the RIF classification scheme need not be mutually exclusive in all aspects and hence must be treated with caution.

Remark 2: Mohaghegh and Mosleh (2009) claim that only technical factors have distinguishable "error" and "functioning" states, while operational and organizational factors do not. However, this need not always be the case. For instance, in certain circumstances operational factors may be defined as "correct" or "incorrect" (e.g. task description). In a similar fashion, technical factors also need not always have well-defined "error" or "functioning" states (e.g. process complexity).
This highlights the importance of acknowledging that each factor has its own configuration, which may or may not relate to a clearly defined, "working" or "failed" condition. It is the combined effect or interaction of these factors that creates unsafe conditions and which is often a challenge for a risk model to analyse.

4.1.3 Measurement

The measured value of a RIF is termed as its score and is the realization of its true underlying value (J Vatn, 2013a). A RIF can be measured in three ways (Mohaghegh and Mosleh, 2009):

- Objectively, via a set of observable risk indicators which provide an indirect measure of the RIF score,
- Subjectively, from the results of surveys, interviews, etc.
- Hybrid, with a combination of the subjective and objective approaches

Objective measurement using observable risk indicators, presents a lot of discussion in the literature. For example, discussions about leading vs. lagging indicators (Hopkins and others, 2009), indicator coverage limitations (Haugen et al., 2012), etc. These discussions are not covered in this presentation. For now it is assumed that all RIFs are measurable and are represented by their scores.

The scale of the score of a RIF can vary depending on the nature of study. For example, if *'r'* is the score of the RIF, the ORIM (Øien, 2001) project defines $r = 1$ as the best case and $r = 5$ as worst case. The BORA (Aven et al., 2006) and RiskOMT (Vinnem et al., 2012) projects use the scale from A to F or 1 to 6. Similarly, a neutral scale of measurement is defined as $r = -1$ as the worst case and $r = +1$ as the best case. No matter what the scale of measurement, an uniform scale of measurement is recommended for all RIFs (J Vatn, 2013a). A uniform scale of measurement is important to aid the risk model to mathematically treat all RIFs within a single unified framework. Also, if a RIF is measured through a set of observable risk indicators, a mapping of the risk indicators observations to the uniform scale of the RIF is needed. This is not easy due to coverage limitations for risk indicators (Haugen et al., 2012). For these reasons, if information about a RIF is limited/unavailable, the uncertainty in the RIF score must be adequately represented.

4.2 RIFs for Work Activities

With knowledge on the definition, classification and measurement aspects of RIFs, this section presents a recommended process for identification of RIFs for work activities. Section 4.2.1 presents a set of principles adapted from various literature sources to support RIF identification. Thereafter, Section 4.2.2 suggests a structured method to identify a selected set of RIFs relevant for a particular work activity.

4.2.1 Principles

Identification and structuring are two important aspects that relate to recognizing and arranging the set of RIFs relevant for work activities, respectively.

The structuring of RIFs depends on purpose for which they are to be used. For example, the RiskOMT method structures the RIFs into planning, execution and control clusters to support integration with the specified risk model. As no risk model is currently developed, RIF structuring is side-lined and only principles to RIF identification are presented here. These are:

a) Utilize logical reasoning combined with knowledge of the system and activities being considered (Tranberg, 2013)
b) If activity is complex, a combination of a top-down approach (utilizing generic lists of RIFs) and a bottom-up approach (events being assessed are chosen as a starting point) (Aven et al., 2006).
c) Once generic lists of RIFs are set up, these lists can be updated with new RIFs by learning from the bottom-up approach as and when necessary (Aven et al., 2006).
d) Reports of accidents and near misses can also provide useful information about relevant factors (Tranberg, 2013).
e) Looking at indirect influence can help identify RIFs (Haugen et al., 2012).

These principles form the basis of the RIF identification process recommended for work activities in this section.

4.2.2 Selection of RIFs

To identify the set of RIFs relevant for a chosen activity, a structured method is required. Principles (b) and (c) both emphasize the importance of using a bottom-up approach to gain confidence in the identified RIFs. Traditionally, this is done using the existing risk analyses (Vatn, 2013b). As there is no explicit available risk model in QRAs or otherwise, to model activities and their influence on major accident risk, Principle (a) states that logical reasoning about the activity can be used to identify the relevant set of RIFs. In light of this, two approaches are possible – **a process-based approach** or a **system-based approach**.

4.2.2.1 Choice of Approach

The process-based approach performs detailed task-wise break down of an activity (i.e. task analysis) and analyses what can go wrong for each of these tasks. For example, the RiskOMT (Vatn, 2013a) uses detailed task analyses to identify critical steps in work execution for HC equipment. The event sequences and failure causes are then modelled via event and fault trees. This approach supports better understanding of work processes and thereby identification of relevant RIFs for each step of the work process. However, while one could model all major scenarios that influence the loss of containment, ignition, escalation, etc., doing so, makes the model so detailed and extensive that it will not be applied effectively in actual analysis work (Vinnem et al., 2004).

The system-based approach identifies accident scenarios related to the chosen activity. These scenarios are characterized by the degradation or impairment of barrier functionality. This approach provides a greater qualitative understanding of issues that could directly or indirectly lead to degradation in barrier performance during activity execution.
This approach is recommended and is elaborated on in this section.

Note: Both approaches inherently address the same hazards but produce very different analysis results. This can be understood by comparing a Hazard and Operability Study (HAZOP) with a Failure Mode and Effect Analysis (FMEA) conducted on the same system. The former is a process approach while the latter, a system approach. Both techniques address the same hazards but provide different results and recommendations to decision makers. This exemplifies the importance of the right choice of approach depending on the context and objective of the analysis.

4.2.2.2 Recommended Approach

The outline of the recommended system-based approach is illustrated in Figure 4.1.

Step 1: Identify hazards and hazardous events introduced by the activity

The execution of safety critical activities (see Table 3.1) introduces a *hazard* or a set of hazards (source(s) of danger that may cause harm to an asset) with respect to major accident risk. These hazards give rise to one or more *hazardous events*.

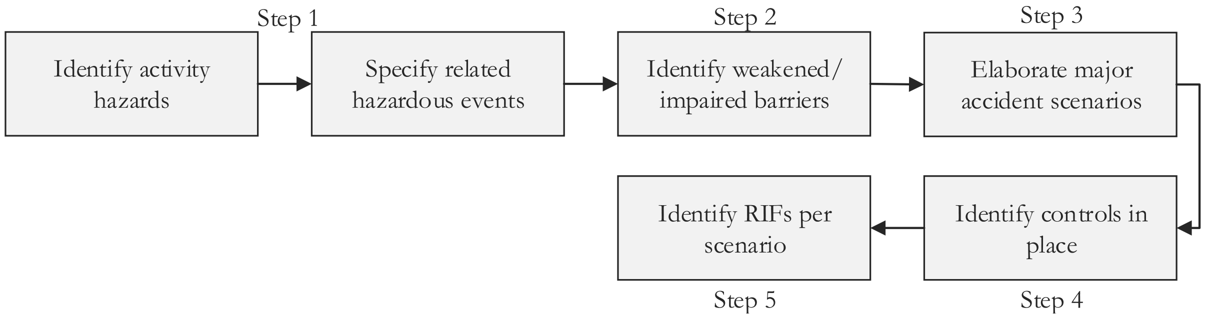


Figure 4.1 Outline of step wise procedure to identify activity based RIFs

Step 2: Identify the weakened/impaired barriers

The purpose or role of a barrier is referred to as a 'barrier function'. A barrier sub-function represents the role performed by various barriers that are necessary to realize the barrier's main-function (DNVGL, 2014). In this step, the weakening or impairment of one or more barrier functions or sub-functions which are caused by the hazardous event is identified. For example, "Release of HC" is the hazardous event and the associated barrier function is "Prevent Release".

Step 3: Elaboration of major accident scenarios

All accident scenarios that relate to the identified hazards and hazardous events are elaborated in this step. A scenario is neither a specific situation nor a specific event, but a description of a typical situation that covers a set of possible events or situations (Khan, 2001). Each scenario is the result of a set of abnormal events which are characterized by a function of several factors/barrier impairments (note: a combination of different factors can lead to the same scenario). Scenario identification is important; it informs what may happen, so ways and means of preventing or minimizing the possibility can be devised.

Step 4: Analysis of existing controls in place

For a possible accident scenario, there are multiple controls/supplementary barriers in place, to minimize the risk. These controls are identified through a safe job analysis (SJA) or other relevant analyses.

The outcome of steps 1 to 4 can be systematically represented and visualized via a tree-structure as in Figure 4.2.

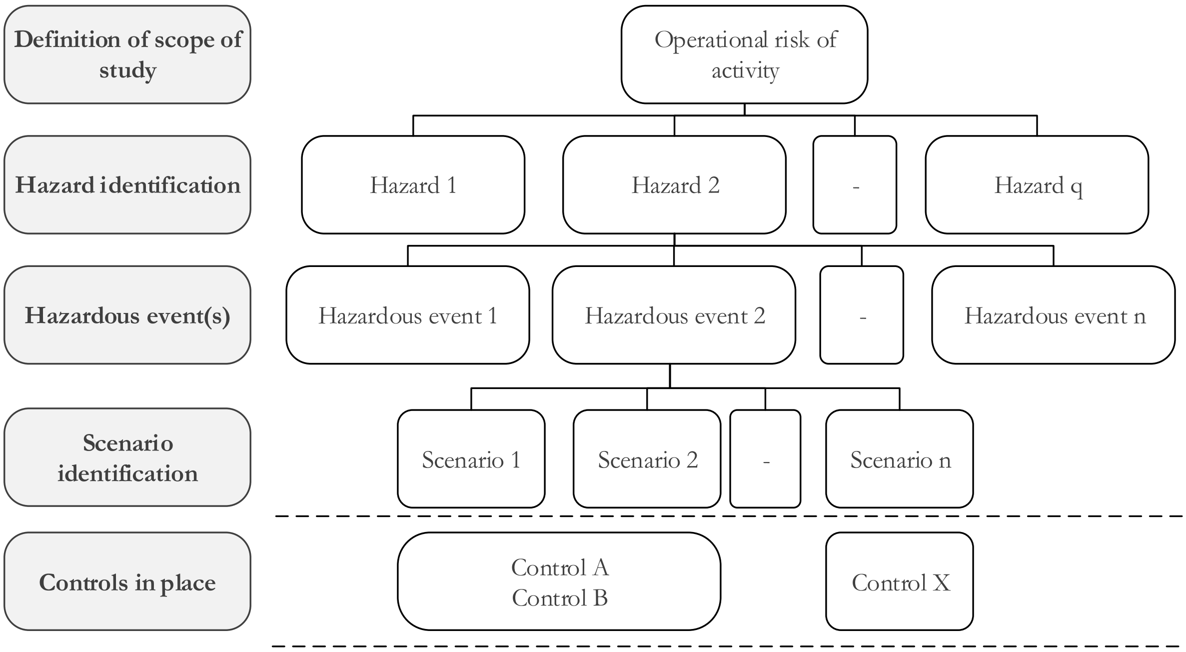


Figure 4.2 Tree structure describing activity hazards, major accident scenarios and associated controls

Step 5: RIF identification for representative scenarios

Once the scenarios are defined, the final step is to identify the factors that influence the development or occurrence of a particular scenario. These RIFs are either technical, operational or organizational (see Section 4.1.2).

4.2.3 Examples

This section illustrates the results of steps 1 through 5 for two work activities – Hot work and HC filter change.

Example 1: Hot Work

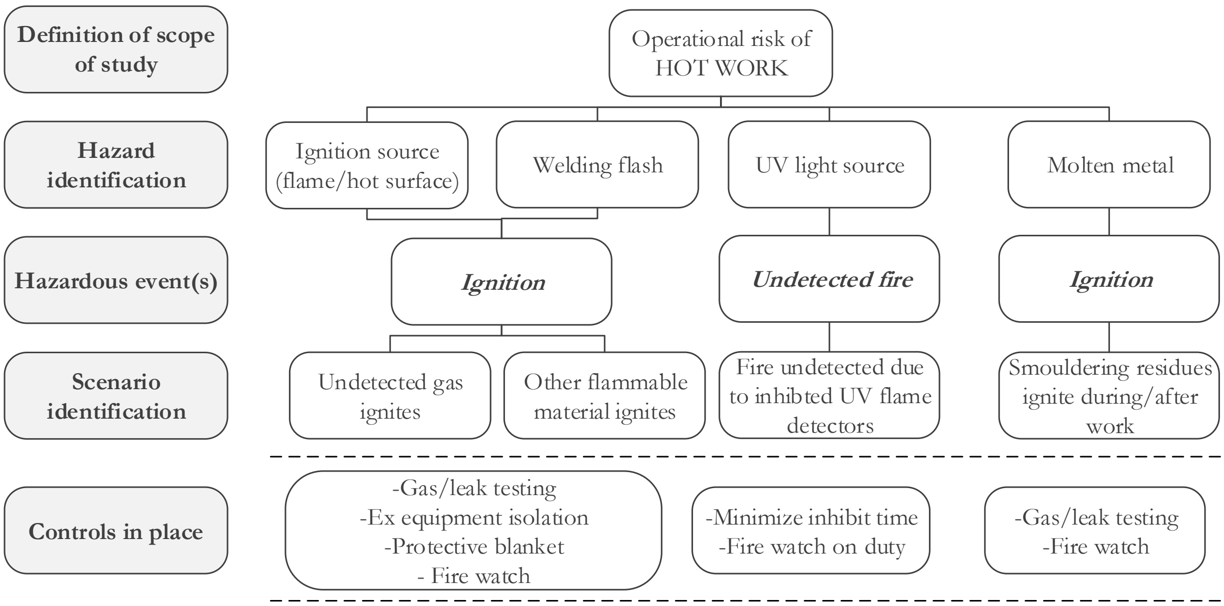


Figure 4.3 Example 1: Elaboration of major accident scenarios for Hot Work

Table 4.1 RIFs related to the hazard "Ignition"/barrier function "Prevent Ignition"

Technical	Operational	Organizational
Area of work	Competence	Work load
Nature of gas	Fatigue	Leadership
Frequency of gas detection	Time pressure	Communication
Equipment used	Task descriptions	Supervision
Work place accessibility		

Table 4.2 RIFs related to the hazard "Undetected fire"/barrier function "Prevent Escalation"

Technical	Operational	Organizational
Area of work	Competence	Work load
Location of fire watch	Fatigue	Leadership
Time of inhibit	Time pressure	Communication
Other compensatory measures	Task descriptions	Supervision
Work place accessibility		

Example 2: Change of HC Filter

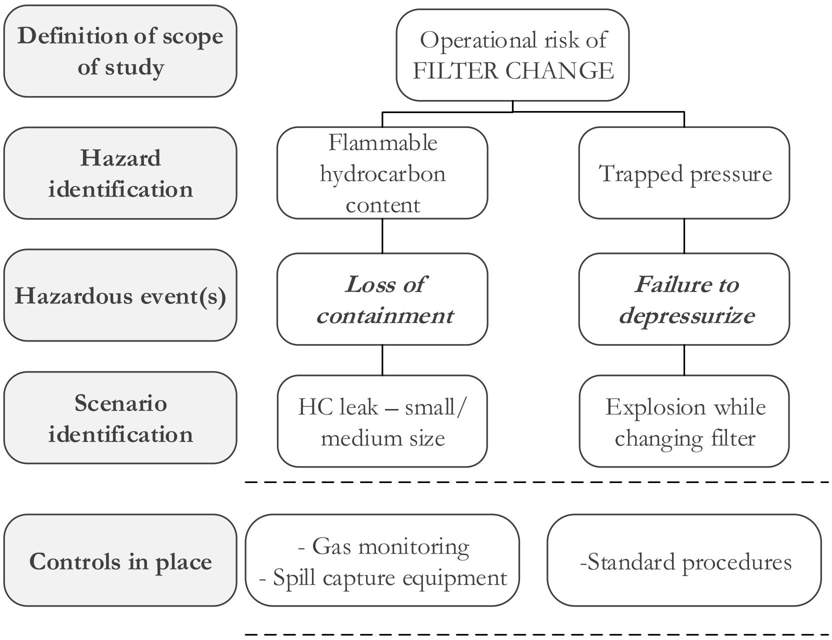


Figure 4.4 Example 2: Elaboration of major accident scenarios for Change of Filter

Although both scenarios in Figure 4.4 are different from each other and represent different barrier impairments, they both relate to the task of disassembling the HC filter. Therefore, only one set of RIFs are identified in relation to the weakening of the prevent release barrier.

Table 4.3 RIFs related to the hazard "Loss of containment"/barrier function "Prevent Release"

Technical	Operational	Organizational
Area/system of work	Competence	Workload
Complexity	Fatigue	Leadership
Monitoring systems	Time pressure	Communication
Equipment used	Task descriptions	Supervision
Work place accessibility	Available documentation	

4.2.4 Obtaining Information on the RIFs

Obtaining information on the identified RIFs must be as easy/automated as possible. All of the activities of relevance in Table 3.1 are planned and executed through a Work Permit system. The Work Permit system provides high levels of control over all ongoing activities. However, they are not explicitly designed to collect and manage information to minimize the risk during operations (Lehmann and Neill, 2013).

This argument from Lehmann and Neill (2013) is weak as it overlooks the basic assumption behind the use of WP systems. I.e. when a work permit is approved, the risk is considered to be minimized and acceptable. On the other hand, to be fair, it can be argued that the information from the WP is not used in risk analyses to quantify risk due to the ongoing activities. With this intention, certain information can be obtained from the work permit system that provide information on the score of the activity RIFs. The work permit electronically logs all relevant information regarding the activity to be executed. A generic set of RIFs that have been identified from the governing template for a Work Permit form (NOG, 2013) is reported in Appendix A. This list serves as a guideline/checklist of RIF information directly available in the WP forms.

4.2.5 Limitations of the approach

The suggested approach to RIF identification has its drawbacks. These are briefly discussed in this section.

4.2.5.1 Other Failure/Degradation Mechanisms

An assumption in the identification of RIFs for risk transients, is that the impairment or degradation of a barrier is due to the ongoing activity itself, or aspects related to the activity. However, there are other hazards and accident scenarios related to these that are out of the direct influence of the activity. These include long-term conditions which result in increased risk levels (see Section 3.1.1) and are either modelled in existing QRAs or managed through other approaches.

For example, the weakened structural integrity in a pipeline due to corrosion, increases the likelihood of a loss of containment with dropped objects. The aspects of corrosion and other inherent degradation mechanisms are not accounted for in the current approach. In reality, it is a combination of both inherent (latent system factors) and activity based factors which lead to the occurrence of a hazardous event.

In other words, the suggested method only identifies activities that represent known barrier unavailability (i.e. inhibited fire/gas detectors, unavailable fire water pumps, etc.). It does not account for conditions with unknown barrier unavailability (i.e. unrevealed faults in safety systems). Sometimes barrier analyses are conducted for offshore installations on a quarterly basis. This is a qualitative analysis where experts and field personnel sit together to evaluate the condition of barriers across the plant. This information could conceptually be included to provide a more accurate risk description.

4.2.5.2 Risk increasing 'activities' vs. 'conditions'

Activities such as inhibiting fire/gas detectors, removal of passive fire protection, etc. represent a direct impairment of a barrier function. Hence, detailed RIF identification of these activities as suggested in Section 4.2.2.2 might not be relevant. Vinnem et al. (2003) refer to these as *risk increasing conditions*. For these conditions only a few task related factors such as location of impairment, duration of impairment, etc. are of relevance. A list of these activities/conditions is given in Table 4.4. These risk increasing conditions account for nearly half of the activities under study in Table 3.1.

Table 4.4 Activities which do not require detailed RIF identification

ID	Activity Category	BF1	BF2	BF3	BF4
2.1	Activity implying inhibit gas detectors		x		
2.2	Activity implying locking of ESV		x		
2.3	Activity implying locking of BDV		x		
3.6	Activity with de-isolation of equipment			x	
4.1	Activity implying removal of PFP				x
4.2	Activity implying inhibit fire detectors				x
4.3	Activity implying inhibit fire water				x
5.1	Scaffolding		x	x	x
5.2	Work on HVAC		x	x	x

As an example, "Inhibiting gas detection" represents a direct degradation of the "Prevent Ignition"/ "Limit size of release" barrier functions. The only RIFs of interest are those which have a direct influence on the inhibit (i.e. duration of inhibit, compensatory controls, etc.). As another example, the risk during the construction and dismantling of scaffolding is negligible in comparison to the increase in risk level while it is standing (the presence of scaffolding in an area with gaseous hydrocarbons impairs ventilation and thereby impacts the spread of gas clouds in the area).

It is recommended to treat these risk increasing conditions as RIFs themselves, within the developed risk model. The absence or presence of these conditions play an important role in influencing the risk level. For example, while modelling the risk of performing Hot Work, the absence/presence of gas detection may be included as a RIF within the model.

4.2.5.3 RIFs dependent on the activity operation mode

For certain activities, the chosen RIFs might vary based on the operation mode considered. However, the method suggested does not differentiate between operation modes.

For example, "Work on HC equipment" – the RIFs chosen and their score vary depending if the activity is preparation or resetting or the actual work itself. In reality, there is heightened risk only during the preparation and resetting phases while the risk during the actual work on the HC equipment is low. For this purpose, "Work on HC equipment" is split into two sub-activities of preparation and resetting. There are treated separately in the classification in Table 3.1.

4.2.6 Modelling using the RIFs

RIFs are the basic unit of analysis in the activity-based modelling framework. This chapter has introduced and defined activity based RIFs that characterize risk transients in operations. Section 4.2.2.2 presents a structured approach to identify activity based RIFs relevant to major accident risk.

The specified method has limitations which are discussed in Section 4.2.5, but is sufficient to provide the background knowledge to identify the best representative set of RIFs for a particular work activity. This method also supports verification of Table 3.1 to identify which barriers are affected by a particular activity. The relevance of modelling risk increasing conditions as RIFs themselves within the risk model is identified.

With adequate knowledge on the set of RIFs that characterize activities and influence major accident risk, the next step is to develop a model to quantify these effects. This is the focus of Chapter 5.

Chapter 5

Quantification Method

This chapter builds on existing models in risk analysis and risk influence modelling literature to develop a suitable method to quantify the effect of activity RIFs on barrier condition.

5.1 Introduction

The fundamental hypothesis behind quantification is that risk control is achievable by measuring changes in the associated RIFs (Vinnem 2012). This is realizable only as long as:

i. All RIFs are identified
ii. The RIFs are measurable
iii. The relationship between the RIFs and risk is known

All identified RIFs must link to an underlying risk model to understand the impact of the RIFs on the risk. In reality, it is practically impossible to identify and include all possible RIFs that can influence an activity. However, through the RIF identification process outlined in Chapter 4, it is assumed that all activity RIFs relevant to major accident risk are identified and theoretically possible to include in the modelling. Even with this limited set of RIFs, a fair amount of control over the risk is achievable, if not complete control.

For this study it is assumed all RIFs are measurable and this aspect of RIFs is briefly introduced in Section 4.1.3. Irrespective of the measurement technique, all RIF scores are standardized and assume states from A to F or 1 to 6. (A/1 being a perfect state and F/6 a completely degraded state). This standardization of RIF scores to a uniform scale is important to simplify the mathematical treatment of the various RIFs in the model.

The quantification method suggested here is limited to the first phase of "Part 1: Simplified Handling" of the method described. The complete flowchart representation of this stage is shown in Figure 5.1. All activities (planned or ongoing) are fed into the model. Decision box 1 in Figure 5.1 filters out those activities that are not relevant to major accident risk. E.g. a minor maintenance activity on a system not containing pressurized HC has little/no influence on major accident risk and hence can be executed without any detailed risk considerations.

The activities that represent an impact to major accident risk are subjected to RIF evaluation (decision box 2). This stage is the focus of the quantification method suggested in this chapter.

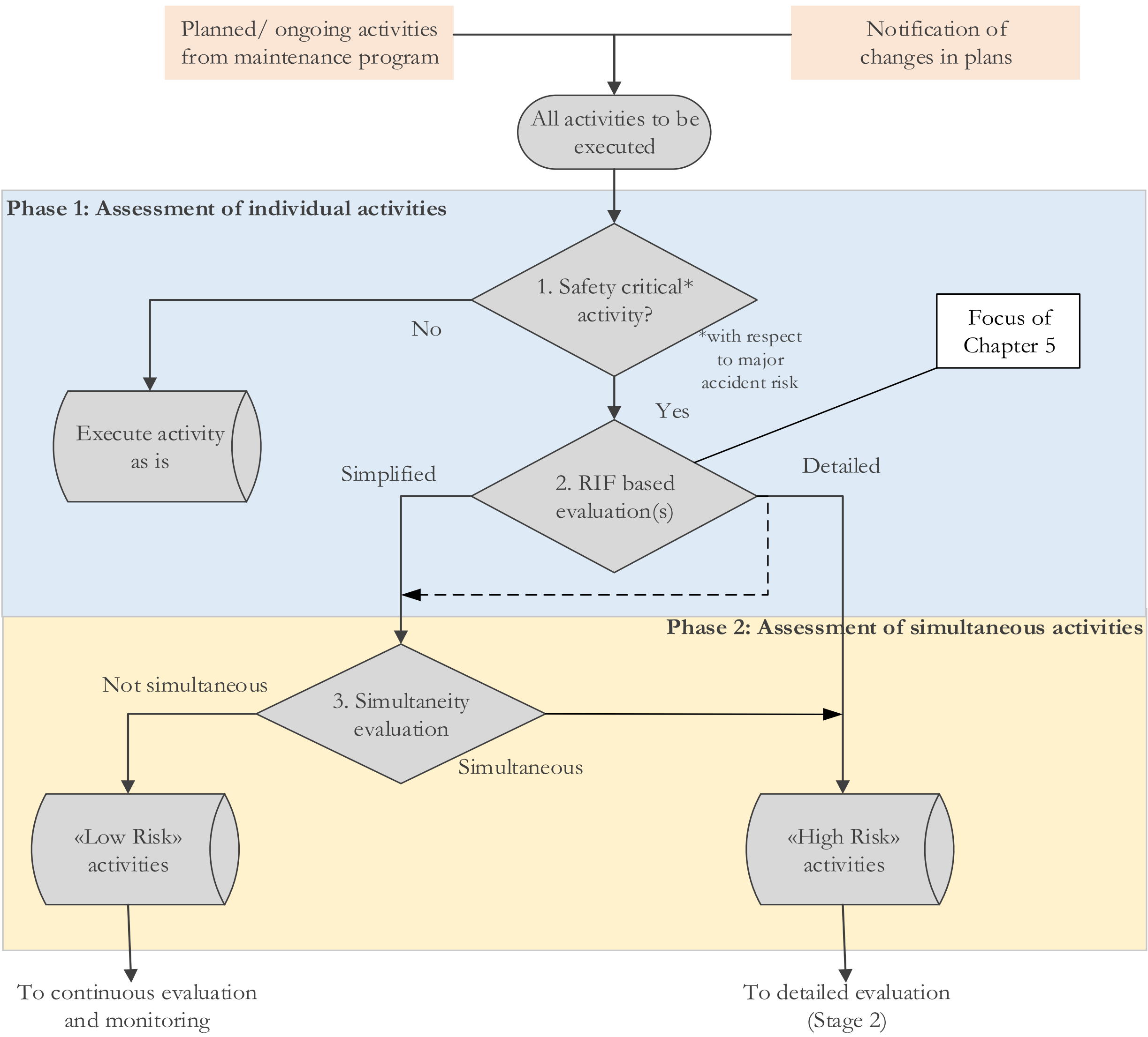


Figure 5.1 Flowchart outlining “Part 1: Simplified Handling”

5.1.1 Scope of Model

The activities which are selected for a RIF evaluation (decision box 2) are divided into two categories based on the findings from Section 4.2.5.2.
(1) Activities whose execution represents an increasing risk level and
(2) Operational conditions which represent an increased risk level (see Table 4.4).
Both (1) and (2) relate to the degradation or impairment of a barrier function. MIRMAP (2015) refers to these as 'active risk' and 'latent risk' categories respectively.

For risk increasing activities, activity execution is characterized by the interaction of technical, operational and organizational factors. Risk increasing conditions themselves represent a degradation/impairment of a barrier function (e.g. removal of passive fire protection, inhibiting gas detectors, etc.). As highlighted in Section 4.2.5.2, the latter may be included as RIFs while modelling activities whose execution represents an increasing risk level (item 1 above).

5.1.2 Choice of Model

The literature presents the use of a number of methods in risk and risk influence modelling. These include traditional risk analysis techniques (event and fault tress), Human Reliability Analysis (HRA) techniques, Social and Behavioural Science Methods, Process Modelling Techniques, etc. (Mohaghegh and Mosleh, 2009). Whichever method/model is chosen, it must best express one's knowledge about the system and the problem at hand to provide effective decision support (J Vatn, 2013b).

5.1.2.1 Evaluation of existing models

Chapter 2 documents the latest developments within the domain of operational risk analysis (ORA) in the oil and gas industry. To develop an appropriate modelling technique, certain selected ORA methods from the literature review from Chapter 2 were studied in detail to identify and adopt suitable properties that are desirable in the activity-based model. The selected models are:

1. **Risk Barometer** (Hauge et al., 2014)
   A recently developed method that addresses mainly breaches/deviations of safety critical functions to provide a resultant 'risk effect' score per area of a facility.
2. **Proscient** (Lehmann and Neill, 2013)
   Although no implementation details about this commercial operational risk analysis tool is available, it appears that the tool addresses the same research problem as the MIRMAP project.

3. **RiskOMT** (Vinnem et al., 2012)
   The RiskOMT method builds on previous work BORA and OTS projects and presents a method to model the impact of organizational and human factors for a set of representative maintenance activities.
4. **HCL** (Wang, 2007)
   The Hybrid Causal Logic (HCL) framework logically integrates Bayesian Belief Networks with event and fault trees to model human and organizational factors in the traditional risk models.

These models are evaluated based on the following criteria:

a) Type of analysis method used
b) Format of results
c) Coverage of factors
d) Nature of factors
e) Representation of uncertainty
f) Frequency of updatability
g) Effort required to setup model
h) Common cause modelling capability
i) Interaction effect modelling capability

The results from the evaluation are presented in Table 5.1.

5.1.2.2 Discussion

The activity-based model must provide a measure of risk transients (short-term changes in risk levels). The individual evaluations reveal that none of the methods above can be directly adopted for modelling activities. Although the risk barometer is a real-time tool that provides a risk number based on the number of barrier deviations and impairments existing at a given moment of time in an area of a facility, the mathematical approach in the tool is heavily reliant on expert judgement and the use of simple weighted averages is too simplistic to completely represent reality. Furthermore, by presenting only a single risk number to the decision maker, any uncertainty in the presentation of results is lost.

The RiskOMT and HCL methods are category 1 ORAs (see Section 2.1.3). They provide updates to already existing risk models or require the creation of extended risk models to link up to the QRA and model the impact of operational and organizational factors on the basic event probabilities in fault trees. Due to the complexity and tedious data requirements for the model, these approaches have a very limited update frequency (greater than one year).

Considering the needs for the activity-based risk model, the desirable characteristics of the suggested model is presented in the last row of Table 5.1.

Table 5.1 Results for the evaluation of selected ORA methods

Method/ Tool	Class of ORA	Method used	Format of results	Factor coverage	Nature of factors	Uncertainty Representat-ion	Update frequency	Effort for model setup	Common Cause Effects	Interaction Modelling
Risk Barometer	Class 2	Linear weighted average	Risk Effect (0-100)	Technical	Deviations, impairments, notifications	No	Real time	Medium	No	No
Procient	Class 2	-	-	-	-	-	Real time	-	-	-
RiskOMT	Class 1	Fault trees, event trees, Bayesian belief networks	Leak frequency #	Operational Organizational	Sharp and blunt end factors	Yes	Yearly	High	Yes*	Yes##
HCL	Class 1	Fault trees, event trees, Bayesian belief networks	Leak frequency #	Operational Organizational	Sharp end factors	Yes	Yearly	High	Yes*	No
Suggested Model	Class 2	Bayesian Belief Networks	Barrier condition (A to F)	Technical, Operational Organizational	Sharp end RIFs, deviations, impairments	Yes	Real time	Medium	No	Yes

*accounted for during the post processing of minimal cutsets in fault trees

#requires a re-run of the QRA for updated risk results

##only available as a part of the RiskOMT hybrid setup (J Vatn, 2013a)

To avoid making the model too detailed or extensive, comprehensive modelling of activities using event and fault trees as required in the RiskOMT and HCL is avoided. Instead, an integrated model to quantify the effects of technical, operational and organizational factors is suggested. In this case, this refers to the execution of safety critical work activities that have an influence on major accident risk.

From the variety of risk analysis methods available - Bayesian Belief Networks (BBN) is a suitable method because of its ability to represent soft, partial or uncertain causal connections between factors (J Vatn, 2013b). The suggested BBN must model the degradation in barrier condition due to a selected work activity. The RiskOMT and HCL both use BBNs as a part of their implementation and aspects from both these methods are adapted for the suggested model.

5.1.3 Model Structure

Barrier failure causes are generally categorized into three event groups (Vinnem et al., 2009):

1. **Inadequate/insufficient barrier specification or functionality**
   This is a kind of systemic failure which is related to a deterministic cause that can only be eliminated by design modification, changes in procedures or documentation.
2. **Technical failures of the system**
   These are caused when management fails to ensure the integrity of the barrier based on its design specifications (Markert et al., 2013). Examples are degradation due to lack of/poor inspection, wrong competence assignment to tasks etc.
3. **Human errors**
   Human errors occur during activity execution and are characterized by attributes that influence the individual, such as competence, experience, time pressure, etc. They are also influenced by management factors such as leadership and supervision.

The execution of frontline work involves three aspects – the people, the plant, and the interaction of people with the plant (Lehmann, 2012). In the Three Bucket Model of error likelihood, Reason (2004) states that the probability of unsafe acts in frontline operations is a function of the amount of unwanted contents in the three buckets: self, context and task. Reason's model can be extended to reflect the situation for frontline operations in hazardous chemical industries as well. The likelihood of occurrence of a particular hazardous event (i.e. barrier weakening/impairment) associated with a particular activity is expressed by the content of the three buckets. This model is illustrated in Figure 5.2.

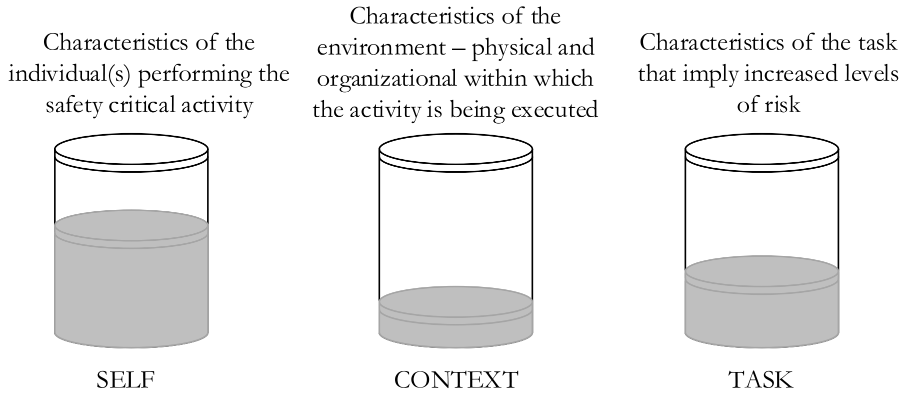


Figure 5.2 Three Bucket Model (Reason, 2004) to promote frontline error wisdom

The aspects of people, plant and their interaction are captured by the self, context and task buckets respectively. The structure of the risk model is based on this construct. These three buckets cover the set of RIFs that influence error in frontline operations (Item 3). In addition, the condition of technical systems also influences the likelihood of barrier degradation/impairment (Item 2).

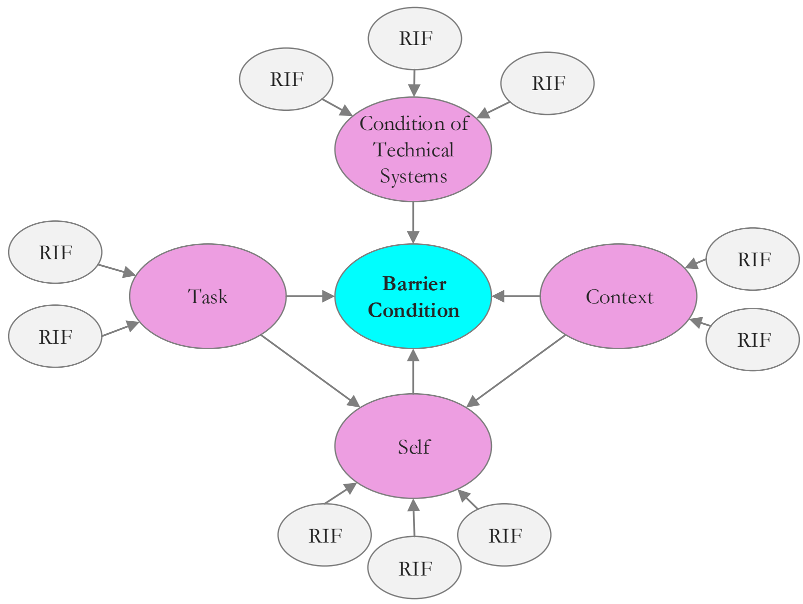


Figure 5.3 Influence diagram illustrating the relationship between the various nodes and barrier condition

It can be argued that these buckets are not independent of each other - the context of the activity and characteristics of the task both influence the performance of the individual (self). This interaction is illustrated via an influence diagram in Figure 5.3, wherein to each of the purple nodes, a set of RIFs is connected. In a similar fashion, influence diagrams illustrating dependence structures between the

RIFs are possible. These dependence structures are not generalized here as they vary based on the activity under consideration and its associated RIFs.

In summary, the impact of an activity on the barrier condition is modelled through the "task", "context" and "self" nodes. The inherent technical condition of the barrier systems, including the presence of any impairments/deviations (risk influencing conditions) are modelled under the "condition of technical systems" node as RIFs.

5.2 Bayesian Belief Network (BBN)

Influence diagrams containing only uncertainty nodes are termed as Bayesian Belief Networks. The structure of the BBN represents a set of random variables and their conditional dependencies, via a directed acyclic graph (DAG). BBNs rely on the assumption that the probability distribution of a node is dependent on the parent nodes (Jensen, 1996).

Bayesian belief networks were initially developed for applications within artificial intelligence, but in recent years they have been adapted to other application areas. Weber et al. (2012) present an overview of the application of BBNs in risk analysis. Some of the more recent developments using BBNs include the Hybrid Causal Logic (HCL) method (Wang, 2007) and the RiskOMT method (Vinnem et al., 2012).

A simple BBN is shown in Figure 5.4. The nodes B and C are "parents" to the "child "node A. The probability distributions of B and C are specified across the possible outcomes/states that it can take. Node A is represented by conditional probabilities which are conditioned on the state of B and C. Detailed mathematical descriptions of BBN setup and working is not presented here. For a brief mathematical introduction to BBN modelling refer to Jensen (1996).

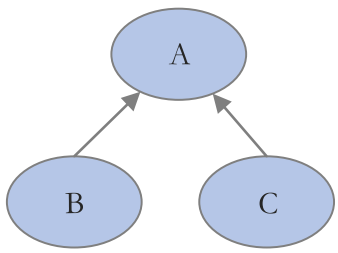


Figure 5.4 Generic BBN network with one parent and two children

A BBN is initialized by entering state probabilities for all nodes without parents and conditional probabilities for nodes with parents. A limitation with BBNs is the large number of conditional probabilities to be manually entered for nodes with parents. A discrete variable with 'n' parents and 'm' states requires an entry of m^n conditional probabilities. To put this in perspective, if all nodes in Fig 5.4 take 6 states, node A requires an entry of 36 conditional probabilities. This number increases exponentially with the number of parents for a given node.

5.2.1 Assigning Conditional Probabilities

Manually assigning conditional probabilities either through expert judgement or use of historical data is cumbersome (Røed et al., 2009). Developing conditional probability tables (CPT's) using experts can be very time consuming, further extensive use of expert judgement introduces large uncertainties in the BBN network which are not easily understood and realised (Hansson and Sjökvist, 2013).

To overcome the limitation of manually assigning hundreds/thousands of conditional probabilities, Røed et al. (2009) suggest a mechanistic procedure for the creation of CPTs. The assumption in this method is that the probability of a child node being significantly different from its parents' state is small (see discussion in Section 6.3.2). In other words, greater the deviation between the observed parents' states and child's states, smaller the probability assigned. This deviation is termed as 'distance'.

This method is described step-by-step with reference to the node structure in Figure 5.4.
Let the number of states 'm'=3 and number of parents 'n'=2.

Step 1: Determine importance of the parent nodes relative to each other

The importance can be expressed in terms of a weight w_i. Where 'i' is the parent node and $\sum_i w_i = 1$. Let w_A=0.4 and w_B=0.6

Step 2: Calculate the 'distance' of the state of the child node from the weighted average parents' state

The distance is calculated for each and every combination of parent and child nodes. In this case - 3^3=27 distances. Or generally, m^{n+1} distances. The distance Z_j for each combination of parent and child states is calculated via the formula: $Z_j = \sum_{i=1}^{n} |Z_{ij}| w_i$

where Z_{ij} is the distance between the state of parent 'i' and the state of the child 'j' under consideration. For example, if B=2, C=1 and A=3, then Z_j= (3-2) x 0.4 + (3-1) x 0.6 = 1.6

Step 3: Assign the probability of finding the RIF in a particular state based on the calculated distance

The probability mass for the CPT is distributed amongst the possible outcomes using the formula: $P_j = \frac{e^{-RZ_j}}{\sum_{j=a}^{f} e^{-RZ_j}}$

R is the outcome distribution index which distributes the probability mass across the possible outcomes. This is a subjective entry made by experts based on their belief of how close the child RIF distribution must be in relation to its parents' state.

Step 4: Assign the conditional probability table for the child node

With the calculated probabilities from step 3, the complete CPT is assigned. For the given example, this is implemented in MS Excel and the CPT generated is shown in Table 5.2.

Table 5.2 Conditional probability table for the described example

Parent B	1			2			3		
Parent C	1	2	3	1	2	3	1	2	3
Child A									
1	0.705768294	0.431660247	0.333333333	0.431660247	0.193866344	0.136679506	0.333333333	0.136679506	0.070759513
2	0.223472193	0.431660247	0.333333333	0.431660247	0.612267312	0.431660247	0.333333333	0.431660247	0.223472193
3	0.070759513	0.136679506	0.333333333	0.136679506	0.193866344	0.431660247	0.333333333	0.431660247	0.705768294

Note: For the outermost nodes of the network, that is nodes without children (nodes B and C in Figure 5.4), unconditional node probabilities are assigned based on historic data or expert belief. An alternative way of expressing uncertainty in unconditional node probabilities is discussed in Section . These are prior probabilities which reflect the belief of the analysts. Once the probabilities for all the nodes are assigned, the BBN can be initialised, evidence for each node provided and conditional probabilities updated for all nodes in the model.

5.2.2 Parameter estimation

5.2.2.1 Estimation of weights w_j

Step 1 from Section 5.2.1 requires the establishment of importance weights between parent nodes connected to the same child. To ease the weight assignment process, the Analytic Hierarchy Process (AHP) is recommended. The AHP is a structured technique for organizing and analysing complex decisions, based on mathematics and psychology (Saaty, 1988). The AHP allows decision makers choose weights that best suit their understanding of the problem. Consider a case where weights are to be assigned between a set of 'n' nodes.

Step 1: Perform pairwise comparisons for every combination of nodes

This is achieved by '$n-1$' pairwise comparisons for nodes which have to be weighted. For each pairwise comparison a score is assigned.

Step 2: Calculate the weight for each node

Via simple matrix algebra, a set of weights w_i are calculated for each node. Where $i = 1,2 \ldots n$

Step 3: Verify the calculated weights

A consistency ratio is generated to verify the validity of the pairwise comparisons made by the decision maker. Based on this index the weights generated are either accepted or rejected.

The AHP algorithm can be easily implemented in MS Excel. A screenshot of the implementation is presented in Appendix B. An advantage of AHP is that it breaks down the decision problem into pairwise comparisons and inputs from various experts can be easily combined into the same model.

5.2.2.2 Estimation of R-value

Calculation of the conditional probabilities in Step 3 of Section 5.2.1 requires the assignment of an R-value that determines how the probability mass across the possible outcomes are distributed.

Røed et al. (2009) suggest that experts determine the R-value based on the intuitive understanding that a high R expresses a low probability of the child node being in a state that is distant from its parents' state. A significant limitation in doing this is that it is difficult to assign such a factor off-hand because it is hard for experts to distinguish between the RIFs when they assign the outcome distribution index (Røed et al., 2009). Therefore, an intuitive graphical method of assigning the R-value is suggested. This is easily implemented in software and provides experts a visual understanding of the implication of their choice of a particular R-value.

This is illustrated for the simple case in Figure 5.4, where w_B =0.2 and w_C=0.8 and all nodes can assume six states (1 to 6). The distribution of the conditional probability mass Pr (A=j|B=3; C=3) is visualized for different R values in Figure 5.5. Based on this, a coarse guide for the assignment of the R-value is given in Table 5.3. This table is based on the subjective belief of the author and may be fine-tuned for actual practical usage.

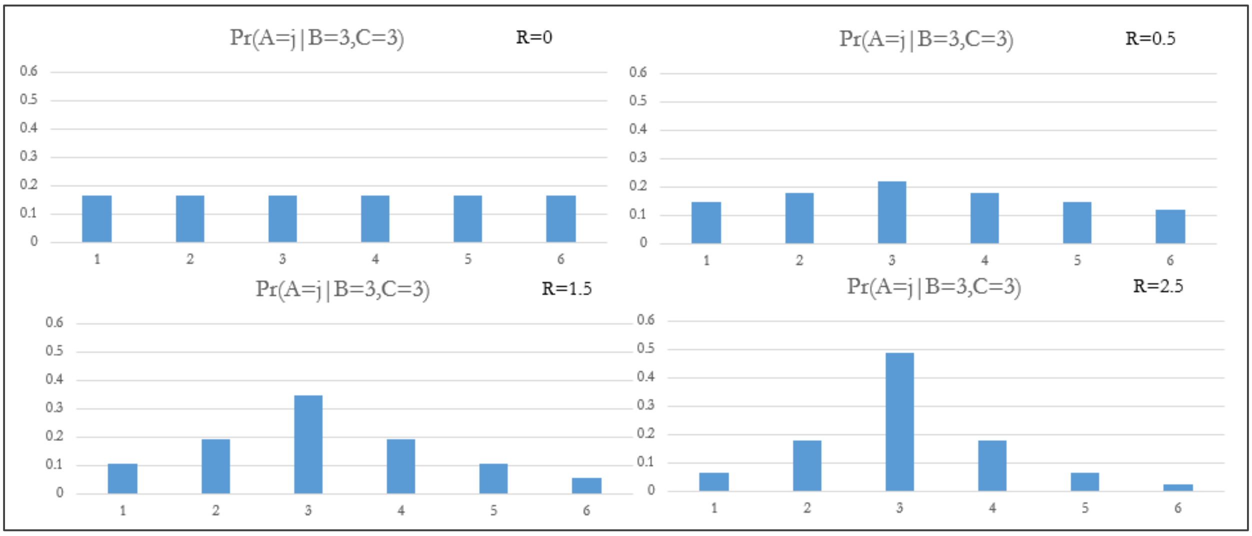


Figure 5.5 Varying conditional probability distributions for different R-values

Table 5.3 Assignment guide for deciding a suitable R-value

R-Value	Assignment Guide
0 - 0.25	Do not trust state of parent RIFs. Uniformly distribute the probability mass across all states
0.25 - 0.75	Base the probability mass distribution of the child on the parents' state to a **slight** extent
0.75 - 1.25	Base the probability mass distribution of the child on the parents' state to a **medium** extent
1.25 - 1.75	Base the probability mass distribution of the child on the parents' state to a **strong** extent
1.75 - 2.5	Base the probability mass distribution of the child on the parents' state to a **very strong** extent

5.2.3 Discussion

In the quantification model outlined in , the outermost nodes in the network (nodes without parents) are the RIFs. Certain aspects on how to quantify and mathematically treat these RIFs is discussed in this section.

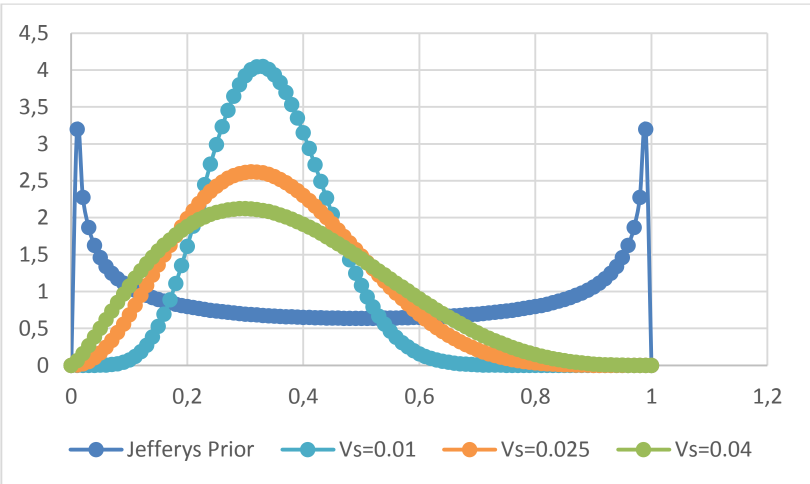
5.2.3.1 Expressing uncertainty in RIFs

The RIF may be treated as a stochastic quantity to reflect the uncertainty in the measurement of its true value. A mathematically elegant probability distribution for random quantities on a scale of 0 to 1 is the beta distribution (Vatn, 2013a). The mean and variance of the distribution is expressed as $E(X) = \frac{\alpha\beta}{\alpha+\beta}$ and $Var(X) = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$. Where X is a random variable.

Let the prior probability distribution of a RIF 'R' be beta distributed with parameters (α_0, β_0). An important property of the beta distribution is that after collecting evidence, the posterior distribution is also beta distributed with parameters $(\alpha_0 + x, \beta_0 + n - x)$; where '$n$' is the number of trials and 'x' is the number of successes.

For RIF measurements, the binomial situation is not relevant and therefore Vatn (2013a) extends this to a situation where (α_0, β_0), are the beta distribution parameters prior to observing the score (S) on a RIF (through risk indicators, surveys, etc.). After certain mathematical arguments, Vatn (2013a) proves that an approximate posterior distribution is also beta distributed with parameters $(\alpha_0 + \frac{s^2(1-s)}{V_s}, \beta_0 + \frac{s(1-s)^2}{V_s})$. Where V_s is the variance which reflects the expert's belief on how accurate the observed score reflects the true score of the RIF.

In Bayesian statistics, Jeffery's prior (α_0=0.5, β_0=0.5) is the best choice to reflect ignorance in a particular parameter. This is against general intuition that a uniform distribution ought to be used. Justification why Jeffery's prior is preferred over the uniform distribution is explained by Dominic (n.d.). Vatn (2013b) also claims that applying Jeffery's prior ensures the method is as data driven as possible. To illustrate this, Jeffery's prior is applied and the posterior beta probability distribution when the observed score is B, for different choices of variance $V_{s,}$ is graphically illustrated in Figure 5.6



Observed RIF score
S = B

Prior Specification
α_0=0.5, β_0=0.5

Figure 5.6 Posterior probability density functions for different choices of variance (V_s)

Remark: The beta distribution spans from 0 to 1. Using simple computer code, point probabilities can be calculated for the six required intervals [0, 1/6], [1/6, 2/6], etc. and provided as evidence to the Bayesian network. This is implemented in MS Excel and is illustrated in Appendix B. Through the above process the RIF (outermost parent nodes) distributions are updated based on the observed RIF score (S). The only parameter to be estimated by the expert is the choice of V_s which is a measure of strength of the experts' belief that the observed score is a realization of the true value of the RIF.

5.2.3.2 Interaction effects between RIFs

Within the current setup, the influence of one RIF is considered independent of the other RIFs. However, in certain cases a very bad condition of one RIF (or a set of RIFs) has a much higher negative influence than the influence of each RIF independently. For example, while modelling human performance, if both competence and experience are in a state F (equivalent to no competence and zero experience), the interaction of these two present a condition much worse than the negative effect expressed by each RIF independently. Similarly, there might be positive interactions or positive conditions which neutralize other bad conditions. Modelling interactions is very important because in reality it is the interaction between a set of degraded factors that cause accidents, not the failure of individual factors themselves (Mohaghegh and Mosleh, 2009).
In simpler terms, it is interactions between factors which introduce non-linearity in the model. This understanding is important to be able to construct a model based on actual performance. In fact, Rasmussen (1997) suggests moving from traditional accident models such as the Swiss Cheese (Reason and Reason, 1997) to models based on "actual performance".

Røed et al. (2009) acknowledge that their suggested approach for CPT assignment doesn't account for interactions and instead suggest using different R-values for RIFs with interaction potential. However, this becomes tedious to understand and too complicated to implement in practice. Therefore, an alternative procedure to model interactions from Vatn (2013a) is suggested.
Note: The steps described below are based on Vatn (2013a) and the method on how to incorporate this into the BBN is presented at the end of this section.

Step 1: Identify clusters or subsets of RIFs with potential interaction effects

Consider a situation with four RIFs (RIF 1-4), each assigned a weight w_i= 0.25. They take any score S_i ranging between 1-6. Based on experience or expert knowledge, RIF1 and RIF3 together exhibit potential negative interaction effects. These are clustered together. Let this cluster be called C_1. Similarly, if applicable, other such interaction clusters C_i are identified.

Step 2: Assign new relative weights between the RIFs in each cluster

RIF1 and RIF3 are assigned new inter-cluster weights w_{c_1}=0.4 and w_{c_3}=0.6 with respect to each other (Note: $\sum_i w_{c_i} = 1$). Similarly, weights are assigned between all RIFs within each defined cluster C_i.

Step 3: Define the threshold level beyond which interaction effects are to be accounted for

It is considered that interaction between the RIF1 and RIF3 begin when their score crosses the average value (i.e. score=3). Similarly, interaction threshold levels for RIFs in each identified cluster are defined.

Step 4: Calculate the new interaction effect weight of the RIFs in each cluster

For each RIF in a cluster, a new weight w_{Xi} is calculated through the formula $w_{Xi} = w_i w_{Ci}.f$.; where 'f' is a correction factor defined on [0,1]. (i.e. f=1 when r_1=r_3=6 and f =0 when r_1=r_3=3). For intermediate values, a linear transformation is used. If the interaction is much stronger, non-linear transformations may be applied. For example, using linear transformation, if RIF1=5 and RIF 3=6; w_{X1}=0.25x0.4x0.833=0.0833 and w_{X3}=0.25x6x0.833=0.125. (0.8333 is 'f' the correction factor)

Step 5: Calculate the total impact of the interaction between the RIFs

This is achieved through the formula $\sum_i w_i.r_i + \sum_{Ci} w_{Xi}.r_i$. Using this formula, as more terms are added to the overall weighted sum, it is possible that the new weighted sum can exceed 6. In such a situation, the weights can either be adjusted such that the weighted sum doesn't exceed the maximum score, or left as it is to reflect the severity of the interaction between the RIFs.

A summary of the described example is presented in Table 5.4. The overall contribution (weighted sum of individual RIFs) before considering interaction effects is 4.50. After considering the interaction between RIF 1 and 3 the weighted sum increases to 5.41.

Table 5.4 Summary of example demonstrating interaction effects between RIFs

Cluster	RIF #	r_i	w_i	w_{ci}	f	w_{xi}	Results	
Cluster 1	RIF 1	5	0.25	0.4	0.8333	0.0833	Old weighted average	4.50
	RIF 3	6	0.25	0.6	0.8333	0.125		
-	RIF 2	3	0.25	-	-	-	New weighted average	5.41
-	RIF 4	3	0.25	-	-	-		

Remark: To model interaction effects between RIFs in the quantification model (Section 5.2.1), the procedure as above is included as a part of the assignment of the conditional probability tables (Steps 2 and 3 in Section 5.2.1). The effect of the interaction is included while calculating the 'distances' of the parents from the child node. Mathematically, the distance formula from Step 4 in Section 5.2.1 changes to: $Z_j = \sum_{i=1}^{n} |Z_{ij}|.w_i + \sum_{i=1}^{n} |Z_{ij}|.w_{Xi}$

In other words, the distance Z_j increases if interaction effects are present.

To illustrate the effect of interaction effects in the assignment of conditional probabilities, the simple case in Figure 5.4 is used. Interaction effects between the parents B and C begin to take over when B>3 and/or C>3. The difference in the conditional probability distribution of outcomes for Pr(A=j|B=5,C=5) with and without interaction effects is seen in Figure 5.7. (R=1.5 is assumed for this calculation).

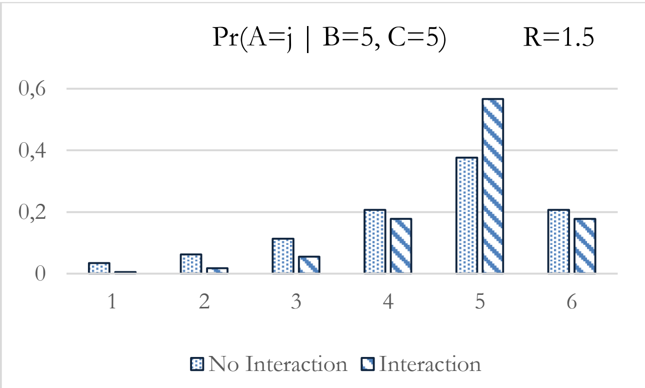


Figure 5.7 Difference in conditional probability distributions with and without modelling interaction effects between RIFs.

A limitation in this setup is that the total effect after interaction cannot be expressed beyond the maximum score of 6. Further, interaction effects can only be modelled between RIFs connected to the same child node. This implies that RIFs connected to different child nodes have to be modelled independently in the model. The interaction modelling is an advancement of the method from Røed et al. (2009). The importance of modelling these interactions is illustrated through scenario simulations in Chapter 6.

5.3 Summary of Method

The developed BBN model provides an intuitive graphical representation of dependencies between factors in the model. A limitation to model interactions in the CPT assignment from Røed et al. (2009)

is overcome and an extension to account for these interactions is included and demonstrated. Uncertainty in RIF measurement is formally treated through assignment of a suitable prior probability and calculation of the posterior based on the observed score and the decision makers' belief in the accuracy of the observation made. This section summarizes the approach to model the impact of activities on barrier condition in step-wise fashion. The overall structure of the model is seen in Figure 5.3.

Step 1: Construct Influence Diagram/BBN

A guideline on how to structure the activity based BBN is presented in Section 5.1.3. The lowest level on the influence diagram is a RIF.

Step 2: Assign prior probabilities for RIFs

This involves selection of a suitable prior distribution. Use of Jefferys' prior with a beta distribution is recommended (see Section 5.2.3.1).

Step 3: Identify RIF clusters with potential interaction effects

RIF with potential interaction effects are identified for quantification purposes.

Step 4: Calculate CPT

Through the algorithm described in Section 5.2.1, CPTs are calculated for each node in the BBN. Interaction effects are accounted for in the CPT through the procedure described in Section 5.2.1 and 5.2.3.2.

Step 5: Initialize the BBN

Once all the required data is entered in the BBN, the network can be initialized in software.

Step 6: Provide evidence

When information on the RIF is collected/available, the node probabilities are updated based on the procedure discussed in Section 5.2.3.1.

Step 7: Monitor barrier condition

The central barrier condition node is of interest. Changes in probability mass distribution in this node are observed when evidence is provided. The probability distribution represents the likelihood of finding the barrier in that particular state. Acceptance criteria must be set up for decision support and identification of risk reducing measures.

Chapter 6

Model Verification and Discussion

To demonstrate the applicability of the model to quantify barrier condition, a sample 'risk increasing activity' is chosen, BBN constructed and simulated in software. This chapter documents the process and discusses results/applicability of the model.

6.1 Model Setup

6.1.1 Introduction

"Hot work" is the chosen activity for the case study. Hot work affects the condition of the "Prevent Ignition" barrier function. All relevant RIFs are selected via the RIF identification process outlined in Chapter 4. A BBN influence model using the identified RIFs is constructed as outlined in Section 5.1.3. The algorithms for data manipulation and CPT generation is maintained in MS Excel. An excerpt of the VBA code used for the CPT generation is presented in Appendix B. The BBN model is implemented in the software GeNIe (https://dslpitt.org/genie/). For easy understanding, the model development is described step-by-step according to the method summary outlined in Section 5.3.

6.1.2 Model Simplification

To ease the model setup and construction, a number of simplifications are made with regard to managing risk indicators and network node configurations. These practical simplifications are discussed here.

6.1.2.1 Use of Risk Indicators

The influence relationship between risk indicators and RIFs while modelling them is illustrated by Haugen et al. (2012) and reported in Figure 6.1. In projects such as the RiskOMT, risk indicators are included as a part of the BBN model. This is avoided here.

As distinct RIFs are measured differently – subjective, objective or through hybrid methods (see Section 4.1.3), it is recommended to separately log indicators describing a particular RIF, and time stamp when the data was collected/made available. This log can then link directly to the BBN model to update the unconditional RIF node probabilities. By doing so, parameters such as time relevance of the data (how old/relevant the data collected is) can also be considered while expressing uncertainty in the score of the RIFs (specifying V_S). For example, a RIF score estimated through data that was collected through a survey a few months ago would have a larger V_S in comparison to a score from a survey conducted last week.
This would also depend on where in the planning process is the activity currently (see strength of knowledge in RIFs from Appendix A) and how often the RIFs change. Certain RIFs might change very slowly (e.g. work culture), while others may vary from one activity to the next (e.g. task complexity).

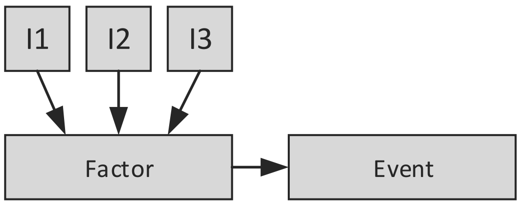


Figure 6.1 Modelling influence diagram showing the relationship between risk indicators and RIFs

6.1.2.2 Parent Divorcing

In projects such as BORA (Aven et al., 2006) and RiskOMT (Vinnem et al., 2012), all RIFs are directly connected to the child node (e.g. Figure 6.2). In this model, RIFs are grouped into sub-categories. This is a mathematically convenient solution to simplify the Bayesian network. Creation of an intermediate node is called parent divorcing (Nielsen and Jensen, 2009). Having fewer parents for a node reduces the computational complexity for generation of CPTs. An example of parent divorcing is illustrated in Figure 6.3.

In the suggested model, parent divorcing is recommended when the number of parents for a node exceeds five <u>and</u> as long as the introduced intermediate state provides for better/intuitive weight assignment. For example in Figure 6.3, weighting between organizational and environmental factors first, followed by weighting between RIFs in each category is easier and more intuitive than weighting between all five RIFs in Figure 6.2. Mathematically, assuming all nodes can have 6 states, the number of conditional probabilities to be assigned reduces from 7776 (6^5) in Figure 6.2, to 288 (6^3+6^2+6^2) in Figure 6.3. Furthermore, such grouping helps to better understand and model interaction effects between similar RIFs.

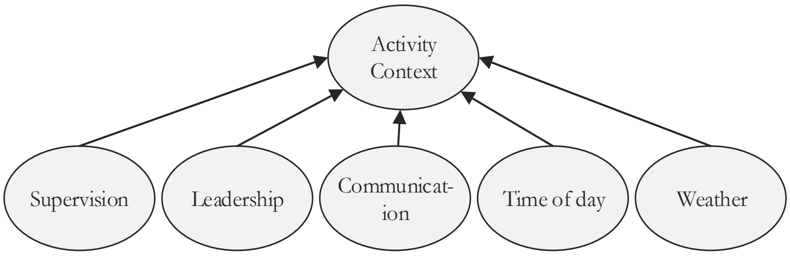


Figure 6.2 Case 1: Child having five parents directly connected to it

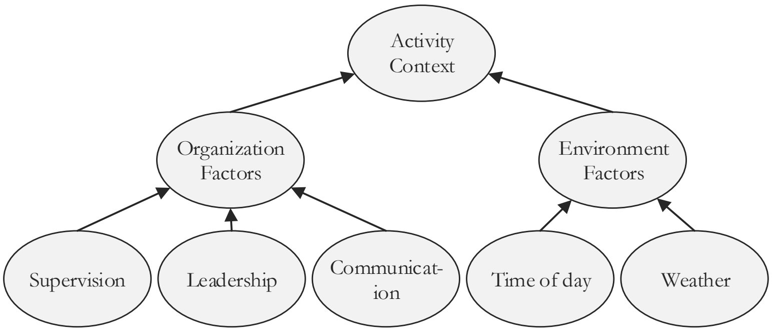


Figure 6.3 Case 2: Example illustrating the concept of parent divorcing

6.1.3 Step-by-step model setup

Step 1: Construct Influence Diagram/BBN

The full BBN model for the activity "Hot Work" is shown in Figure 6.4. The central node of the network, "Barrier Condition" is influenced by the characteristics of the task, the context within which the activity is being conducted and the characteristics of the personnel executing the work. This is modelled in the bottom half of the BBN in Figure 6.4. Further, the condition of technical systems (e.g. nature of process equipment, design of systems, availability of safety systems etc.) is represented in the upper half of Figure 6.4.

The nodes in light green – the outermost nodes of the network (i.e. nodes without parents) are the RIFs and nodes in light gray are divorced parent states (see section 6.1.2.2). As specified earlier, all nodes in the network assume six states, ranging from A to F or 1 to 6. State A or 1 represents a perfect/near-perfect condition while state F or 6 represents complete impairment/ degradation.

Step 2: Assign prior probabilities for RIFs

All RIFs in the model are assigned Jeffery's prior with a beta distribution. The point probabilities for each state is calculated in MS Excel. First, the scores A to F are translated on a scale of 0 to 1. For example, A=0.17, B=0.33, C=0.5 and so on. Next, the probability for being in each state is calculated using the cumulative distribution function (CDF).

For example, $\Pr(RIF = k) = F(k) - F(k-1)$; where F is the cumulative distribution function for the beta distribution, and k=A,B...F. In MS Excel, the CDF is calculated through the inbuilt function "BETA.DIST".

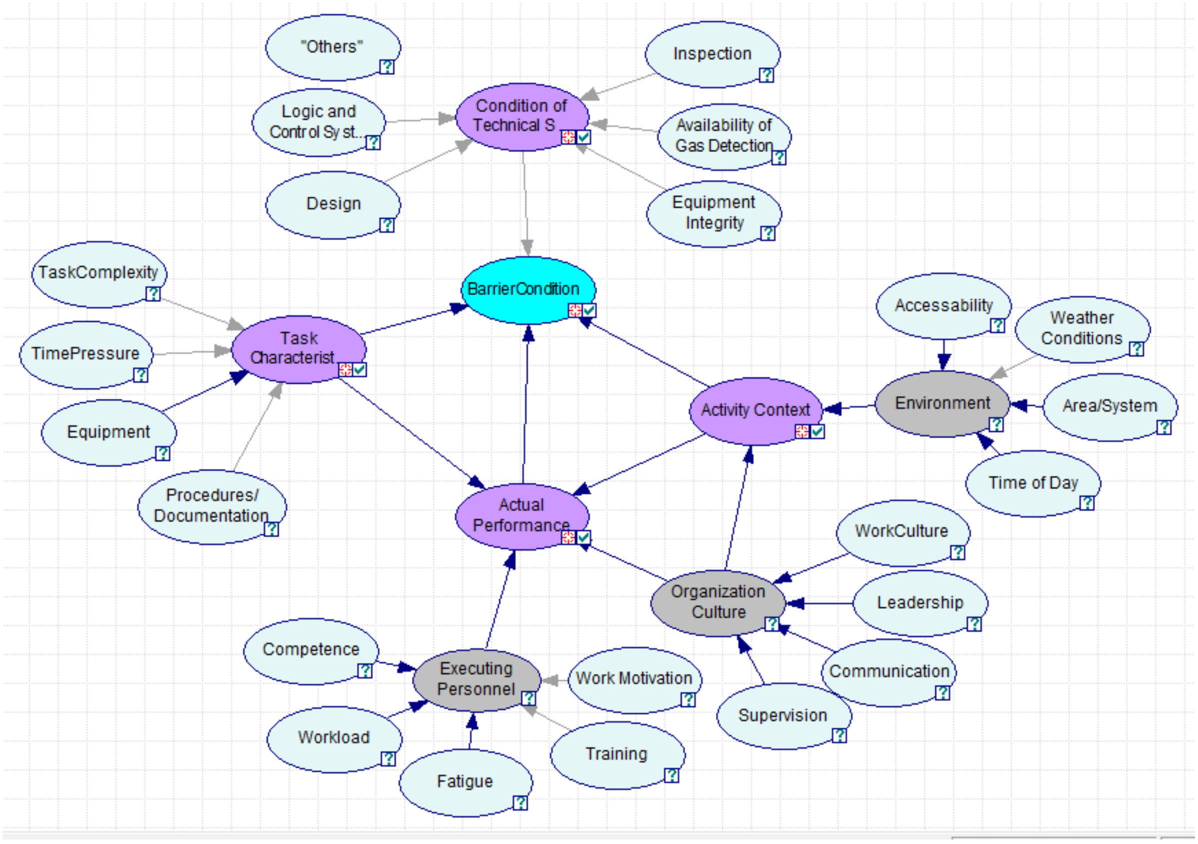


Figure 6.4 Full BBN model for Hot Work

Step 3: Identify RIF clusters with potential interaction effects

The set of RIFs for which interaction effects are identified are listed in Table 6.1. For simplicity, the following assumptions are made: (1) interaction effects take over when the score of each of the RIFs exceed C/3, and (2) for each child node, only one interaction cluster is modelled. The interaction effects for intermediate states from C to F are approximated using simple linear interpolation (see Section 5.2.3.2). Note that the interaction effects identified in Table 6.1 are based on subjective belief of the author. In practice, all possible interaction clusters must be identified by experts so as to obtain an as accurate as possible representation of the real-world.

Table 6.1 Interaction effects defined for the model

Interaction Cluster	RIFs	Inter-cluster weight	Description
Cluster 01	Competence	0.5	Lack of competence in a particular task coupled with low training
	Training	0.5	
Cluster 02	Time Pressure	0.5	Time pressure to execute a complex task as soon as possible within a limited time frame.
	Task Complexity	0.5	
Cluster 03	Accessibility	0.5	Limited accessibility to work site coupled with the time of day and weather the work is being carried out in.
	Weather	0.2	
	Time of day	0.3	

Step 4: Calculate the CPTs

Through the algorithm described in Section 5.2.1, CPTs are calculated for each node in the BBN. The weights for the parent nodes and the chosen R-values are listed in Table 6.2. These are based on the authors' intuition about the relative importance of the nodes. The interaction effects (Table 6.1) are modelled while assigning the conditional probabilities through the procedure described in Section 5.2.3.2. This algorithm is programmed in MS Excel for a programmable choice of up to six nodes, which can each assume up to six states with one interaction cluster. An outline of the VBA code and MS Excel interface developed for the same is presented in Appendix B.

Step 5: Initialize the BBN

The CPTs generated in Step 4 are entered into the nodes of the BBN developed in GeNIe. Once all the required data is entered in the BBN, the network is initialized. Initialization requires the instantiation of "target nodes". Target nodes are those nodes based on which the inference is focused. The central node, "BarrierCondition" is set as the target node.

Step 6: Provide evidence

When information on the RIF is collected/available, the RIF node probabilities are updated by providing evidence into the model. To represent uncertainty in RIF measurements the posterior distributions for the RIFs are calculated via the procedure outlined in Section 5.2.3.1. A suitable V_S is chosen based on the experts' degree of belief that the observed RIF score reflects the underlying true score of the RIF.

Step 7: Monitor barrier condition

When evidence is provided, the probability mass distribution for the child nodes are updated. Changes in barrier condition are monitored as and when evidence is made available and updated in the model.

Table 6.2 Chosen weights and R-values for nodes in the BBN model

Child Node	**Parent Node**	**Weight**	**R-value**
Executing Personnel	Competence	0.4	2
	Workload	0.05	
	Fatigue	0.2	
	Training	0.3	
	Work motivation	0.05	
Organization Culture	Work culture	0.25	1.5
	Leadership	0.25	
	Communication	0.25	
	Supervision	0.25	
Environment	Accessibility	0.25	2.5
	Weather conditions	0.2	
	Area/System	0.3	
	Time of day	0.25	
Task Characteristics	Task complexity	0.3	2.5
	Time pressure	0.4	
	Equipment	0.1	
	Procedures/documentation	0.2	
Actual Performance	Task characteristics	0.3	2
	Executing personnel	0.4	
	Organization culture	0.1	
	Activity context	0.2	
Activity context	Environment	0.5	1.5
	Organizational culture	0.5	
Condition of technical systems	Logic and control systems	0.2	2.5
	Design	0.05	
	Inspection	0.2	
	Availability of gas detection	0.5	
	Equipment integrity	0.05	
Barrier condition	Task characteristics	0.2	2
	Actual performance	0.4	
	Activity context	0.1	
	Condition of technical systems	0.3	

6.2 Model Evaluation

6.2.1 Inference

The basic goal of a Bayesian Network is to compute the posterior probability distributions for a set of query variables, given an observation of a set of evidence variables. This is referred to as inference (Pearl, 1986). What does it mean for the barrier condition to be in a state ranging from A to F? For the model to provide decision support, predefined acceptance criteria needs to be set up. For example, a total probability mass greater than 0.4 in states E and F together, may be defined as unacceptable. The acceptance criteria will also depend on the condition of the other barrier functions (see discussion in Section 6.3.6).

It is important to note that the probability mass distributions from the BBN do not express the likelihood of the barrier being impaired or degraded. For example, Pr(BarrierCondition=F)=0.1 does not imply that the barrier is impaired with a 10% probability. Røed et al. (2009) present an approach to use the probability mass from the BBN to calculate updated probabilities for binary events. For instance, the probability of a failure or an accident. However, this method involves a lot of subjective reasoning using adjustment factors etc. In the current application, presentation of a standalone 'probability' is not considered directly relevant for decision support and this is therefore not discussed further.

Primary inference is directed at the "BarrierCondition" node. Based on arguments from Reason (2004), the likelihood of barrier impairment depends on the activity characteristics, personnel characteristics, activity context and the actual condition of the technical systems. Therefore, secondary inference may be directed at these nodes and hence these are also set as "target" nodes in the BBN model.

The initialised model with all RIF nodes assigned state probabilities using Jeffery's prior for a beta distribution to express ignorance in the RIF scores is shown in Figure 6.5.

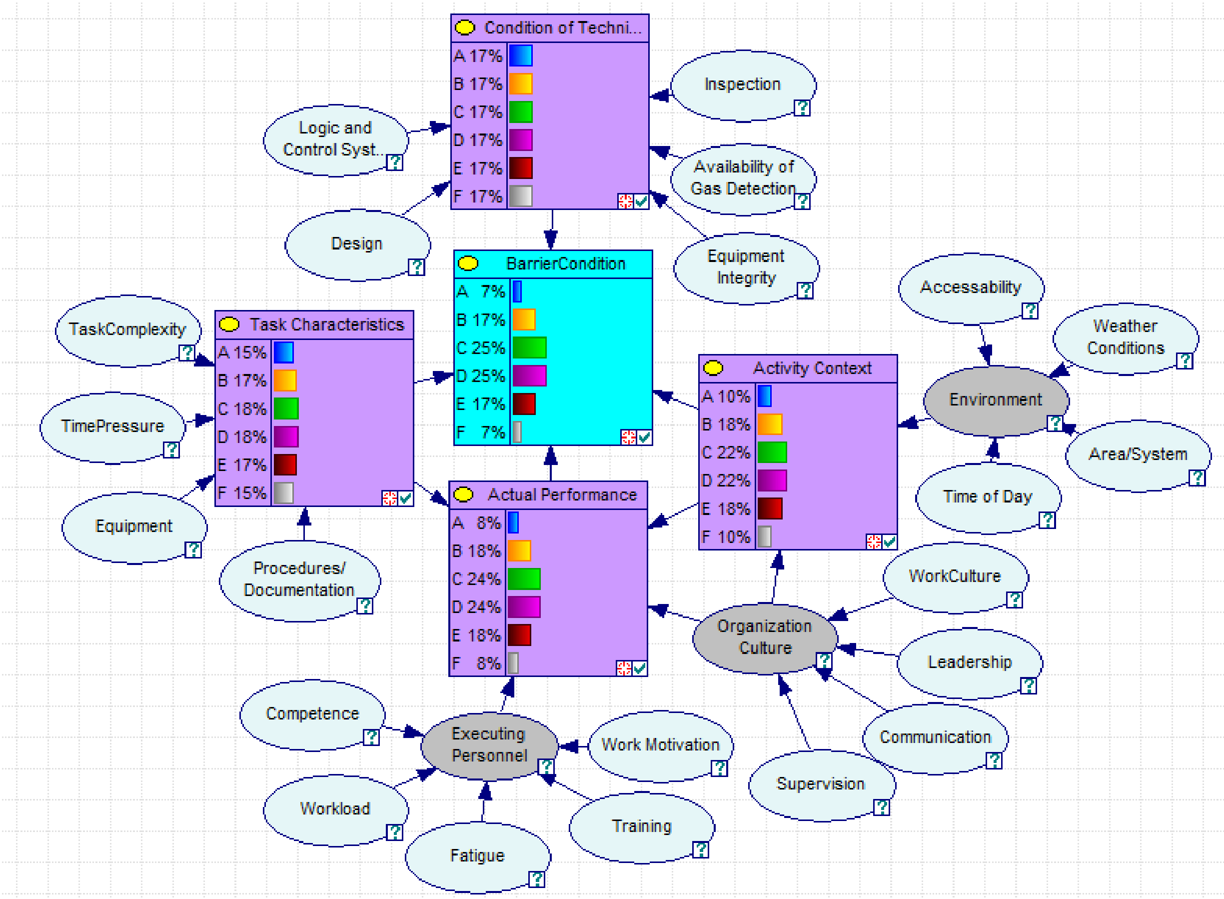


Figure 6.5 BBN model initialised with all RIFs given Jeffery's prior

6.2.2 Scenario Description

To evaluate the model, and demonstrate the effect of modelling with/without interactions, two specific scenarios are simulated: (1) scenario without any interaction between RIFs (2) same scenario with interactions between RIFs.

The following base scenario is defined: Consider a situation where the main executing technician is unavailable and a junior technician steps in to assume his role. However this technician lacks in both the experience and training for the task. This implies Competence=E and Training=F. In addition, the complexity of the task is rated above average and it is required to be completed within the day. This implies Time Pressure=E and Task Complexity=D. The area the task is being carried out in contains several process equipment and therefore Area/System=E. A low variance (V_S= 0.0025) is chosen to reflect a very high degree of confidence in the observed RIF scores. The state of the other RIFs are in an unknown state, i.e. no evidence provided. The results without and with interaction effects modelled, is seen in Figure 6.6 and Figure 6.7 respectively.

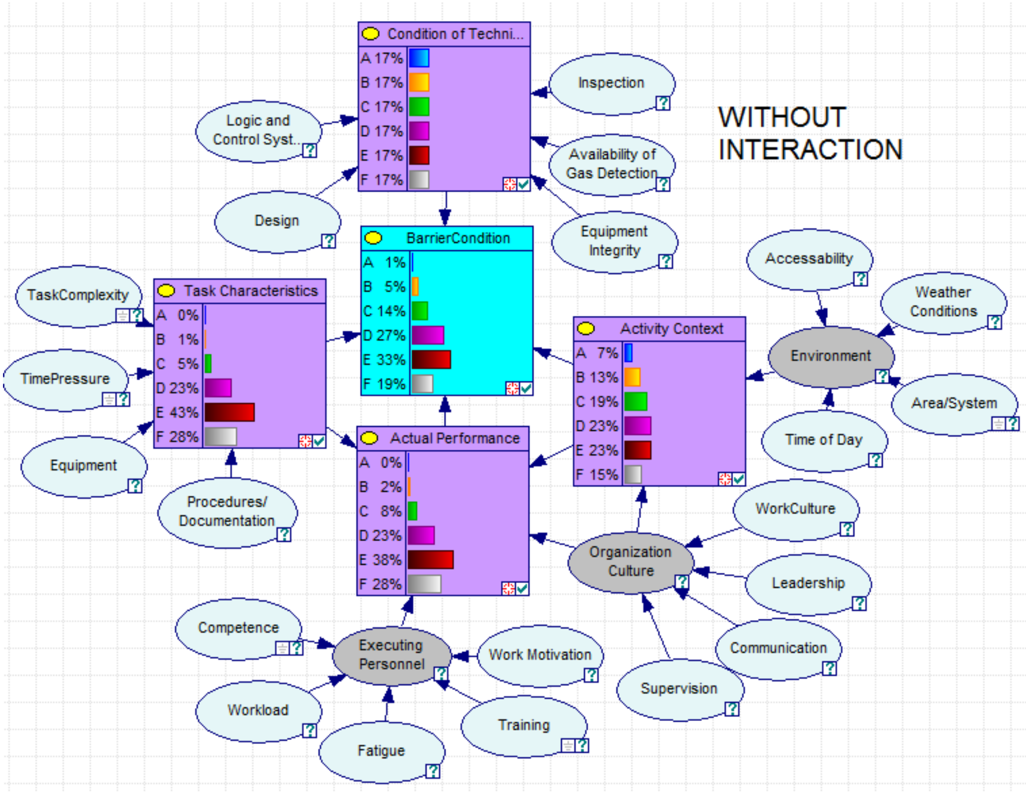


Figure 6.6 Results of the BBN model considering no interactions between RIFs.

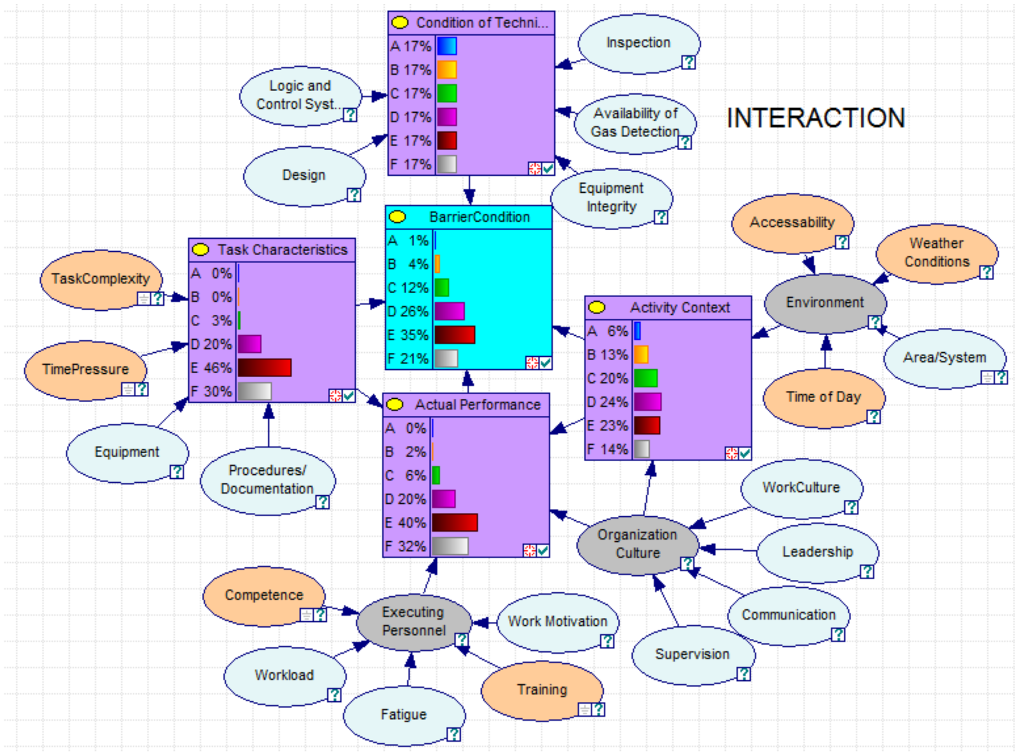


Figure 6.7 Results of the BBN model after including interaction effects between RIFs. (Nodes in orange represent the nodes which are configured for interaction effects)

6.2.3 Scenario Comparison

The results from this analysis demonstrate the benefits of modelling RIF interactions. The probability mass of barrier condition in state F increases from 0.19 to 0.21. Further, the probability mass distribution for task characteristics changes from 0.43 to 0.46 and 0.28 to 0.30 for states E and F respectively.

It can be argued that the changes in the probability mass distributions are small enough to be considered insignificant to make a practical difference for decision support. However the claim is that when more interaction effects are studied and modelled explicitly based on expert judgement, these effects will begin to dominate and hence prove useful in reflecting the real world conditions better in the BBN model.

The importance of this is explained by Mohaghdeh and Mosleh (2009) who emphasize that modelling actual performance involves being able to detect the emergence of abnormal behaviour from interactions and interdependencies between factors. However, this hinges on the assumption that all possible interdependencies and interactions are identifiable to the experts who develop the BBN model.

6.2.4 Risk reducing measures

One of the main objectives of the model for decision support is to aid identification of risk reducing measures. Risk reducing measures are identified to prioritize actions to ensure (1) critical factors do not go out of control and result in a critical barrier condition and (2) that areas of focus where improvement efforts can be directed are identified. Both (1) and (2) are achieved through a sensitivity analysis. A sensitivity analysis shows how the uncertainty in the output of a model can be allocated to different sources of uncertainty in its inputs (Saltelli et al., 2008). For a Bayesian Network, a sensitivity analysis yields insight into the relation between the probability parameters of the network and its posterior marginal (Kjaerulff and van der Gaag, 2000).

In GeNIe, a one way sensitivity analysis can be conducted through the 'sensitivity tornado' functionality. The sensitivity analysis reports the spread of posterior probabilities of the specified target node. The results are reported using a tornado diagram which is a special type of bar chart used to report results from a sensitivity analysis. The tornado chart displays the parameters which yield largest changes in the posterior. For the sensitivity study, the variable under study is modelled as an uncertain value while the others are held at a stable state. The tornado diagram in GeNIe reports the "Top N" factors that contribute the most to the variability of the outcome, and therefore what should be focussed on by the decision makers. GeNIe also allows the user to decide the range of variability for a chosen parameter.

To illustrate this, the tornado sensitivity graph for the scenario described in Section 6.2.2 is presented in Figure 6.8. The parameter variability is set to 50% of the current value. The plot identifies that risk reduction should be primarily targeted at Time Pressure conditions and Gas Detection systems.

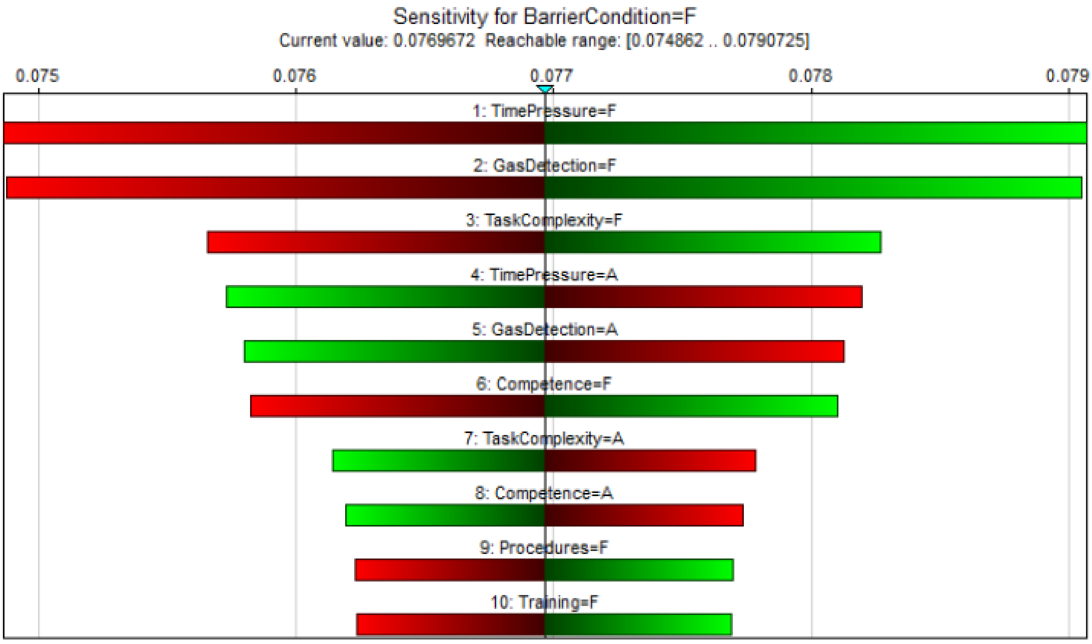


Figure 6.8 Sensitivity Tornado identifying the top 10 factors that contribute most to the variability of BarrierCondition=F

6.3 Discussion

6.3.1 Implementation practicalities

Development of the BBN model requires a high level of competence from the personnel involved. An understanding of conditional probabilities is a pre-requisite. Furthermore, understanding of the activity, the RIFs and interactions between them is required to be able to develop a model that mirrors the real world as close as possible. Once the BBN is constructed, expert input is needed for the weight calibration and R-value assignments. With support from weight calibration methods such as the AHP, this workload for the task is considered reasonable.

The BBN model was implemented in the GeNIe (Graphical Network Interface) software package which supports creation of decision theoretic models via a graphical drag and drop interface. The creation of the conditional probability tables was implemented in MS Excel using some of Excel's inbuilt functions and VBA code. VBA code (see Appendix B) was used to (1) generate all possible combinations of 'n' RIFs each with 'm' possible states and (2) create the conditional probability tables. Once the conditional probabilities were generated for a parent node, they had to be manually transferred into GeNIe using copy-paste. While the compatibility of GeNIe for direct-copy paste between its own interface and MS Excel is handy, for a large number of nodes this becomes tedious. It is equally tedious to manually assign the RIF prior and posterior probabilities through the graphical interface. Hence it would be relevant to study if seamless integration is possible via a spreadsheet interface or something similar. If this model had to prove of practical use in operations, this limitation would need to be overcome.

The execution time for the VBA code was found to be reasonable for up to five RIFs with six states each. Beyond this, the MS Excel interface became very slow and difficult to handle. This is not seen as a significant limitation because the algorithm can be easily implemented in other programming compilers such as C++ or Python without any limitations in computation.

6.3.2 Uncertainties and implications of the model

The model structure is based on how the interaction of the many aspects of an activity (the activity characteristics, the executing personnel and the context) impact the condition of a barrier function. Preliminary runs of the model and the case scenario evaluated in this chapter seem to provide reasonable results. A limitation with the current setup is that the barrier functions and sub-functions are not explicitly modelled, neither as a part of the BBN, nor using event and fault trees. Instead a certain number of these barrier systems are referred to as risk increasing conditions and are included as RIFs within the model. (E.g. as done with "gas detection" in the BBN model for hot work – Figure 6.5). Therefore, the technical aspects of these barriers are not modelled very comprehensively, and as a result might not be attributed sufficient importance as they ought to be given.

If it is believed a restructure of the BBN is required to better represent the real-world (technical barrier systems or otherwise), this does not render the discussed method irrelevant. All the mathematical aspects discussed with regard to uncertainty in RIFs, CPT table generation, interaction modelling etc. can be applied as discussed in Chapter 5.

Another uncertainty in the model is the use of the mechanistic procedure for the creation of conditional probability tables. The assumption that a small probability is assigned, given a large deviation between the parents' states and the child node might be too simplistic. This can be interpreted as a somewhat linear relationship expression between the state of the parents and child in the BBN. However, this assumption is reasonable due to three reasons, (1) by giving experts control over the 'strength' of the relationship between the parents and child through the R-value, a reasonable CPT distribution can be obtained, (2) through interaction effect modelling, non-linear effects are accounted for to provide a better representation of the real-world, and (3) the automated process to calculate the CPT aids easy model setup which otherwise would not be possible through manual input.

6.3.3 Simplifications and Limitations

The inclusion of all possible RIFs in the model resulted in the need to introduce parent divorcing (Section 6.1.2.2) into the model. This reduces the computational complexity, as well as eases interpretation and calibration of the model. However, this increases the size and number of intermediate nodes of the model. To avoid this, only the RIFs with strongest influence may be chosen and the others omitted. However, for the case example described in this chapter, as the model complexity is not considered limiting, a RIF reduction is not seen as a necessity.

As pointed out in Section 5.2.3.2, the model cannot account for interaction between RIFs connected to different child nodes. For example, if the experts believe interaction to exist between 'competence' and 'area of work', this cannot be implemented within the current setup. It might be rare to identify such combinations, but it is important to recognize this limitation.

6.3.4 Interaction and common cause effects

Two important phenomena that are dominant in real-world scenarios are interactions and common causes.

The BBN method to model barrier condition elegantly treats uncertainties in RIF measurements and interaction effects between RIFs. The integration of interaction effect modelling into the CPT assignments is an advancement over the method from Røed et al. (2009) and this provides a better representation of the real-world. In the model implementation, only negative interaction effects have been accounted for. In reality there might be positive interactions as well, however by neglecting these effects, the results of the model can be claimed to be more conservative.

Øien et al. (2015) discuss that a focus on only operational and technical aspects in barrier management might overshadow the impact of organizational dimensions that can act as catalysts for common cause failures. Therefore, the potential for organizational multiple barrier failures must be accounted for in some way or the other. Common causes effects are not treated within the current setup. These will have to be considered in more detail while developing the extended risk model (see Section 6.3.6).

6.3.5 Conclusions on usefulness of the Model

The suggested BBN model is a generalization and adaptation of the work from the RiskOMT, HCL and Risk Barometer methods to a different context. The over simplifications from using linear weighted averages as done in the Risk Barometer is overcome through the use of Bayesian Belief Networks. The tiresome manual determination of conditional probability tables is overcome by adapting the CPT generation algorithm from the HCL methodology. The CPT algorithm is further extended to include interaction effects based on interaction modelling concepts from the RiskOMT project. Lastly, formal treatment of uncertainty in RIF measurements is treated in a similar fashion as suggested by the RiskOMT method.

The model has made the assumption that information about all RIFs is readily available to be inputted into the model. Even if this is not the case, Jeffery's prior can be applied specified for the RIFs with "no information" to reflect ignorance in these parameters. This flexibility ensures that the model functioning is not limited by the necessity of data availability.

While the suggested model provides relevant and as-expected results, the model in its current form is not completely useful in a decision context. Modelling the interaction of other activities and conditions themselves is not a simple task. The BBN model suggested looks at only a single activity and its impact on the condition of the barrier under consideration. To be relevant and useful for decision support in a risk context, the model requires to be extended to include the condition of other barrier functions. See discussion in Section 6.3.6.

6.3.6 Model Extension

The model summarized in Section 5.3 measures the condition of a barrier as a function of activities which impair/degrade the barrier performance. This is illustrated by the vertical link between activities/conditions and a single barrier function illustrated in Figure 6.9. For example, the influence between "Work on pressurized HC system" and "Inhibit PSV" on the same barrier function "BF1 Prevent Release".

To provide a holistic risk picture (i.e. activity and period risk – see Chapter 2), two additional aspects must be considered (1) the current technical condition of other barriers (that are not affected by any risk increasing activity/condition) and, (2) the impact of other ongoing simultaneous activities/risk increasing conditions.

Item (1) calls for the development of a single risk measure. See illustration above the horizontal line in Figure 6.9. For item (1), information from available qualitative studies/monitoring systems, for example barrier analyses, can be used to gauge the current technical condition of all barrier functions in a particular area of the facility. This information, along with the impact of the ongoing activities in the area must be integrated in a single model to provide a measure of the real-time major accident risk.

Item (2) provides an understanding of the impact of multiple activities and conditions on the state of a particular barrier. This is illustrated below the horizontal line in Figure 6.9. In such a case, two scenarios are possible:

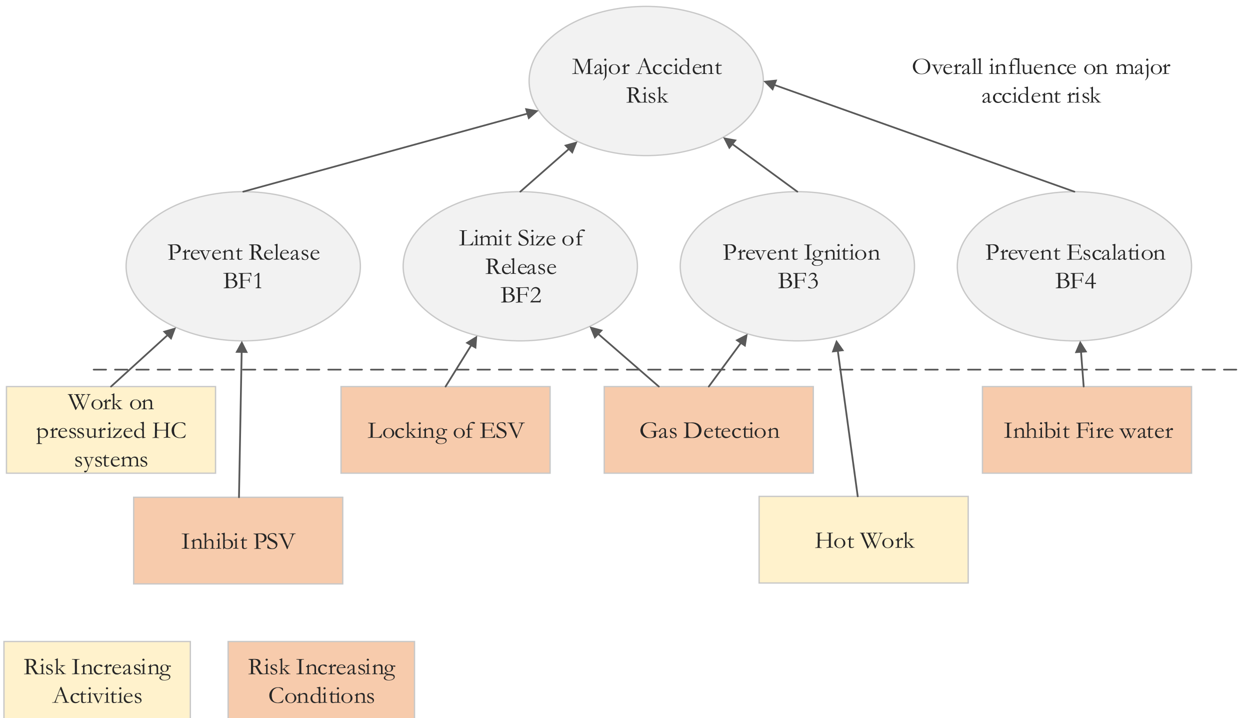


Figure 6.9 Conceptual outline of entire risk model

1. Activities/conditions affect different barrier functions.
   In this case, hazards of two different activities together introduce a third hazard and thereby change the accident type, likelihood and consequence. This challenge can be tackled by a

systematic hazard specification for each individual activity which promotes awareness of any potential dependencies (David, 2008).
Example: Hot Work occurring along with maintenance on a HC pump.

2. Activities/conditions affect the same barrier function - this involves two types of interactions:
    a. Two or more risk increasing activities that relate to the same hazard but (i) are dependent due to certain common cause elements (ii) their simultaneous occurrence affects the spectrum/severity of possible consequences. For (i) common cause effects can be modelled in the analysis and for (ii) the increased level of barrier degradation due to multiple activities need to be modelled. Example: Simultaneous maintenance activity on three pressurized HC pumps in the same area of the facility
    b. A combination of a risk increasing activity and a risk increasing condition. In such a scenario, the risk increasing condition can be modelled as a RIF in the BBN model for the activity. Example: Execution of hot work (activity) with simultaneous inhibition of gas detection (condition).

The method specified in this thesis and discussed in Chapters 5 and 6 covers only aspects of 2b (modelling a risk increasing activity's impact on barrier function along with possible risk increasing conditions on the same barrier function). Understanding and modelling items 1 and 2a need to be further developed to be able to quantify the overall risk level.

Chapter 7

Summary and Recommendations for Further Work

This chapter summarizes the work performed in the thesis and the results therein. The results are discussed, findings documented and recommendations for further work given.

7.1 Summary and Conclusions

Operational risk analysis is an area of recent focus in the oil and gas industry, with an objective to provide decision support to help increase production levels while minimizing risk. However, gaining insight into short-term changes in risk levels, also known as risk transients in operations, is a challenge.

The first objective of this thesis is to review existing solutions for operational risk analysis in the oil and gas industry. A comprehensive interpretative literature review is documented in Chapter 2. The literature review begins with differentiating between strategic, operative and operational risk analysis in Section 2.1.2. The review focuses operational risk analysis in Section 2.1.3 and reveals that there is much to be done to gain insight into understanding short-term changes in operational risk. The existing tools and methods in the oil and gas industry are predominantly qualitative studies that promote integrated management of safety critical information through visualization and better information management (Section 2.1.4). However, these do not provide a quantitative understanding of the risk situation. The few methods that perform a quantitative analysis are either limited in coverage/applicability, or too tedious to apply in daily practice due to procedural complexity and this limits the frequency of updatability of the model.

Chapter 3 introduces activity based modelling as an approach to measure these transient risk levels in operations. The relevance of understanding and modelling risk transients is illustrated through two examples in Section 3.1.4. Section 3.2.4 critically reviews ideas for a new activity based modelling approach based on the 'Modelling Instantaneous Risk for Major Accident Prevention' (MIRMAP) project research work. A simplified and revised approach to the model is suggested in this section.

The second objective of the thesis is addressed in Chapter 4 and discusses Risk Influencing Factors (RIFs) for work activities. To systematically identify RIFs, a tree-hierarchy breakdown for work activities is suggested in Section 4.2.2 to support better understanding of the relevant hazards, hazardous events, accident scenarios and controls in place. The ideas are explained through examples in Section 4.2.3. This approach supports the identification of relevant RIFs for work activity risk modelling. One of the key takeaways from this study is the need to distinguish between risk increasing 'activities' and 'conditions'.
The work permit system is identified as an important source for RIF information that is often underutilized. Relevant RIFs that are available as a part of the work permit form are identified and listed in Appendix A.

The third objective calls for the development of a model to quantify the impact of planned and ongoing activities on barrier condition. To develop a suitable method, existing and relevant models from literature are reviewed in Section 5.1.2. Various features from each of these models are adapted to develop the suggested method. As activities are characterized by the interaction of technical, operational and organizational factors – Bayesian Belief Networks (BBNs) are the best available method to model these factors. A BBN model is developed and documented in Section 5.2. The developed model quantifies barrier condition on a scale from A to F. The method to easily generate conditional probability tables for the BBN based on the Hybrid Causal Logic approach is improved upon by including the quantification of interaction effects between RIFs. Further, formal treatment of uncertainty in RIF measurements using a beta distribution to quantify users' belief in the accuracy of a RIF measurement is adapted from the RiskOMT approach and discussed in Section 5.2.3.

The fourth objective is to verify the BBN model, analyse the results, and identify shortcomings and areas for improvement. The working of the method is verified by implementing the BBN algorithms in software. Results are documented and briefly commented upon in Chapter 6. The model runs show the benefits of including interaction effects between RIFs to better represent real world conditions (Section 6.2.3). Through sensitivity analysis in Section 6.2.4, suitable areas for risk reduction can be easily identified to support prioritization for decision-making. It is important to note that the model was tested based on subjective belief of the author for the assignment of the various parameters in the model. It is recommended that this be re-evaluated and performed in collaboration with field experts for the model to be as accurate as possible. If a restructure of the BBN model is required to better represent the real-world, this can be achieved. The mathematical treatment of RIFs, uncertainties and interactions will remain the same as discussed in the report.

7.2 Shortcomings/Limitations of the Work

The suggested method for RIF identification for work activities in Chapter 4 and the model discussed in Chapter 5 is unable to explicitly treat risk increasing conditions. For simplicity, they are included as RIFs within the defined risk model (see Section 6.3.2). The appropriateness of this approach needs to be justified, critically evaluated and alternative methods of modelling these conditions need to be explored.

The model presented in this report, in its current ofrm is not relevant for decision support. The developed model for barrier condition is limited in scope to account for the impact of only a single activity on a particular barrier function. In reality, there are multiple activities ongoing simultaneously which affect different barriers. For a holistic risk picture, the condition of the these barriers needs to be incorporated into a single risk model. Moreover, the impact of simultaneous activities/conditions needs to be modelled. Section 6.3.6 presents a brief discussion on these aspects.

7.3 Recommendations for Further Work

The findings from this master thesis represents a step forward towards the quantification of risk transients of operations. However there is still a lot of work to be done. Avenues for further work are divided into two broad categories:

Short-term goals

1. Chapter 4 presents a structured approach for RIF identification for work activities. This approach needs to be applied systematically for all relevant work activities in Table 3.1 to develop representative RIF sets for each activity which can be used for the modelling.
2. The QRA defines the average risk level based on certain generic operational assumptions. The QRA can prove as a vital information source for data that might be used as RIFs in the risk model. For example, equipment count, equipment type, process medium type, etc. A typical QRA must be reviewed to identify information that can be potentially used/integrated into the risk model (either as RIFs or otherwise).
3. As pointed out by the literature review in Chapter 2Managing Risk in Operations, in particular Table 2.1, many operators have their own proprietary solutions for operational barrier/risk

management. A possible generic approach to combine this information within the developed risk model needs to be explored.

4. The impact of multiple activities on the same/different barrier functions is a challenge for the risk model to analyse – due to interactions, common causes, etc. A best possible approach to tackle this challenge of mathematically modelling these aspects needs to be developed. See discussion in Section 6.3.6.

Long-term goals

5. Information management across multiple data sources is a challenge. A bigger challenge is being able to map all the relevant RIF information and corresponding observable risk indicators to a uniform standardized scale for the risk model to analyse (see Section 4.1.3). The need for doing so should be critically argued, and a possible procedure suggested.
6. An important aspect of decision support is how the risk information is presented to the user. The field of "Risk Visualization" has to be explored to understand the best way to present information to the user. The aspects of visualization and information presentation has not been discussed in this report. A key challenge here is how to present aggregated information to the user without any loss.

Appendix A

Risk Influencing Factors Available in the Work Permit Form

Sarchar et. al (2015) outline the typical planning process for Integrated Operations (IO) in the oil and gas industry. Risk transients by definition are caused due to activities in the short-term, therefore only the short-term planning horizons (operational (OP), work order (WO) and work permit (WP) plans) are focussed on in this study.

Operational plans are made every two weeks and focus on risk and production levels. The WO Plan is developed based on the operational plan. It comprises of a number of smaller subtasks which can be sequentially carried out. Before executing tasks from the WO, a WP is generated as a permission to perform work. The WP lays down the main precautions needed to complete the activity safely (NOG, 2013).

Table A.1 RIFs identified from the WP form (NOG, 2013)

Stage	**RIF**	**Type of RIF**	**Knowledge about RIF**		
			OP	**WO**	**WP**
Planning	Competence of applicant	Operational			
	Need/ Availability of disposable work descriptions (SJA)	Operational			
Approval	Leadership	Organizational			
	Supervision	Organizational			
	Competence of HSE function/Platform manager	Operational			
Operation and Safety Preparations	Competence of Area technician	Operational			
	Location of work	Technical			
	Time of work	Technical			
	Work Extension needed	Operational			

	Depressurization/ Draining/ Isolation/ Ventilation etc.*	Technical			
	Other special requirements*	Technical			
	Inspection policy	Technical			
	Governing documents	Operational			
Execution	Competence – Executing skilled worker	Operational			
	Supervision	Organizational			
	Inspection	Technical			
	Permanent procedures/task descriptions	Operational			
	Tools used	Technical			
	Nature of worksite**	Technical			
Completion and Reinstatement	Competence – skilled worker, area technician	Operational			
	Work site condition	Operational			
	Isolations/Safety systems reinstalled	Technical			

* The RIFs chosen here depends on the type of activity being carried out. E.g. certain activities need isolation, others depressurization, others both.

**The characteristics of the work site chosen here are dependent on the type of activity being carried out. E.g. If the activity was Hot Work, a relevant RIF would be to see if the work site is exposed to flammable gas concentration or not.

Strength of Knowledge	
	Unknown
	Partially Known
	Known

OPS – Operational Plan
WO – Work Order Plan
WP – Work Permit Plan

Note: In concept, detailed risk considerations could be made at a considerably early stage of the activity planning process. In Table A.1, the knowledge dimension is added to identify where in the planning process information on the RIF might be available. This is based on the subjective understanding of the author and work by the MIRMAP project group. Wagnild et al. (2015) draw attention to the fact that although the WP electronically provides most information regarding the plan and related risk information, most information about the activity is well known early-on during the WO formulation itself. This is highlighted as an area for potential improvement in current planning processes.

Appendix B

VBA Code and MS Excel Interface

Basic knowledge in VBA coding and use of pivot tables in MS Excel is required to understand code syntax and formulation.

B.1 Create all possible parent-child combinations

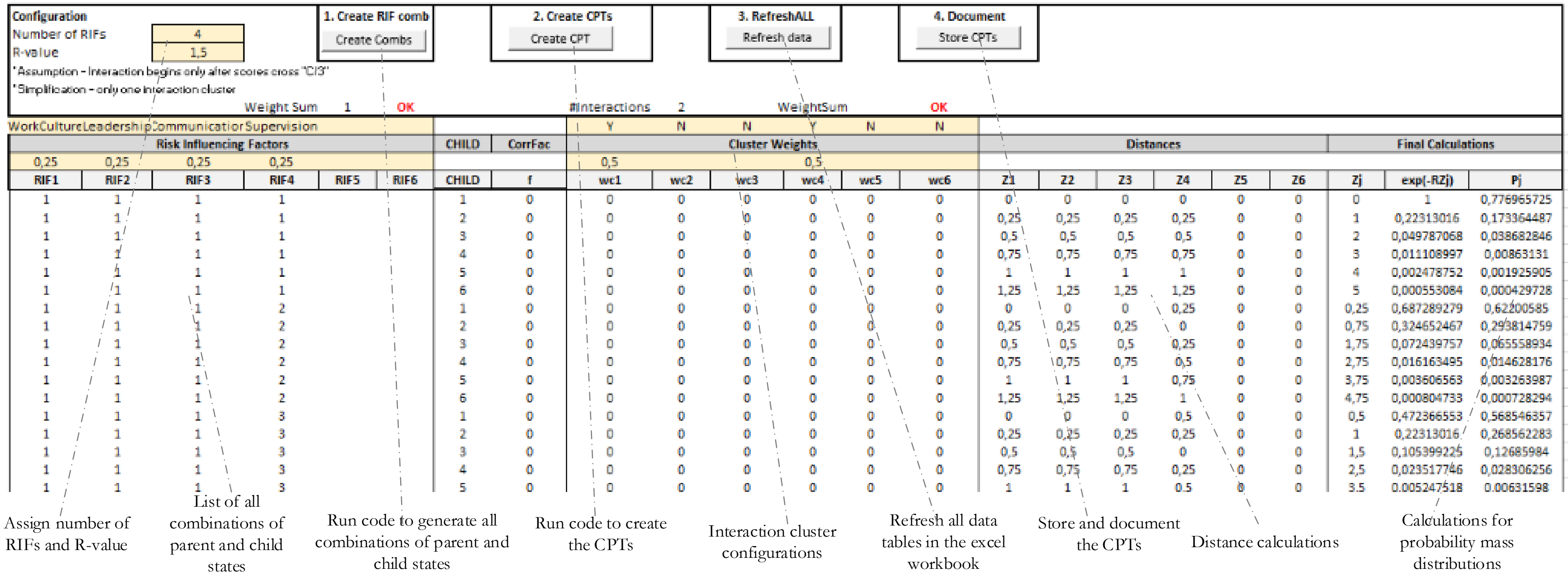
```
Sub CreateRIFCombs()

'Delete already existing data in worksheet
Sheets("CreateCPT").Range("A12:ZZ46666").Cl
earContents
Sheets("CreateCPT").Range("A11:G46666").Cle
arContents
Sheets("CreateCPT").Range("A9:F9").ClearCon
tents
Application.ScreenUpdating = False 'To
speed up calculations
Count = 11 'Index row number to start
creating combinations

'CODE TO CREATE ALL POSSIBLE COMBINATION OF
RIF(PARENT) AND CHILD STATES
If Range("NoRIFs") = 2 Then 'If number of
parents=2
    For i = 1 To 2
    CreateCPT.Cells(9, i) = 1 / 2
    Next i
    For RIF1 = 1 To 6 'number of States for
each RIF
    For RIF2 = 1 To 6
    For Child = 1 To 6 'number of States
for the child
    CreateCPT.Cells(Count, 1) = RIF1
    CreateCPT.Cells(Count, 2) = RIF2
    CreateCPT.Cells(Count, 7) = Child
    Count = Count + 1
    Next Child
    Next RIF2
    Next RIF1
ElseIf Range("NoRIFs") = 3 Then 'If number
of parents=3
    For i = 1 To 3
    CreateCPT.Cells(9, i) = 1 / 3
    Next i
    For RIF1 = 1 To 6
    For RIF2 = 1 To 6
    For RIF3 = 1 To 6
    For Child = 1 To 6
    CreateCPT.Cells(Count, 1) = RIF1
    CreateCPT.Cells(Count, 2) = RIF2
    CreateCPT.Cells(Count, 3) = RIF3
    CreateCPT.Cells(Count, 7) = Child
    Count = Count + 1
    Next Child
    Next RIF3
    Next RIF2
    Next RIF1
    CreateCPT.Cells(Count, 4) = RIF4
    CreateCPT.Cells(Count, 5) = RIF5
    CreateCPT.Cells(Count, 7) = Child
    Count = Count + 1

 Next Child

'… for all RIFs…

Else
End If
 'Update in spreadsheet formulas for entire
datarange
 Range("H11:W11").Select
    Selection.AutoFill
Destination:=Range("H11:W279946")
    Range("H11:W279946").Select
End Sub
```

B.2 Code to Create Conditional Probability Tables

```
Sub CreateCPT()

    'Delete already existing CPT
    Sheets("CPT").Select
    ActiveSheet.PivotTables("PivotTable2").PivotSelect "", xlDataAndLabel, True
    Selection.ClearContents

   'Selecting DataRange
   Worksheets("CreateCPT").Activate
    Sheets("CreateCPT").Range("A10").Select
    Range(Selection, Selection.End(xlToRight)).Select
    Range(Selection, Selection.End(xlDown)).Select
    'Create PivotTable
    ActiveWorkbook.PivotCaches.Create(SourceType:=xlDatabase, SourceData:= _
        "CreateCPT!R10C1:R46666C23", Version:=xlPivotTableVersion15).CreatePivotTable _
        TableDestination:="CPT!R1C1", TableName:="PivotTable2", DefaultVersion:= _
        xlPivotTableVersion15
    Sheets("CPT").Select
    Cells(1, 1).Select
        'Create the row child state variables for the CPT
     With ActiveSheet.PivotTables("PivotTable2").PivotFields("CHILD")
        .Orientation = xlRowField
        .Position = 1
    End With

    'For 2 Parents
        'Create the column headers for the various states of the RIFs
    If Sheets("CreateCPT").Range("NoRIFs") = 2 Then
    With ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF1")
        .Orientation = xlColumnField
        .Position = 1
    End With
    With ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF2")
        .Orientation = xlColumnField
        .Position = 2
    End With
        'Remove unwanted fiels from the pivottable
        ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF1").Subtotals = Array( _
        False, False, False, False, False, False, False, False, False, False, False, False)
     ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF2").Subtotals = Array( _
        False, False, False, False, False, False, False, False, False, False, False, False)

      'Replicate similar code For 3,4 and 5 Parents

    Else
    End If
    'populate the table with the Conditional probabilities
ActiveSheet.PivotTables("PivotTable2").AddDataField ActiveSheet.PivotTables( _
        "PivotTable2").PivotFields("Pj"), "Sum of Pj", xlSum
End Sub
```

B.3 MS Excel Interfaces

1. Interface for CPT creation



2. Interface for RIF uncertainty and calculation of point probabilities

RIF Uncertainty

Prior	
α0	0,5
β0	0,5

Specify prior distribution

Degree of belief

Vs
0,0025

Observed Score		
S	3	0,5

Observed score

CDF
TRUE

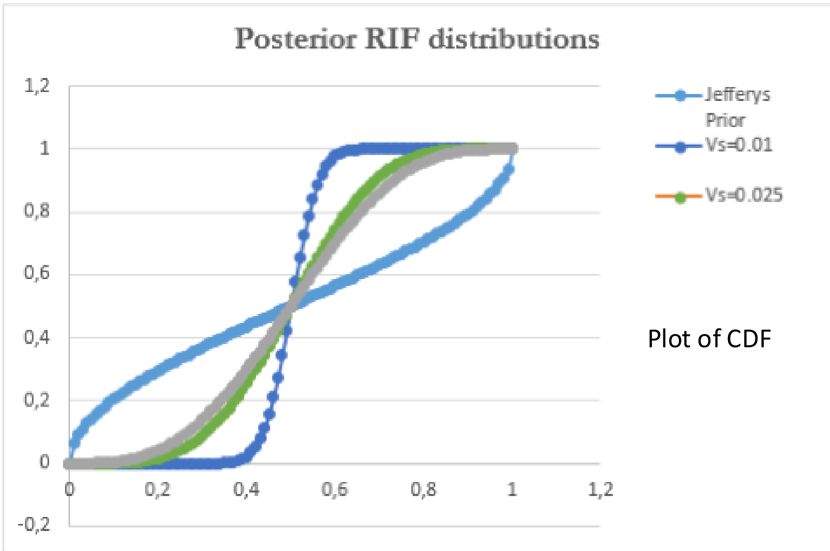
Posterior	
α	50,5
β	50,5

Estimated posterior

Plot CDF/PDF

RIF Point Probability Distribution

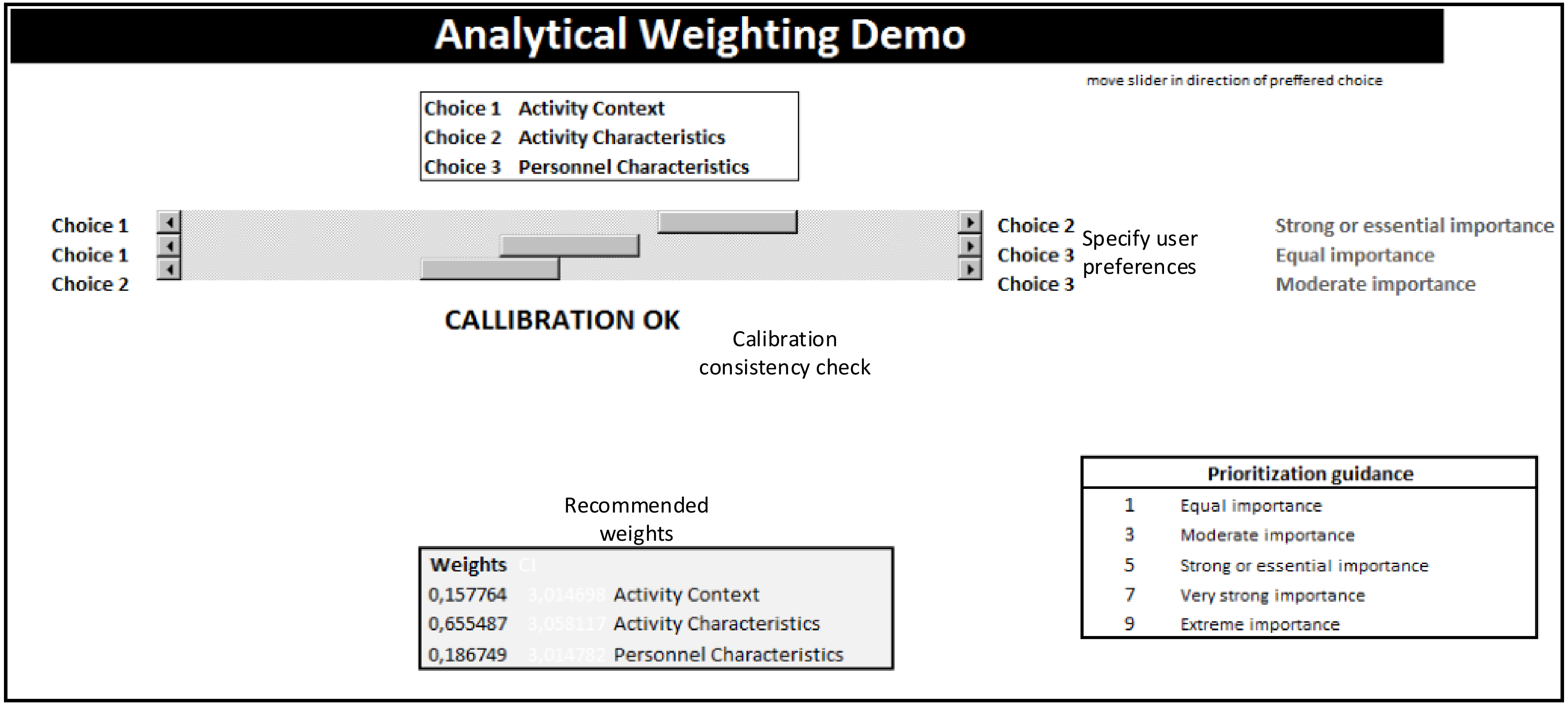
	Score		PosteriorProbMass	Prior Prob Mass
A	1	0,17	1,69032E-14	0,270556262
B	2	0,33	0,000220873	0,11901666
C	3	0,5	0,499779127	0,110427078
D	4	0,67	0,499779127	0,110427078
E	5	0,83	0,000220873	0,11901666
F	6	1	1,68754E-14	0,270556262
		Sum	1	1



Plot of CDF

Point probabilities

3. Interface for Weight Calibration (Analytical Hierarchy Process)



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  Scientific Assistant – Modelling Instantanoeus Risk for Major Accident Prevention