NTNU – Trondheim
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Science and Technology

Modeling of Technical, Human and Organizational Factors and Barriers in Marine Systems Failure Risk

Modeling of Stability Operations on a
Semi-Submersible Unit with the use of
Bayesian Belief Networks

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Submission date: June 2014
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Preface

This thesis is written as a completion of the MSc. program in Marine Technology at the Norwegian University of Science and Technology, Department of Marine Technology. The thesis was written during the spring semester 2014, and it accounts for 30 credits.

The thesis summarizes the research and work that I have done during this semester. This has been an interesting and challenging task, and I feel that I have learned a lot from this work, both about the topic of the thesis and about conducting and writing a scientific text.

I would like to use this opportunity to express my gratitude to phd candidates Audun Borg at UiS/PiD Solutions AS and Anders Arnhus at NTNU/PiD Solutions AS, for constructive discussions and guidance with writing this thesis. In addition I would like to thank my supervisor professor Jan Erik Vinnem at the Department of Marine Technology, NTNU. The support and guidance have been very valuable for my work with this thesis.

Trondheim, June 6, 2014

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Summary

Offshore operations in the relatively harsh conditions on the Norwegian Continental Shelf requires a strict safety focus. In order to conduct safe operations, a range of risk analysis tools are needed to monitor the risk level. In recent years there have been a great focus on avoiding hydrocarbon leaks, but in the last 25 years there have not been any in-depth work focusing on marine systems in general, and stability in particular. It is found that most risk analyses treats stability in a superficial way (PSA, 2011a). Furthermore, it is found that most accidents results from inadequate operational safety (DNV, 2014), and that human and organizational factors often causes these accidents. The objective of this thesis is therefore to develop a model that can be used to analyze the risk involved with technical, human and organizational factors in stability operations.

Due to the limited amount of work that have been done in this area, this thesis starts out by defining and explaining the basic concepts of stability of semi-submersibles, and the systems that are installed to perform stability operations. Further, the theory of bayesian belief networks (BBN) is explained. BBN is a method that can be used to analyze risk, and it is particularly suited for handling uncertainty, non-deterministic and non-sequential relationships.

A thorough review of technical, human and organizational factors and the interaction between these factors is done. It is found that technical factors often works on the unifinality side of the scale, meaning that there is one way for these factors to perform their tasks. Organizational factors on the other hand are on the equifinality side of the scale, meaning that there are many ways for these factors to perform their work and still yield the intended output. Human factors, are somewhere in between, and acts as the link between the organization and the technical systems. The unifinal properties of technical factors means that they are well suited for traditional risk analysis tools such as fault and event trees. These tools can, however, not be used to analyze the risks involved with organizational factors, due to their equifinal properties. That is why it is suggested to use BBN to develop a risk model for stability operations.

A thorough investigation of incidents and accidents has been done to determine the root causes to include in the model. The model has then been built, based on experiences from previous incidents and accidents. In this process it was found that most accidents occurred due to three types of failure:

- Failure to conduct normal operations
- Failure to respond to abnormal situations
- Failure of technical systems

The model has therefore been built around these three failure types, by focusing on the root causes for why these three failure types occurs. A semi-mechanized algorithm is used to quantify the model. This is used due to the massive workload associated with quantifying a BBN. This algorithm requires expert judgment input about how important each risk influencing factor (RIF) is compared to the other RIFs, and to what extent the RIF will influence its child node. This means that the model to a small degree is based on real data. Because of this it is concluded that the model it not suited to determine a specific risk, but rather to monitor how the risk level is developing over time, and how it develops when certain RIFs change their state. It is also recognized that the model need some more refinement and validation before it can be applied in real situation in the industry.

Sammendrag

Offshore operasjoner i det relativt tøffe miljøet på den norske kontinentalsokkelen behøver et strenget sikkerhetsfokus. For å gjennomføre sikre operasjoner trengs det en rekke risikoanalyseverktøy for å overvåke risikonivået. De siste årene har det vært et stort fokus på å avverge hydrokarbonlekkasjer, men gjennom de siste 25 år har det ikke vært noen dyptgående studier med fokus på marine systemer generelt og stabilitet spesielt. Det er funnet ut at de fleste risikoanalyser behandler stabilitet på en overfladisk måte (PSA, 2011a). Videre er det funnet at de fleste ulykker resulterer fra utilstrekkelig operasjonell sikkerhet (DNV, 2014), og at menneskelige og organisatoriske faktorer ofte er årsaken til disse ulykkene. Målet med denne oppgaven er derfor å utvikle en modell som kan bli brukt til å analysere risikoen involvert ved tekniske, menneskelige og organisatoriske faktorer i stabilitetsoperasjoner.

På grunn av den begrensede mengden arbeid som har blitt gjort i dette fagfeltet tidligere vil denne oppgaven starte med å definere og forklare den grunnleggende teorien for stabilitet på halvt nedsenkbare plattformer, og de systemer som er installert for å gjennomføre stabilitetsoperasjoner. Videre vil teorien bak bayesianske nettverk (BBN) bli forklart. BBN er en metode som kan bli brukt for å analysere risiko, og er spesielt egnet til å håndtere usikkerhet, ikke-deterministiske og ikke-sekvensielle forhold.

En grundig gjennomgang av tekniske, menneskelige og organisatoriske faktorer og samhandlingen mellom dem er gjennomført. Det ble funnet at tekniske faktorer ofte er på den entydige siden av skalaen, hvilket betyr at det kun er én måte for disse faktorene å gjennomføre sine oppgaver. Organisatoriske faktorer er derimot på den flertydige siden av skalaen, hvilket betyr at det er mange måter for disse faktorene å gjøre jobben sin, og fortsatt produsere det ønskede resultat. Menneskelige faktorer er et sted i mellom, og fungerer som et bindeledd mellom organisasjonen og de tekniske systemer. De entydige egenskapene til tekniske faktorer betyr at de er velegnede til å beskrives med tradisjonelle risikoanalyseverktøy, slik som feil- og hendelsestre. Disse verktøyene kan derimot ikke bli brukt til å analysere risiko knyttet til organisatoriske faktorer, på grunn av de flertydige egenskapene. Derfor er det foreslått å benytte BBN for å utvikle en risikomodell for stabilitetsoperasjoner.

En grundig granskning av hendelser og ulykker har blitt gjennomført for å fastslå hvilke bakenforliggende årsaker som bør inkluderes i modellen. Denne modellen har derfor blitt bygget

på tidligere hendelser og ulykker. I prossessen er det funnet ut at de fleste ulykker forekom på grunn av tre typer feilhandliger:

- Mislykket håndtering av normale operasjoner
- Mislykket respons til unormale tilstander
- Feil i teknisk system

Denne modellen har defor blitt bygget rundt disse tre feilkategoriene, med et fokus på bakenforliggende årsaker for hvorfor disse feilene forekom. En tildels mekanisk algoritme har blitt brukt for å kvantifisere denne modellen. Dette er gjort fordi det er en overveldende oppgave å kvantifisere et BBN. Denne algoritmen behøver ekspertvurderinger i form av hvor viktig hver enkelt risikopåvirkende faktor (RIF) er, og i hvilken grad hver RIF påvirker barnenoden sin. Dette betyr at modellen i liten grad er basert på reelle data. På grunn av dette er det konkludert med at modellen ikke er egnet til å avgjøre en bestemt risiko, men kan heller brukes til å overvåke utviklingen i risikonivået over tid, og hvordan det utvikles når bestemte RIFer endrer karakter. Det er erkjennes også at modellen trenger noe mer arbeid før den kan anvendes i reelle situasjoner i industrien.

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Chapter 1

Introduction

The objective of this chapter is to familiarize the reader with this thesis, its background and objectives. The introduction includes some background information, a problem formulation and the limitations of this study.

1.1 Background

The concept of risk has been understood for millennia. The largest and most well known "barrier" ever constructed is perhaps the Great Wall of China. Barriers and risk reduction strategies have evolved a lot since the building of the Great Wall, but the concept is still the same: to reduce risk. Offshore operations on the Norwegian Continental Shelf (NCS) can be a potentially dangerous occupation. It is therefore placed a major emphasis on avoiding accidents. Risk analysis methods are important tools to monitor risk levels, and as an aid in making decisions.

In recent years there have been a lot of research focused on developing methods to calculate the risk of hydrocarbon leaks. However, there have not been any detailed analysis on stability loss since the completion of the RABL program in the late 1980's (Vinnem, 2014b). RNNP (2014) therefore states that is is necessary to increase the attention to marine systems.

Even though major accidents are a great concern for all companies, it is found that most risk analyses treat stability in a superficial way (PSA, 2011a). The recent Macondo disaster and other accidents still reminds us that is is necessary to reduce major accident risk even further. Accident investigations shows that human and organizational factors are often partially of fully responsible for causing the accident. Through the work with this thesis it is found that a limited amount of work is done with the focus of modeling human and organizational factors.

Most quantitative risk analyses (QRA) are concerned with technical factors, and are often unchanged for long periods of time. This means that these analyses are not able to capture small changes in operational conditions, and most of these analyses are based on generic data so that they cannot account for installation specific conditions. From the Macondo disaster we learned that multiple small changes that were not sufficiently monitored, turned out to become a major accident (DHSG, 2011).

It is recognized by the industry that there have not been enough attention to marine systems in the past. A representative from an engineering company said “ballast and bilge is not as hot as process – where the values are created” (RNNP, 2014), and Roy Erling Furre, HSE manager at SAFE said: “It is unacceptable that we repeatedly find that rigs lose stability. Enough is enough, now we have to press supervisory authorities and ensure that the entire rig industry learns from these events.” (Offshore Energy Today, 2013)

All companies operating on the NCS must comply with the Petroleum Safety Authority’s (PSA) regulations. These regulations states clearly that risk analysis must be performed and safety barriers must be implemented to reduce the risk to as low as possible. It is thus a paradox that there does not exist good tools for performing such analyses. This thesis will therefore take on the task to develop and test a model that can handle technical, human and organizational factors in stability operations.

1.2 Problem Definition

The title of this master’s thesis is “Modeling of technical, human and organizational factors and barriers in marine systems failure risk”. The research objective is to develop a bayesian belief network (BBN) for modeling how technical, human and organizational factors affects stability operations on a semi-submersible.

The purpose of this thesis is to start the research into the field of marine systems. Marine systems includes the ballast system, dynamic positioning and anchoring systems. The focus of this thesis would then be the ballast system, and the factors that influences the operation of this system. The limited amount of work that has been done in this field suggests that this thesis must start more or less from scratch.

1.2.1 Objectives

The main objectives of this thesis are:

1. Determine the current research frontier by conducting a literature survey, and exploring similar modeling cases in related fields.

2. Describe the basic concept of stability theory, and systems used in stability operations.

3. Describe and explain the theory and use of bayesian belief networks in order to have a foundation for using this theory to model stability operations.

4. Identify the most common technical, human and organizational factors that influences risk of loosing stability, by investigating incidents and accidents where stability or buoyancy was lost or uncontrolled.

5. Develop a BBN network with the identified RIFs.

6. Evaluate the model, results and applicability of this model.

1.2.2 Limitations

The scope of this thesis is to model the causal side of stability accidents, meaning that only the factors and events leading up to a loss of stability is considered. Further consequences such as loss of life and environmental damage are not considered in this thesis. The modeling is further limited to the scenarios described as marine systems of the DFU8 category in the RNNP report (RNNP, 2014).

The main goal of this thesis is to start the work in the field of marine systems, by suggesting a complete and functioning model based on a BBN. It is, however, recognized that more work is needed to make this model representative to the industry and specific installations. It is thus not within the scope of this thesis to make a perfect, ready to use, model, since unit specific conditions and expert judgment must be taken into consideration.

1.3 Structure of the Report

The structure of this report is as follows:

- Chapter 2 define and explain stability theory for semi-submersibles. An introduction is given to the main systems used for ballasting, and how technical, human and organizational factors are involved in normal and emergency stability operations. Last a discussion of the ballast system as a safety barrier is done.

- Chapter 3 explain the concepts and theory of bayesian belief networks, and the requirements for quantification of the model. Last, some existing models that uses the BBN approach is summarized.

- Chapter 4 introduce the concept of risk influencing factors, and how to identify and quantify them through risk indicators. Two qualitative RIF models are presented to further explain the RIF concept. A method for generating conditional probabilities is presented, and methods to establish generic probabilities are discussed. A thorough discussion on the use of expert judgment is presented.

- Chapter 5 starts out with a discussion of the meaning of the terms technical, human and organizational factors in general, and further evaluates the interaction between these factors. Investigations of incidents and accidents are performed to establish the root causes of these accidents. Based on this, a table of RIFs is identified.

- Chapter 6 presents the complete BBN model. Furthermore, a simplified case is presented to explain the quantification process and CPT generation. Thereafter, a full quantification of the completed BBN is done. A case study, and some example cases of risk analysis using the model is then carried out.
- Chapter 7 evaluates the modeling, quantification and expert judgment process. Furthermore, BBN as a risk analysis tool is evaluated, and compared to other more traditional tools. At last the model is evaluated.
- Chapter 8 concludes this master's thesis, and suggests recommendations for further work.

1.4 Abbreviations

ALARP	As Low As Reasonably Practicable
B	Centre of Buoyancy
BBN	Bayesian Belief Network
BF	Barrier Function
BORA	Barrier and Operational Risk Analysis
CCTV	Closed Circuit TeleVision
COOP	COntrol room OPerator
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
DFU	Defined Hazards and Accident Situations (Definerte Fare- og Ulykkessituasjoner)
DNV	Det Norske Veritas
ETA	Event Tree Analysis
FAR	Fatal Accident Rate
FTA	Fault Tree Analysis
G	Center of Gravity
GM	Metacentric Height
GZ	Rightening Lever
HCL	Hybrid Causal Logic
HEP	Human Error Probability
HMI	Human Machine Interface
HOF	Human and Organizational Factors
HPU	Hydraulic Power Unit
HRA	Human Reliability Assessment
HSE	Health and Safety Executive (UK)
HSMC	High Speed Marine Craft
IRPA	Individual Risk Per Annum

K	Center of the Keel
KG	Center of mass over keel
M	Metacenter
MMS	Mineral Management Service
MO(D)U	Mobile Offshore (Drilling) Unit
MTO	Man, Technoloy and Organization
NCS	Norwegian Continental Shelf
OREDA	Offshore Reliability Data
ORIM	Organizational Risk Influence Model
OTS	Operational Condition Safety
P.I.	Prediction Interval
PLM	Platform Manager
PSA	Petroleum Safety Authority [Norway]
PSF	Performance Shaping Factors
QRA	Quantitative Risk Analysis
RABL	Risk Assessment of Buoyancy Loss
RIA	Risk Influence Analysis
RIF	Risk Influencing Factor
RNNP	Trends in risk level in the petroleum activity (RisikoNivå i Norsk Petroleumsvirksomhet)
SSL	Stability Section Leader
THERP	Technique for Human Error Rate Prediction
T	Draft
TTS	Technical Condition Safety
UKCS	United Kingdom Continental Shelf
UPS	Uninterrupted Power Supply

Chapter 2

Stability and Ballast Systems

All semi-submersible units are subject to a fundamental requirement, to stay afloat and upright. Understanding the concepts of stability control and the limitations of the semi-submersible are therefore important to ensure optimal conditions. There have been examples where stability operations have been neglected or performed by personnel without proper training, that resulted in a total loss of the semi-submersible. This happened in the Ocean Developer accident in 1995 outside Angola, where an inexperienced crew member operated the ballast system (COWI, 2003). The most recent stability incident on the Norwegian Continental Shelf (NCS) is the semi-submersible, Scarabeo 8, that developed a 5.7° list due to wrongful operation of ballast system, by an unqualified control room operator (Eni and Saipem, 2012).

This chapter introduces the basics about stability of a semi-submersible unit and ballast systems used to control the stability. Further, this chapter introduces the ballast control practice that ballast operators must perform, and also discuss the interaction between technical, human and organizational factors in stability control.

2.1 Stability of a Semi-Submersible Unit

The stability of a semi-submersible refers to it's ability to return to the original position after it has been inclined due to an external force (Hancox, 1996). Stability is mainly determined by the center of gravity and the center of buoyancy of the unit in question. The center of gravity is fixed for any inclination angle, assuming that no loads are shifting due to the inclination. The center of buoyancy does on the other hand depend on the inclination angle. The buoyancy force acts through the center of the volume of the immersed part of the vessel (Amdahl et al., 2003).

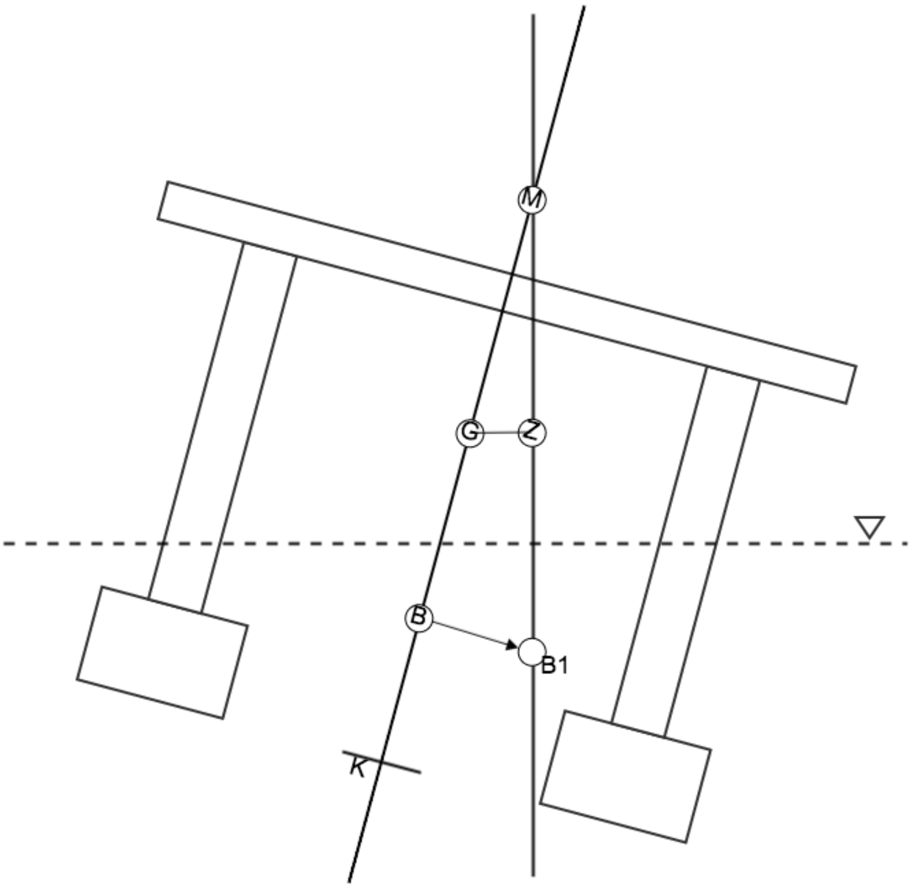


Figure 2.1: Important positions and centers in stability. Source: based on Hancox (1996)

Figure 2.1 illustrates the center of gravity, G, and center of buoyancy, B, as well as the position of the keel, K, and the metacenter, M, of a simple semi-submersible structure. As the unit is tilted, the illustration also shows how the center of buoyancy is shifted towards B1. The metacenter is an imaginary point, that for angles up to about 10-15°, can be regarded as fixed (Amdahl et al., 2003; Pursey, 2006). The metacenter is defined by the point where the vertical line through B1 intersect the center line. The point Z is perpendicular to the vertical line and in the same height of the center of gravity. The distance between G and Z, named GZ, is the distance between the downward gravitational force and the upward buoyancy force. Thus, this distance act as a lever between the two forces, creating a torque that returns the semi-submersible to its original position (Hancox, 1996). For the unit to be in a stable condition, the length GZ must be positive, with a negative GZ the torque will act to capsize the semi-submersible. The GZ is positive as long as the metacenter is above the center of gravity. The distance between the center of gravity and the metacenter is named the metacentric height and denoted GM.

The metacentric height can be interpreted as (Amdahl et al., 2003):

- GM>0: The unit has a positive initial stability, and is defined as a stable unit.
- GM=0: The unit has indifferent stability and in principle it will float steadily at any inclination angle up to about 10°.
- GM<0: The unit is unstable and it will heel or capsize.

All mobile offshore units (MOU) registered in the Norwegian ship registry are required to have a GM value of at least 1 m for all operations, transit and safety conditions, and no less than 0.3 m for any temporary conditions (NMD, 2011). To control the GM value the ballast operating crew must have knowledge about the center of gravity. This is subject to changes on a daily basis, because it depends on the distribution of weights. When the semi-submersible is new built, an inclining test is performed to find the lightship center of gravity of the unit (Hancox, 1996). Lightship refers to a unit without any consumables or cargo onboard, in other words, only the hull, machinery and equipment are included (Amdahl et al., 2003). Any additional weights will influence the position of the center of gravity. The ballast operating crew must therefore monitor all the weights being loaded or unloaded on the semi-submersible, and their position onboard. Weights include fuel, water, sewage and other liquids, usually stored in the lower hull, and materials for operations usually stored on deck (Hancox, 1996).

When weights are moved around on the platform, consumed or replenished, the position of the center of gravity changes. This can result in a trim or heel of the semi-submersible, or in worst cases a negative GM resulting in a capsize. In many cases certain weights have a predefined space onboard, and must be stored in these places. In different load scenarios, the combinations of weights stored around the semi-submersible will have a varying effect on the center of gravity and hence also the GM value. Ballast water is used to counteract any combination that produces an unwanted center of gravity or GM. There are a combination of ballast tanks in various strategic places, that when filled or emptied are able to bring the center of gravity and GM to more ideal values.

2.1.1 Free Surface Effect

A tank or a volume that is completely filled with a liquid can be regarded as a solid mass, with a center of gravity in the volume center of the liquid (Pursey, 2006). However, in a tank which is partially filled, the liquid is free to move and hence the center of gravity changes. The result of this is that the center of gravity of the liquid appears to be at some height above the actual centre of gravity, this is known as a virtual center of gravity (Pursey, 2006). For stability calculations, its effect will be the same as raising a mass equal to the liquid to the height of the virtual center of gravity. This is especially important in accidental situations where uncontrolled water ingress to the semi-submersible causes the virtual center of gravity to increase. The loss of stability in these situations will occur very fast (Sillerud, 2013a).

The free surface effect is also a self propagating effect. As more water changes position, the center of gravity changes more and tilts the platform, which then causes more water to move. This was the case in the Ocean Ranger accident in 1982, where water was allowed to migrate between compartments in the semi-submersible, due to a malfunctioning control unit and human error. The result was that water moved towards one end of the platform, creating a heel such that the pump suction height of 10 m was exceeded (Vinnem, 2014b). The pumps that were meant to discharge water were located in the wrong side of the platform.

2.2 Ballast System and Functions

The ballast system is designed to control the heel trim and draft of the vessel. In a semi-submersible the lower hull sections (the pontoons) and lower sections of the columns are capable of being filled and emptied with sea water in order to submerge the vessel (Hancox, 1996). As discussed above, the changing loading conditions in terms of liquids, materials and consumables demand a constant change monitoring of the trim, and movement of the ballast water. In this chapter the ballast system will be described in terms of it's functions and main components necessary to perform these operations.

2.2.1 Functions of a Ballast System

The main function of the ballast system is, as already mentioned, to control the draft and trim of the semi-submersible. There is one fundamental difference between a ship and a semi-submersible unit, that is the water plane area. Because of the small water plane area, semi-submersibles are more sensitive to weight increases than ships. Tinmannsvik et al. (2011) states that in general a 2% increase in mass of a semi-submersible will result in a 1 m submersion, whereas the same mass increase of a ship results in a submersion of about 20-30 cm. This shows that it is crucial to monitor the weights being loaded or unloaded to the semi-submersible.

In addition to the ballast system there are some other related systems that also influences the stability of the semi-submersible. Systems such as bilge water handling, cooling water for machinery, sprinkler/deluge systems and fuel and fresh water supply from lower hull storage to upper deck ready use tanks will also affect the stability (Hancox, 1996). These systems are usually controlled from the ballast control room. Supervision of these systems therefore also lies with the ballast control operators (Hancox, 1996).

2.2.2 Main Components of a Ballast System

A ballast system can be divided into the following subsystems (Moen, 2012; NMD, 1991):

- Ballast tank configuration
- Pumps, pipes and valves
- Electric power systems
- Hydraulic power system
- Ballast control system

These subsystems will be further described in this chapter.

Ballast Tanks Configuration

Ballast tanks are in general placed in the lower hull and columns, and symmetrical within each hull (Hancox, 1996). The reason for the symmetric distribution is to be able to distribute loads evenly, to avoid shear forces and bending moments to build up, and also to be able to trim the vessel evenly. To avoid the free surface effect, the tanks are often divided into small volumes, rather than large and less complicated designs. The smaller tanks also reduces the risks from a damaged point of view, the subdivision of tanks reduces trimming and heeling levers should the tanks be accidentally flooded (Hancox, 1996).

The tendency to favor more compartmentalization of the hull and smaller tanks increases the complexity of the ballast system. However, the bilge system is also affected by the increased complexity. The function of the bilge system is to pump water out of any compartment or void space if such action is required.

Pipes, Pumps and Valves

All ballast tanks are connected to the pumps by pipe and valve systems. The pump rooms are often located as four small rooms, one in each corner of the twin pontoons. This allows for considerable cross connection between each end of a pontoon, and should the vessel be excessively trimmed the low end of the pump rooms will have a positive suction height (Hancox, 1996). Ocean Ranger lacked this configuration, and the outcome of the accident may have been considerably different with a pump room in each end of the pontoons.

According to "the regulations relating to ballast systems on mobile facilities", by the Norwegian Maritime Directorate, the pumps should be connected to the ballast tanks with pipes and valves such that with any pump out of order, it should still be possible to bring the vessel back to upright condition (NMD, 1991). To perform such actions, valves are used to route the water through the pipe network so that water is pumped into or discharged out of the correct ballast tank. Valves can be remotely controlled from the ballast control system or manually controlled in case the control system does not function. In the case where the valves looses electric power or control power, the valves should fail to a closed position (NMD, 1991).

Electric Power System

The electric power system consists of the main power supply, emergency backup generator and the uninterrupted power supply (UPS) (Moen, 2012). Electric power is mainly used for ballast control system, pumps and hydraulic units. The UPS is intended to supply electricity in the mean time in the occasion where the main power does not supply electricity, until the backup generator is running (Hancox, 1996).

Hydraulic Power Systems

Hydraulic power is used to operate ballast valves. An electrically driven pump unit called a hydraulic power unit (HPU) provides pressure to the control console that provides pressure to each actuator/valve in the system (Hancox, 1996). For emergency situations where the HPU does not function, hand pumps can be connected into the pressure side of the system to manually control valves.

Ballast Control System

The ballast control system is often located on the bridge and/or in the main control room. From here the ballast system is controlled. The system can be run in automatic mode, such that computers operate the system and monitors the stability condition (Hancox, 1996). Even though the system is automatic, the ballast control operators must have close supervision of weight distribution and ballast level, in case manual intervention is needed.

2.3 Ballasting Operations

The draft of a semi-submersible depends on what operation or weather conditions it is exposed to. In transit the draft would be small, to reduce resistance. In an operating condition the draft is larger to increase stability of the unit. The deciding factor for the draft is the center of mass over keel (KG), refer to figure 2.1. Ballasting curves for the semi-submersible must be developed in accordance with the “regulations relating to stability, watertight subdivision and watertight/weathertight closing mechanisms on mobile offshore facilities” (NMD, 2011). The main concern in these regulations is to have a KG less than the maximum allowed value, or a GM higher than the minimum value that is given in the ballasting curves. The ballasting

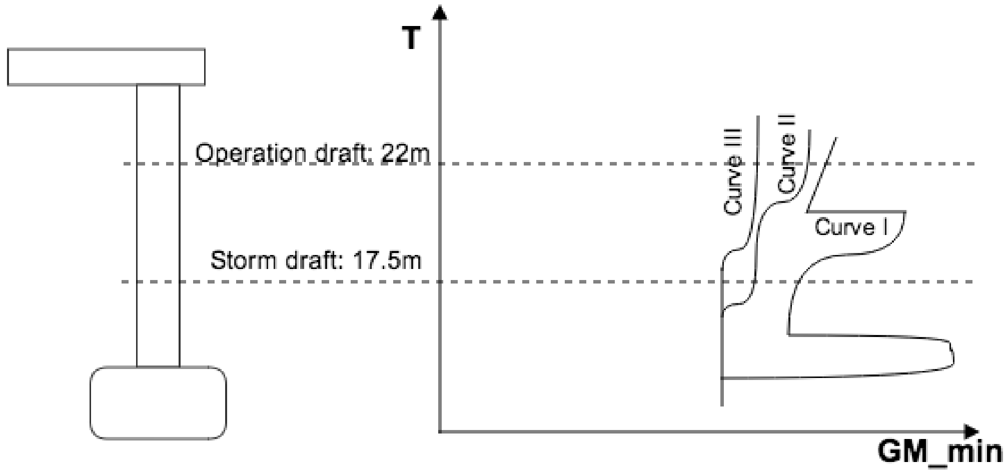


Figure 2.2: Deballasting curve from operation to storm draft. Source: partly based on Sillerud (2013b)

curve shows the draft, T, vs. GM_{min}. Figure 2.2 shows how the GM is related to the draft when deballasting from operation to storm draft.

Figure 2.2 illustrates a conceptual principle of how a stability curve shows the relationship between the minimum allowable GM and the draft for an Aker H-3 semi-submersible. The three curves shows (Sillerud, 2013b):

- Curve 1: Shows the $T - GM_{min}$ relationship for operation and transit conditions at any fixed drafts. It defines the damage stability requirements which are always to be satisfied together with the 70 knots wind intact stability requirements.
- Curve 2: Shows the storm and survival conditions. It shows conditions to satisfy stability and “air-gap” to ensure enough free board to avoid waves slamming on to the deck structure. This curve should be used when winds of more than 70 knots is to be expected.
- Curve 3: Shows temporary conditions that may be expected during ballasting or deballasting operations.

The majority of semi-submersible vessels must be deballasted from operational draft and ballasted to operational draft using a set sequence of tanks to fill and empty (Hancox, 1996). This is done to make sure the trim and structural strain and moments are kept within acceptable limits, and to avoid free surface effects that could affect stability. To trim the semi-submersible the loading conditions must be taken into account. The trim tanks are generally at the ends of the vessel to give maximum trimming effect for the smallest draft/ballast change (Hancox, 1996).

Operation of the ballast system requires a combination of technical, human and organizational factors. These factors will be described in the following sections, and a further more detailed discussion is given in chapter 5.

2.3.1 Technical Factors

As described above the ballast system consists of a range of technical systems and subsystems. The safety of the rig and it's personnel depends on the functioning these systems. There are therefore requirements of redundancy for technical components of the system. HSE (2005b) states that the ballast system needs to be designed and constructed so that, in the event of a failure of any single component, the remainder of the system continues to be capable of effective operation.

The systems available today are intelligent and can make accurate measurements of the weight, center of gravity, deadweight and metacentric height of a semi-submersible (HSE, 2006b). These systems are well designed and reliable, and if used properly these tools can make a real contribution to the overall safety (HSE, 2006b). However, experience have shown that systems can break down or be misused, meaning that the personnel operating these systems cannot rely 100% on the automated equipment. This means that automated systems can be regarded as an aid to personnel, but never as a substitute for crew with training and experience.

A technical system is not worth much if the user interface is bad. In the Scarabeo 8 incident, it was discovered that the human machine interface (HMI) was difficult to understand, resulting in confusion and stress of the operating personnel who could not determine the error, hence the situation was allowed to escalate while searching for the error.

2.3.2 Human Factors

The ballast operating crew are responsible for maintaining and altering the draft and trim, as well as monitoring the stability and ballast control systems (Hancox, 1996). In addition the ballast crew may have other duties such as monitoring: fire water system, watertight integrity, fuel and bulk liquid transfer, mooring and station keeping, and weather conditions (Hancox, 1996).

In ensuring operation within the accepted limits of stability it is necessary to have thorough knowledge of stability characteristics of the semi-submersible. The operator should also have good knowledge of hour by hour activities in order to anticipate changes in stability (Hancox, 1996). In order to work as a ballast operator on a semi-submersible unit a formal qualification is required. The required level of education is a course in rig stability and ballasting according to the syllabus given by IMO (2000). In addition, DNV (2011) states that personnel should be appropriately qualified, trained and competent for the work they are expected to undertake. This must be interpreted as such that formal education is not enough, personnel also need practical experience. Quite a few stability accidents and incidents have happened due to the lack of experience of the operator, this is further discussed in chapter 5.

2.3.3 Organizational Factors

The foundation necessary for the functioning of technical and human factors, is a good organization. In chapter 5 it will be explained how the organization is linked to technical and human factors. The organization should provide all necessary support material, personnel and equipment. The organization of the work is usually performed in two twelve hour shifts on all offshore units. In many semi-submersible units, the ballast control room is also the control center, so that several watchstanders may be present with separate interconnected duties (Hancox, 1996). According to the guidelines of PSA's activities regulations, section 31, there shall always be at least two persons to handle the monitoring and control functions in the central control room on permanently manned facilities (PSA, 2014b). This includes the ballast control.

The organization is responsible for providing vessel documentation, operating manuals and contingency plans, and keep the documents up to date. Accoring to DNV (2011) vessels should have on board a complete inventory of manufacturers' technical, maintenance and operating documentation for marine systems and equipment. In later chapters of this thesis it is illustrated that documentation, or rather the lack of documentation, is a major factor in a number of accidents and incidents. It will later be shown that the problem associated with documentation is often that they are non-existing, difficult to understand, does not contain necessary information or that it is not used properly.

The organization is also responsible for ensuring that the personnel have the required qualifications, training and experience to conduct the work in a safe manner, and to ensure their own and others safety onboard the platform. This has also been the cause of major accidents and serious incidents. The Scarabeo 8 incident on the NCS in 2012, occurred due to lack of experience of the ballast operator. In this case the organization failed to comply with internal guidelines and external regulations when employing unexperienced personnel. This shows that the organizational factors may have an important impact on the safety, and later is will be shown that even if the organization complies to regulations and guidelines, accidents and incidents may still happen. The Ocean Ranger disaster highlights the importance of having trained and experienced personnel and clear operating documentation. This chapter is summarized well by quoting Bradley and MacFarlane (1995) "good operators will manage their rigs well, regardless of the regulatory regime, whereas bad operators may continue to operate unsafely".

2.4 Stability Operations in Emergency Situations

A response from the ballast control operator is needed in situations where unexpected hazardous events happen. Emergency situations can include, but are not limited to, collision damage, heavy weather, structural damage, main structure failure, failure of the ballast control system which causes uncontrolled flooding, or ballast transfer resulting in excessive list or trim angles (Hancox, 1996). All these situations requires different response actions from the crew, who must first correctly diagnose the problem. The crew must therefore be well trained to be able to handle an emergency situation. Regular emergency drills and exercises is a way of stimulating and improving the skills of the personnel.

Loss of stability generally occurs because flooding takes place in compartments which were previously empty or and/or watertight (Hancox, 1996). This is important to bear in mind in emergency situations. It is obvious that a collision with a damage below the waterline will cause a flooding, however flooding is also an important factor in case of a fire. Firewater that is being used to take out the fire can cause problems with stability of the semi-submersible. Incidents on the NCS includes Visund, Snorre B and West Vanguard that gained a heel angle after firewater was released (refer to appendix A for more information in these incidents), and firewater is believed to have contributed to the capsize and sinking of the Deepwater Horizon (DHSG, 2011) and the P-36 accident outside the Brazilian coast (ANP/DPC, 2001). A well functioning bilge system and adequate means of draining all compartments and watertight sections is an important tool in handling emergencies (HSE, 2005b). In the case where uncontrolled flooding occurs it is also important to have in mind the effect of a free surface and it's contribution to the metacentric height.

In cases where the bilge system is not enough for controlling undesired trim or list, the practice of counter ballasting may be applied. Counter ballasting is the filling and emptying of tanks (and sometimes voids) as a means of controlling the trim list and sinkage caused by the flooding of space within the vessel (Hancox, 1996). The downside of counter ballasting is the reduction in freeboard, causing down-flooding points to be closer to the water line, system (pumping) performance degradation or failure and reduction in water plane area thus also reduction in GM and GZ moment (Hancox, 1996). Certain rigs pass through a low metacentric height condition when going from operational to transit draft, or vice versa, and such cases might lead to a negative metacentric height and a large heel angle (Standing, 2003).

There have been incidents and accidents where the situation have been made worse due to wrong treatment of the situation and incorrect initial actions as a result of panic, poor training, insufficient knowledge and ineffective command and control (Hancox, 1996). A three step procedure of a general approach to damage control has been suggested by Hancox (1996):

1. Isolation
2. Investigation
3. Remedial action

Step 1 to isolate the damage, means to confine a flooding to the damaged parts of the semi-submersible, by closing off vents, hatches, doors and pipelines. A positive confirmation that the isolation is effective should be obtained before step 2 is started. The investigation part (step 2) consists of assessing the consequences with respect to stability, survivability of the vessel, further progressive flooding, physical and mental capabilities of the crew, the remaining capability of of pumps, power, counter flooding etc. and weakening of the boundaries of the damaged area. (Hancox, 1996)

Remedial action must be based on the results from step 1 and 2. Taking action without knowing the situation or capabilities of the semi-submersible can be disastrous. The Ocean Ranger accident is a perfect example, where the crew tried to correct the problem, without knowing the situation or assessing the capabilities of the system. Hancox (1996) outlines the most important aims of remedial action:

1. Prevent further loss of GM
2. Stabilize, then rectify excessive trim and list
3. Prevent progressive flooding
4. Preserve the viability of lifesaving systems so far as possible, to allow the greater number of crew members to get off the vessel if foundering is imminent

2.5 Ballast System as a Safety Barrier

The concept of safety barriers is important in risk analysis. PSA (2013a) defines a safety barrier as a technical, operational or organizational element which are intended individually or collectively to reduce possibility for a specific error, hazard or accident to occur, or which limits harm or disadvantages. According to Sklet (2006) safety barriers should therefore be physical and/or non-physical means planned to prevent, control or mitigate undesired events or accidents. The ballast system could in this context be regarded as a safety barrier against unacceptable inclination and draft (Moen, 2012).

Moen (2012) points out that the ballast system is a secondary barrier for stability of the semi-submersible. The primary barrier lies in the design of the vessel, and the stability obtained by the hull shape and position of the center of gravity. Due to the many applications of a ballast system, it could be regarded as a barrier system. A barrier system is a system that has been designed and implemented to perform one or more barrier functions (Sklet, 2006). A barrier function is a function planned to prevent, control or mitigate undesired events or accidents (Sklet, 2006).

The barrier functions (BF) proposed for a ballast system in this thesis is listed below, and a more detailed description can be found in chapter 5.4. It is believed that these functions will work to prevent, control and mitigate unacceptable inclination and draft. These barrier functions are defined based on stability accidents and incidents that have occurred. These have been grouped into a broad category of where the failure occurred. It was found that in most cases the accident or incident occurred due to a failure of performing normal operations, a wrongful handling of an abnormal situation, or a failure of a technical system. Therefore the barrier functions defined in this thesis are as follows (further discussion in chapter 5):

- **BF 1:** Conducting normal operation
- **BF 2:** Response to abnormal situation
- **BF 3:** Condition of technical systems

Barrier elements are technical, operational or organizational measures or solutions which play a part in realizing a barrier function (PSA, 2013a). HSE (2005b) suggests a list of barrier elements that should be incorporated into a ballast system:

- Valves that enable transfer of ballast should close automatically on loss of control or actuating power.
- Communication between any two tanks or between any tank and the sea should be via at least two independently remote controlled valves.
- Ballast manifolds should be arranged such that water cannot be transferred from one end or side of the unit to the other without the initiation of a special operational procedure.
- The system should be arranged in such a way that in the event of a burst pipe in any part of the system connected to the sea, the flooding can be brought quickly under control.
- Upon reactivation of control power, those valves intended to close upon loss of control power should remain closed until the ballast control operator assumes control of the reactivated system.

Even when these barrier elements were implemented, accident still happen. In chapter 5, previous incidents and accidents are described, and it can be shown that one or more of the above mentioned barrier elements and factors were breached in most of the cases studied. The big question is then: why did accidents happen even if barriers were implemented to prevent them from happening? The hypothesis of this thesis is that the answer lies in a combination of factors, more precisely the combination of technical, human and organizational factors. It is therefore obvious that a more thorough study of the interaction between these factors, and how these contributes to risk is important. In the following chapters a risk analysis method will be introduced. This method is known as bayesian belief network (BBN). BBN is particularly well suited for modeling non-deterministic causal relationships such as human and organizational factors (Røed et al., 2009).

Chapter 3

Bayesian Belief Networks

This chapter presents the basic concepts and methodology for using Bayesian Belief Network (BBN) in risk analysis. A BBN is a graphic method for reasoning under uncertainty (Korb and Nicholsen, 2010). It is particularly useful for modeling non-deterministic causal relationships, such as human and organizational factors (Røed et al., 2009). The following chapter presents the reasoning behind BBN and introduces how to set up a model for risk analysis.

3.1 Bayesian Belief Networks

The term Bayesian Network was coined by Judea Pearl in 1985 (Pearl, 1985). The initial research on BBNs was for the purpose of artificial intelligence, however in recent years the method has also been applied to other research areas. For risk analysis BBNs have been used in the aviation and nuclear industry as well as in the offshore industry for example in the “Risk Modeling – Integration of Organizational, Human and Technical Factors (Risk_OMT)" project (Vinnem et al., 2012).

A Bayesian Belief Network can be considered as a graphical representation of dependence relations and conditional independence between factors within a domain (Wang, 2007). A BBN consists of nodes and directed arcs that connects pairs of nodes, representing direct dependancies between variables (Korb and Nicholsen, 2010). A BBN is, however, constrained to only allow non-cyclic modeling, meaning that it should not be possible to start out in one node and follow the arcs, and then end in the same node as the starting point. This non-cyclic modeling is known as a Directed Acyclic Graph (DAG) (Kjærulff and Madsen, 2013).

A very simple BBN is illustrated in figure 3.1. K, L and M are nodes, and the arrows represent the directed arcs. In the literature the nodes are named parent and child. For the BBN in figure 3.1 K and L are parents to M, and M is the child of K and L.

In order to establish a BBN, the relevant nodes must be identified. This can be done by answering the following two questions: what are the nodes to represent, and what values can they

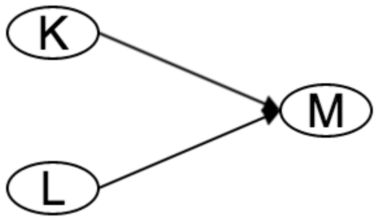


Figure 3.1: A simple BBN

take, or what state can they be in? (Korb and Nicholsen, 2010). The nodes (also known as the variables) can take on any discrete or continuous values. The values can be for example yes/no, true/false, a number, or a color of a car. The important thing about the values is that they are mutually exclusive, which means that the node can only take on one value at the time. For example when throwing a die, the value on the die must be either 1, 2, 3, 4, 5 or 6.

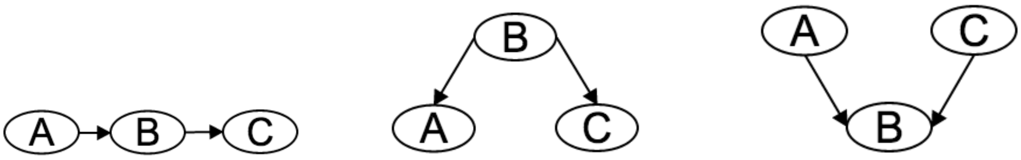
The structure of the network must resemble the real world. One node that affect the other node must be connected by an arc, or an arrow, with the direction shown. It is important that the arcs does not lead to conditional independence that cannot be true for the system that is studied. More on this in section 3.1.4.

3.1.1 Causality and Causal Networks

The concept of causality refers to a cause and its effects. This is an important concept in BBN analysis, and in causal networks. A causal network is a DAG where the arc represents the certainty of the effect, given the cause. (Jensen and Nielsen, 2007). It is distinguished between a deterministic and probabilistic causality. Deterministic causality means "if A happens, then B must happen", whereas a probabilistic causality means "if A happen, then B may happen". Jensen and Nielsen (2007) describes this using an example of a car that cannot start. If the car's fuel tank is empty, then we can say that the car is 100% certain not to start. This is a deterministic causality. Probabilistic causality is described by looking at the spark plugs, if these are dirty, this may be a cause for why the car cannot start. A probabilistic causality can be interpreted as a probability between 0 and 1, that a cause will lead to an effect on the variable it is connected to (Pettersen, 2012). Following this intuition, we can say that deterministic causality is a special case of probabilistic causality where the probability of the effect is 1, and it is therefore the probabilistic understanding of the concept of causality that is used in literature (Pettersen, 2012).

3.1.2 Node Structure

In modeling a BBN the Markov property is a required assumption. This states that there should not be any direct dependencies in the system being modeled which is not explicitly shown via arcs (Korb and Nicholsen, 2010). This implies that BBNs that satisfy the Markov property express conditional independence. There are three possible ways for nodes to be connected in a BBN. This is illustrated in figure 3.2, where (a), (b) and (c) is known respectively as serial connection, diverging connection and converging connection.



(a) – Serial connection (b) – Diverging connection (c) – Converging connection

Figure 3.2: Possible node connections in a BBN. Source: based on Korb and Nicholsen (2010)

A serial connection is a causal chain, where A causes B which in turn causes C. This gives rise to conditional independence such that (Korb and Nicholsen, 2010):

$$\mathrm{P}(C|A \cap B) = \mathrm{P}(C|B) \tag{3.1}$$

This basically means that whether or not we know A, does not affect the probability of C, given that B has occurred. To exemplify this conditional independence think of car. If the fuel tank is empty (A), the engine cannot run (B), causing the car to not move (C). If we already know that the engine cannot run (B) then it will not make any difference to the probability that the car cannot move (C) by knowing that the fuel tank is empty (A).

The diverging connection in figure 3.2(b), is a common cause connection. Both (A) and (C) have a common cause (B). Common cause give rise to the same conditional independence structure as for chains as explained by equation 3.1 (Korb and Nicholsen, 2010).

The converging connection in figure 3.2 is a common effect connection. The effect (B) has two causes (A) and (C). This produces the opposite conditional independence structure as that for serial and diverging connection (Korb and Nicholsen, 2010). They are conditionally dependent, given information about the effect (B). If the state of (B) is unknown, then the causes (A) and (C) independent, meaning that knowledge about one cause (A) does not give any information about the other possible cause (C).

3.1.3 Explaining Away and Evidence

In a converging connection, a special kind reasoning can be used to increase the certainty of one cause, given that we have evidence of the other cause and information about the consequences. Figure 3.3 illustrates a converging connection with evidence about node (F). A node is said to be instantiated if evidence with a single value has been observed with probability one (Krieg, 2001).

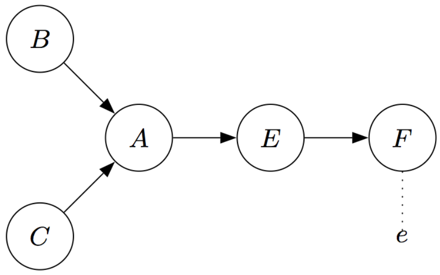


Figure 3.3: Dependent connection. Source: Jensen and Nielsen (2007)

The explaining away effect is a special case where knowledge of one cause may explain something about another cause. This is best explained by an example of a car, and this is based on Jensen and Nielsen (2007). Suppose there are only two causes for why a car engine fail to start, no fuel (B) and dirty spark plugs (C). If we know that the engine cannot start, we cannot say which node that causes this problem, and the nodes are independent. However, if we now get evidence that the fuel tank is empty, the probability of the spark plugs being dirty will decrease. The opposite is also true, if we have evidence of dirty spark plugs, the probability of the fuel tank to be empty will decrease. This is known as the explaining away effect, and we say that causes has been explained away.

Evidence can be transmitted through a converging connection only if either the variable (node) in the connection or one of its descendants have received evidence (Jensen and Nielsen, 2007). This can be explained through figure 3.3 where (F) has received hard evidence, or in other words, (F) is instantiated. Knowing the state of (F) explains something about the state of (E), which in turn can say something about (A). In this case we have soft evidence for the sate of (A).

3.1.4 D-separation

D-separation refers to the independence between nodes. Jensen and Nielsen (2007) defines d-separation as: *Two distinct variables A and B in a causal network is d-separated if for all paths between A and B, there is an intermediate variable V (distinct from A and B) such that either:*

- *the connection is serial or diverging and V is instantiated, or*
- *the connection is converging, and neither V or any of V's descendants have received evidence.*

A d-connection is the opposite case where A and B are not d-separated.

The assumption of conditional independence in BBN says that, in serial and diverging connections, knowing the value of (B), blocks information of (C) being relevant to (A), and vice versa (Korb and Nicholsen, 2010). The opposite is true for converging connections, where information about (B) would activate a relationship between (A) and (C). (Refer to figure 3.2 for graphical interpretation of the nodes).

This concept also applies to larger set of nodes, not only to pairs. Given that the Markov property holds, it is possible to determine whether a set of nodes **A** is independent of another set **B**, given a set of evidence nodes **E** (Korb and Nicholsen, 2010). If the sets **A** and **B** are independent, they are said to be d-separated.

To determine whether nodes (A) and (B) are d-separated or not, the ancestral graph must be constructed. The ancestral graph to (A), (B) and **E** consists of (A), (B), **E** and all other nodes that have direct connection to (A), (B) and **E** (Pettersen, 2012). Figure 3.4 illustrates a causal network, with the corresponding ancestral and moral graph.

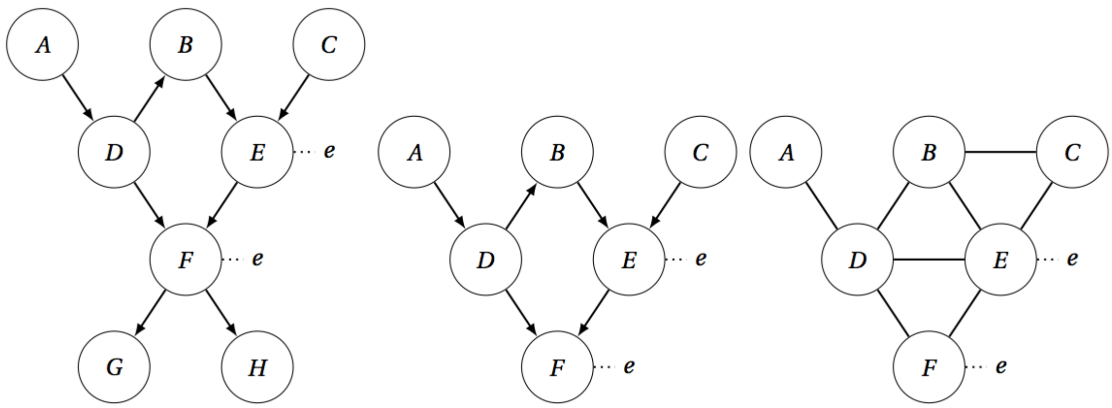


Figure 3.4: Causal network, Ancestral graph and Moral graph. Source: Pettersen (2012)

The moral graph is developed from the ancestral graph, by removing the directions of the arcs, and including a non-directed connection between nodes that have a common child (Jensen and Nielsen, 2007). (A) and (B) are d-separated given **E**, if all paths connecting (A) and (B) intersects **E**.

3.2 Chain Rule for BBN

A causal network can be seen upon as a qualitative version of a BBN. A BBN is a causal network where each node has a finite set of mutually exclusive states, and with an attached conditional probability table to each node (A) with parents $(B_1), \ldots, (B_n)$, such that $\mathrm{P}(A|B_1, \ldots, B_n)$ is determined (Jensen and Nielsen, 2007).

When establishing a BBN it is important to verify that the d-separation principle holds, and that the model does not include conditional independences that do not hold for the real world (Jensen and Nielsen, 2007). This means that for nodes (A) and (B), with a set of evidence **E**, the following must be true $\mathrm{P}(A|\mathbf{E}) = \mathrm{P}(A|B, \mathbf{E})$.

Now let $\mathscr{U} = \{A_1, \ldots, A_n\}$ be the variables (nodes) in the BBN. To represent the probability distribution reflecting the properties specified in the BBN, we need to determine P($\mathscr{U}$) (Jensen and Nielsen, 2007). Two conditions must be satisfied to determine P($\mathscr{U}$): *(i): the conditional probabilities for a variable given its parents in P($\mathscr{U}$) must be as specified in the BBN and (ii) if the variables (A) and (B) are d-separated in the BBN given **E**, then (A) and (B) are independent given **E** in P($\mathscr{U}$).* (Jensen and Nielsen, 2007).

The independence condition *(ii)* above means that the chain rule can be used to determine P($\mathscr{U}$). In a case with one variable (X), then $P(X) = P(\mathscr{U})$ is unique. However, this also holds for a set of variables, proved by the chain rule. Equation 3.2 refers to the general case, and equation 3.3 is adapted to the use in BBN analysis (Jensen and Nielsen, 2007):

$$\mathrm{P}(\mathscr{U}) = P(A_n|A_1,\ldots,A_{n-1})P(A_{n-1}|A_n,\ldots,A_{n-2})\ldots P(A_2|A_1)P(A_1) \tag{3.2}$$

$$\mathrm{P}(\mathscr{U}) = \prod_{i=1}^{n} P(A_i|parent(A_i)) \tag{3.3}$$

One problem with calculating the probability distribution for a BBN is that P($\mathscr{U}$) grows exponentially with the number of variables, and $\mathscr{U}$ need not be very large for before it becomes too large to handle (Jensen and Nielsen, 2007).

3.2.1 Conditional and Joint Probability Tables

After identifying the DAG, a Conditional Probability Table (CPT) must be established for each node in the network. Pearl (1988) states that the advantage of using CPTs are due to the fact that only variables with direct influence are considered, even though the workload could be too great to handle. Mathematically the CPTs are a compact description of a common probability table for all the variables in $\mathscr{U}$ (Pettersen, 2012).

Assume that a variable (A) has the following set of states (a_1, a_2), and another variable (B) has these states (b_1, b_2). This could be presented in a CPT as shown in table 3.1.

	b_1	b_2
a_1	$P(a_1\|b_1)$	$P(a_1\|b_2)$
a_2	$P(a_2\|b_1)$	$P(a_2\|b_2)$

Table 3.1: Simple example of a CPT

The probability of seeing joint outcomes for different experiments can be expressed by the joint probability for two or more variables: For each configuration (a_i, b_j) of the variables (A) and (B), P(A,B) specifies the probability of seeing both $A = a_i$ and $B = b_j$ (Jensen and Nielsen, 2007). This means that P(A,B) is a table of size $n \times m$, similar to a CPT. The fundamental rule for variables can be used to convert conditional probabilities to joint probabilities:

P(A)	
a_1	0.4
a_2	0.6

Table 3.2: Probability for states of (A)

P(C)	
c_1	0.2
c_2	0.8

Table 3.3: Probability for states of (C)

$$P(a_i|b_j)P(b_j) = P(a_i, b_j) \tag{3.4}$$

The states of both (A) and (B) are mutually exclusive and exhaustive[1], which means that the combinations of their states are also mutually exclusive and exhaustive, hence equation 3.5 must be satisfied (Jensen and Nielsen, 2007):

$$P(A, B) = \sum_{i=1}^{n} \sum_{j=1}^{m} P(A = a_i, B = b_j) = 1 \tag{3.5}$$

To explain the relationship between CPT and joint probabilities, a simple example is given. Consider the diverging connection in figure 3.5. Assume that the variables (A) and (C) have only two states. The probability tables for these two states are shown in table 3.2 and 3.3.

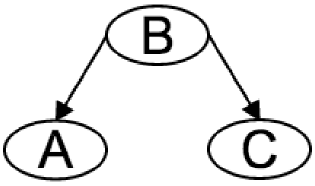


Figure 3.5: Diverging connection. Source: based on Jensen and Nielsen (2007)

Table 3.2 and 3.3 shows the probability of the variables (A) and (C) of being in state a_1, a_2 and c_1, c_2 respectively. The probability of (B) given (A) and (C) must now be worked out. This can be based on statistics or expert knowledge of the system. This is the part of the BBN analysis that is most time consuming. A method for simplifying the CPT generation will be explained later. Table 3.4 shows the conditional probability of (B) given the state of (A) and (C).

$P(B\|A,C)$	c_1		c_2	
	a_1	a_2	a_1	a_2
b_1	0.6	0.3	0.2	0.1
b_2	0.4	0.7	0.8	0.9

Table 3.4: Conditional probability table, $P(B|A,C)$

[1]Mutually exclusive means that the outcome can only take one value that is not common to any other, and exhaustive means that the outcome must be a part of the universe, $\mathscr{S}$. In mathematical terms: Mutually exclusive: $P(A \cap B) = 0$, Exhaustive: $P(A \cup B) = \mathscr{S}$

To make use of the conditional probabilities it must be converted to joint probability, by using the fundamental rule for variables given in equation 3.4. This expression can be adopted to account for three variables, this is shown in equation 3.6.

$$P(A, B, C) = P(B|A, C) \cdot P(A) \cdot P(C) \tag{3.6}$$

The joint probabilities are given in table 3.5. From this table it is possible to determine the probability of variable (B) being in state b_1, b_2, by taking the sum over all possible values of b_1, b_2 respectively.

$P(A, B, C)$	c_1		c_2		$P(B)$
	a_1	a_2	a_1	a_2	
b_1	0.048	0.036	0.064	0.048	0.196
b_2	0.032	0.084	0.256	0.432	0.804

Table 3.5: Joint probability table, $P(A, B, C)$

3.3 Applications of BBN

BBN has been used in different projects to make quantitative risk analyses. A short introduction to some of these projects will be given in this section. To make use of BBN to risk analysis, an important term must be defined, risk influencing factors (RIF). A RIF is defined as an event or condition in a system or activity that influence the risk level of the system/activity (Øien and Sklet, 2001). Or in other words RIFs could be treated as conditions that have a direct or indirect effect on the occurrence and consequences of an undesired event. RIFs will be further treated in chapter 4. The nodes in a BBN are to be considered as RIFs. In this way RIFs can be used to illustrate conditional probabilities and hence get a more comprehensive risk analysis.

3.3.1 Hybrid Causal Logic

The hybrid causal logic (HCL) has been developed to combine traditional fault/event trees with BBN (Røed et al., 2009). This method is especially good for combining human, organizational and technical factors (Wang, 2007). In HCL the nodes in the BBN can be used as basic events in fault trees, and be connected directly to an event tree. The strengths of combining BBN and fault/event trees is to utilize the ability of BBN to analyze non-deterministic relationships, the ability of fault trees to model deterministic relationships and using event trees to model sequences of events (Pettersen, 2012).

However, using BBN to calculate probabilities for basic events in fault trees and event trees creates a dependency between the fault and the event tree (Røed et al., 2009). Algorithms are developed to account for the dependency (Wang, 2007). Figure 3.6 illustrates how the BBN is related to a fault tree and an event tree.

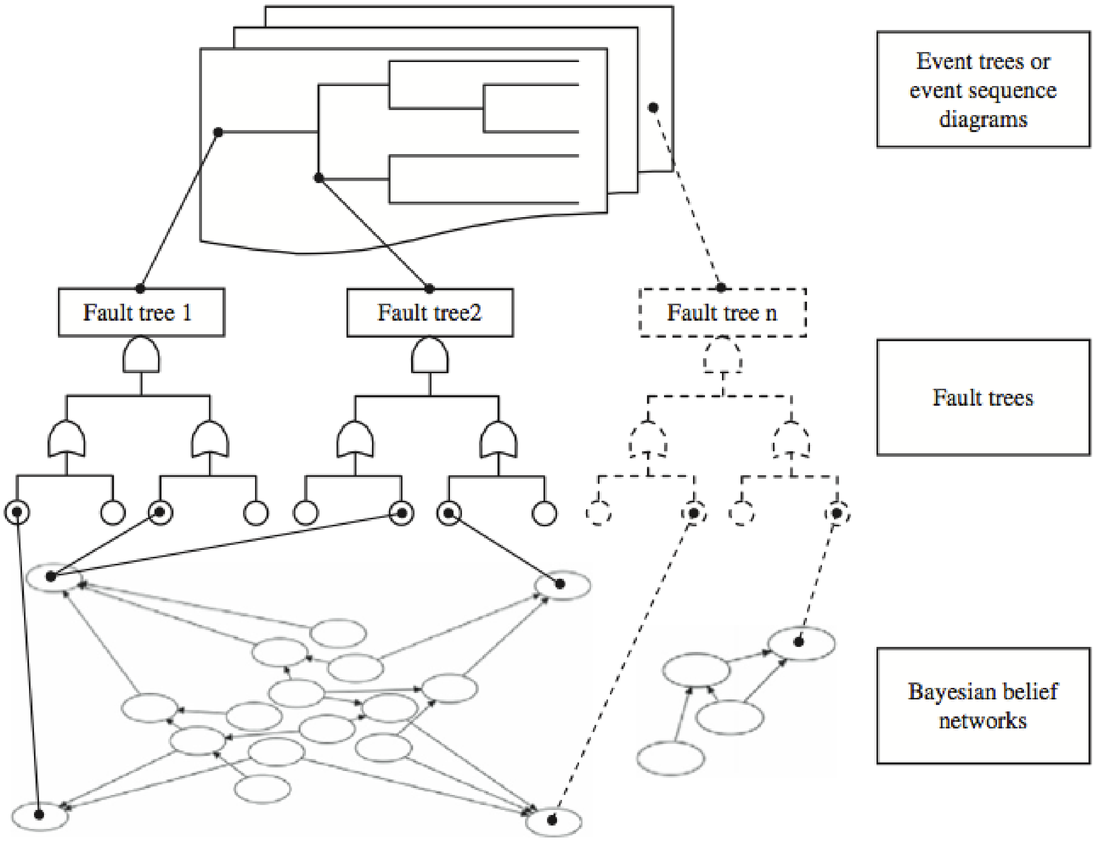


Figure 3.6: The HCL framework. Source: Røed et al. (2009)

Røed et al. (2009) discuss the challenges related to assigning the conditional probability tables. Assigning all conditional probabilities directly will be unmanageable, and the relevant historic data is often limited or too specific and conditioned on other events (Røed et al., 2009). A method for semi-mechanizing the assignment of probabilities is therefore proposed. This method builds on the assumption that a probability assigned for a node being in a state that differs significantly from its parents' state should be smaller compared to a state equal to its parents' states (Røed et al., 2009). The method is presented in chapter 4.5.

3.3.2 Risk_OMT

The Risk_OMT method aims to integrate organizational, human and technical factors. This model build on the previous research projects BORA and OTS (Gran et al., 2012). BORA is short for barrier and operational risk analysis and this was a research project in quantitative risk analysis for hydrocarbon release in the operational phase when taking technical, human and organizational factors into account. For more information see for example Vinnem et al. (2009); Haugen et al. (2007). The OTS refers to the operational condition safety project, that presents a more thorough view on human and organizational factors. See for example Sklet et al. (2010).

The goal of the Risk_OMT project was to improve the modeling of RIFs to operational barriers, compared to the BORA method (Vinnem et al., 2012). Risk_OMT builds on the HCL framework and utilizes the combination of BBN with fault and event trees. The RIFs are organized in two levels, where the top level is assumed to have a direct influence on the basic events of the fault trees and the bottom level influences the RIFs at the top level (Vinnem et al., 2012).

Risk_OMT builds on a set of generic scenarios that were identified through the BORA project. These are initial events that if all barrier systems fail, a hydrocarbon leak occurs. In the process the most common barriers used on the NCS were identified (Vinnem et al., 2009). A method for scoring each RIF is also adopted from BORA. This method allows the RIFs to be measurable by comparing their state to the industry average. The hypothesis of the Risk_OMT is that risk control can be achieved through control of the changes in the RIFs (Vinnem et al., 2012). The following conditions must be satisfied for this hypothesis to be valid (Vinnem et al., 2012):

1. All relevant RIFs are identified
2. The RIFs are measurable
3. The relationship between the RIFs and the risk is known.

It is difficult to make sure that all relevant RIFs are identified. To overcome this challenge, it is necessary to have good knowledge of the system in question. The rating of the RIFs to make them measurable also requires a good knowledge of the industry in order to compare the RIFs to the industry standard.

3.3.3 Organizational Risk Influence Model – ORIM

The organizational risk influence model (ORIM) was a research project with the aim of developing a method for updating the information about the risk level of an offshore installation, due to changes in the organizational factors during operation (Øien and Sklet, 2001).

The principal results from the project is the development of an organizational factor framework from which organizational risk indicators[2] can be established and used for risk control during operation of offshore installations (Øien, 2001a). The framework includes (Øien, 2001a):

1. An organizational model
2. Organizational risk indicators
3. A quantification methodology.

[2] The concept of indicators is discussed in chapter 4.2

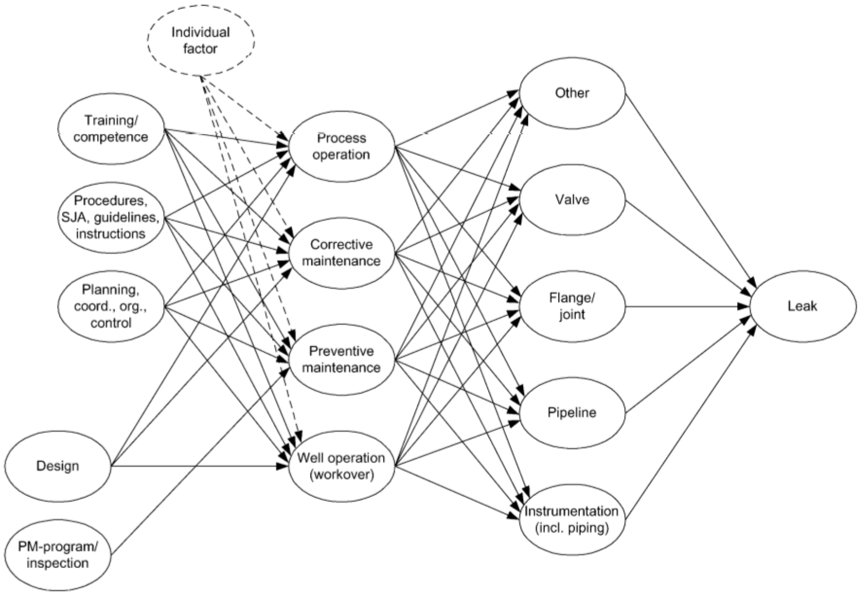


Figure 3.7: ORIM causal network model for leak freqency. Source: Øien (2001a)

Figure 3.7 shows a causal network of an organizational model for determining leak frequencies. This was developed to show the relationship between the most important organizational factors and the leak frequency (Øien and Sklet, 2001). The model is divided into three levels in addition to to the leak event. Level 1 represents the source of the leak (equipment/component), level 2 represents the front line personnel that can cause or prevent the leak and level 3 consists of the organizational factors that are implemented to ensure that the personnel does their work in a way that prevents leaks from occurring (Øien and Sklet, 2001).

The qualitative organizational model (figure 3.7) is an important result by itself. Even if a quantitative analysis is performed or not, this model can still be used as a tool for identifying the root causes of a leak (Øien and Sklet, 2001).

For the organizational factors in figure 3.7, a set of risk indicators are identified. The condition of the factors are measured continuously (every three months), through the use of the indicators (Øien and Sklet, 2001). Indicators can for example include “ratio of employees with formal training” and “average number of years of experience” for the training/competence node in figure 3.7.

To quantify the leak frequency, a simplified BBN has been developed. This is illustrated in figure 3.8. The goal of the quantitative analysis is to obtain an estimate of the leak frequency, λ. In the model $OF1, \ldots, OF5$ represents the organizational factors, the personnel and equipment nodes are not included in this analysis as the goal of this analysis was to analyze the effect of the organizational factors on the leak frequency (Øien, 2001a).

Based on indicator measurements the condition of the organizational factors are rated on the scale 1 to 5, where 1 represents very bad and 5 represents very good conditions. Each organizational factor can be rated based on one or more indicators, and it is assumed that this represent

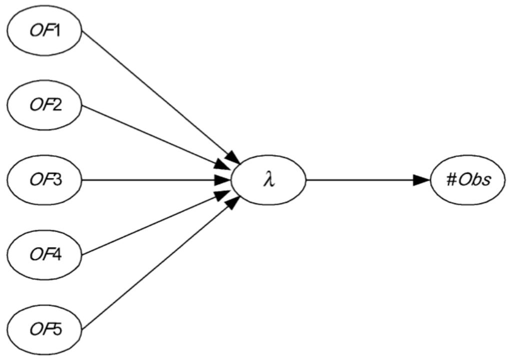


Figure 3.8: DAG for quantitative model. Source: Øien (2001a)

the condition of the organizational factor such that the node is instantiated and λ can be determined Øien (2001a). Based on the leak frequency, λ, the number of observed leaks #Obs can be estimated.

Chapter 4

Risk Influencing Factors

This chapter will define and discuss the term Risk Influencing Factor (RIF). It is important to understand the concept of RIFs in order to accurately model a BBN. In BBN analysis RIFs are modeled in a causal network. A RIF can either influence an event directly, or indirectly through other RIFs. The BBN in figure 4.1 illustrates how the RIF influences the probability of an event. The RIFs are divided into different factors, in this example the factors are organizational, human and technical, but it can also include other groups of factors.

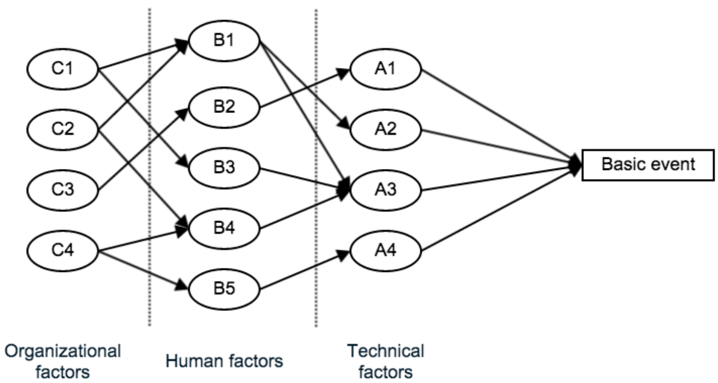


Figure 4.1: BBN with technical, human and organizational factors. Source: based on Rausand (2011)

The rationale behind the modeling of RIFs in a BBN, such as the one in figure 4.1, can be explained by a simple example. Let us assume that an engine is malfunctioning, this is obviously a technical factor that is not working properly. However, the fault may be due to bad maintenance, which is a human factor, and the maintenance work can again be influenced by organizational factors such as time pressure or lack of maintenance procedures.

The example above shows that the risk of a malfunctioning engine is not only a result of technical factors, but a multi factor problem. That is why it is necessary to understand the concept of RIFs, and how RIFs influence the probability of the basic event. This chapter discusses RIFs, indicators for making RIFs measurable, and how to identify and select RIFs. Further, qualitative and quantitative modeling of RIFs are also discussed and explained in detail.

4.1 The RIF Concept

There are multiple definitions of the RIF term. Øien (2001b) defines RIF as an aspect of a system or an activity that affects the risk level of this system/activity, whereas Rausand (2011) defines it as a relatively stable condition that influences risk. Hokstad et al. (2001) indicates that RIFs are not events and that RIFs does not fluctuate on a day-by-day basis, but that they represents the average level of some conditions, which may be influenced/improved by specific actions.

RIFs are also known simply as factors. Factors can be divided into groups such as technical, human, organizational, environmental, regulation and customer related. The main focus of this thesis is the three first mentioned factors. To assess the risk level of a system or an activity all RIFs that are relevant must be identified as well as the structure of the RIFs.

A RIF can either influence an event directly or indirectly through another RIF. Tranberg (2013) define an event as a significant deviation from a normal operation. Events can include for example equipment fault, latent errors in a system or bad decisions. A major accident is the result of a chain of events that develops from a safe state, and several different event chains could lead to the same type of major accident (Tranberg, 2013).

RIFs are treated in different ways in projects. In the before mentioned BORA project, the RIFs are more specific than in the high speed marine craft (HSMC) project that uses the RIA methodology[1]. In the HSMC project one RIF is defined as “competence, training and motivation”. Whereas table 4.1 lists the set of RIFs used in BORA. These RIFs describes the factors that may influence the basic events of fault trees of hydrocarbon leaks. We can see that the BORA RIFs are more specific, and the reason for this is discussed more thoroughly in chapter 4.3.

[1] Risk Influence Analysis (RIA) is explained in chapter 4.4.1

RIF group	RIF
Personal characteristics	Competence Working load/stress Fatigue Work environment
Task characteristics	Methodology Task supervision Task complexity Time pressure Tools Spares
Characteristics of the technical system	Equipment design Material properties Process complexity HMI (human machine interface) Maintainability/accessibility System feedback Technical condition
Administrative control	Procedures Work permits Disposable work descriptions
Organizational factors/ operational philosophy	Programs Work practice Supervision Communication Acceptance criteria Simultaneous activities Management of changes

Table 4.1: Risk Influencing Factors used in the BORA project. Source: Aven et al. (2006)

4.2 Risk Indicators

A RIF is in principle a theoretical variable meaning that is it not (necessarily) specified how to measure this variable (Øien, 2001b). When this is the case an indicator is used as an operational variable that represents the theoretical RIF (Øien, 2001b). The term indicator can be understood as a measurable variable that describes the condition of a factor. Tranberg (2013) specifies that the main purposes of indicators are to monitor the safety level and to decide if, when, where and how to take action. Indicators can also be used as evidence to instantiate nodes in a BBN (Pettersen, 2012).

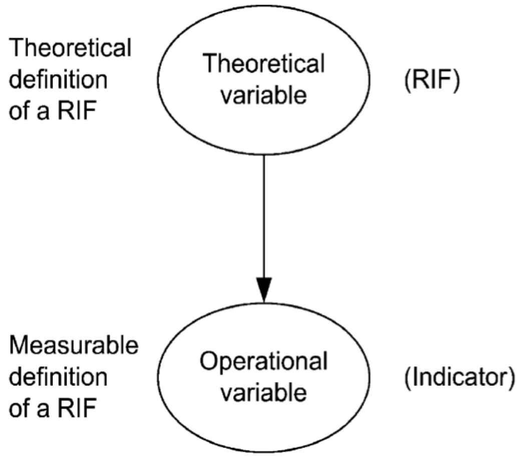


Figure 4.2: Relationship between RIF and indicator. Source: Øien (2001b)

A given RIF, for example an organizational factor, might not be directly measurable. This is denoted 'the measuring problem' within social science research methodology (Hellevik, 1999; Øien et al., 2011). The indicator is then used to quantify the RIF. For instance, the RIF can be training, and the indicator for this could be the ratio of employees with formal training. The relationship between RIF and indicator is illustrated in figure 4.2.

Some RIFs may need more than one indicator to fully describe the status of the RIF. An example is the factor maintenance crew. This is far too complex and many-sided to be measured by one indicator (Haugen et al., 2012). It is therefore necessary to identify suitable indicators that measure the important characteristics of the factor (Haugen et al., 2012). Øien et al. (2011) lists three important properties that are fundamental to indicators:

1. They provide numerical values (such as a number or a ratio)

2. They are updated at regular intervals

3. They only cover some selected determinants of overall safety or risk, in order to have a manageable set of indicators.

Indicators are classified as leading and lagging. A lagging indicator measure factors which only becomes measurable after a desired safety outcome has failed, in contrast to leading indicators that considers process inputs and can give a warning before an accident occur (Hopkins, 2009). It is commonly accepted that leading indicators are preferred over lagging indicators (Vinnem et al., 2006a). However, lagging indicators are easier to identify, and a set consisting of only leading indicators will often be difficult and expensive to obtain (Tranberg, 2013). The dual assurance principle states that a combination of leading and lagging indicators can provide a holistic measure of performance to confirm that the risk control system is operating as intended and provide early warning should problems arise (HSE, 2006a; Tranberg, 2013).

4.3 Identification and Selection of RIFs

A common starting point for all risk analysis methods is that all methods require the identification of all the relevant RIFs. This is important in order for the analysis to reflect real world conditions, and to be as comprehensive as possible. It is of course impossible to include all RIFs in the analysis, however, by limiting the system and selecting the most important RIFs, the analysis can still give a good indication of the risk level. In the process of selecting RIFs, the author presents a three step method for RIF selection and identification. This method is based on the work of Rosness (1998), Øien (2001b) and Haugen et al. (2012).

The conditions influencing the risk of a system are usually large. Therefore the first step of selecting the appropriate RIFs is to limit the system in question and define the goal for the analysis (i.e. what level of the system should the analysis represent). Rosness (1998) has defined three system levels for analysis purposes:

1. The total system: possibly including many organizations and a range of infrastructures
2. Macro systems: organizations or organizational units with the capability to develop and implement their own strategy for adapting to the environment
3. Micro systems: delimited systems which are directly (physically) involved in potential accidents.

The next step is to select the categories of accidental events contributing most to the total risk (Øien, 2001b). This step is a first screening to establish possible accident scenarios that can occur for the system in question. The third step is to identify RIFs contributing to the accident scenarios (Øien, 2001b). Haugen et al. (2012) proposes that the identification and selection of possible RIFs can be based on an existing quantitative risk analysis (QRA) and other risk assessments, overview of barriers, governing documents, accident investigations or cause analysis of the event being considered.

Tranberg (2013) points out that there are two main principles applied when identifying RIFs: (1) logical reasoning combined with knowledge of the system and activities being considered and (2) information from accidents, near misses and risk assessments of the relevant major accident type. The identification of RIFs are not always easy, however looking at indirect influence may help identifying some RIFs. Haugen et al. (2012) illustrates this with an example – it may be easier to answer the question “what influences the performance of the navigator?” (which in turn can influence the probability of ship collision), rather than directly looking for all factors that influences the probability of collision.

When the appropriate RIFs are identified, they should be structured in an ordered way, and necessary information should be readily available. Øien (2001b) proposes to list the RIFs in tables, including notations, denominations, current numerical values and comments. The RIFs should be structured according to the barriers in the system, except for the RIFs that are not connected to any specific barrier (Øien, 2001b).

4.4 Qualitative Analysis of RIFs

This section presents two methods to analyze RIFs and the influence RIFs have on other RIFs and accidental events. This is an important concept to understand when modeling a BBN. Both these models are used in the development of the BBN model in chapter 6.

4.4.1 Risk Influence Analysis

The Risk Influence Analysis (RIA) project was aimed to develop a methodology for identification and assessment of risk reduction strategies in large scale distributed systems (Rosness, 1998). This is not a BBN approach, as RIA focuses on the identification of RIFs and RIF structures. However, this is also an important step in the understanding and development of a BBN and a description of RIA is therefore included in this thesis. The method was developed to give decision support for managers and to get a broad overview of factors which influence risk, the strategies for risk reduction and evaluation of such strategies (Rosness, 1998). The RIA methodology provides a conceptual framework which integrates technical, human and organizational factors.

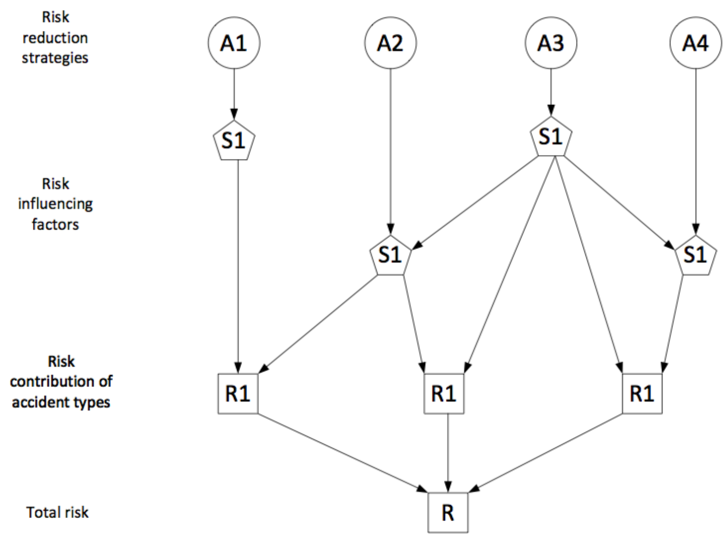


Figure 4.3: Relationship between risk reduction strategies, RIFs, risk contribution of accident type and total risk. Source: based on Rosness (1998)

The specific objectives of the methodology are (Rosness, 1998):

1. Identify important RIFs
2. Identify and describe risk reduction strategies defined in terms of actions to change the RIFs
3. Assess the effects on the total risk level on implementing each risk reduction strategy.

Figure 4.3 illustrates the relationship between risk reduction strategies and total risk, as the RIA methodology suggests. The RIFs influences one or more risk contributions, or other RIFs. The total risk is found as the sum of all contributions. Step 3 of the RIA objective is to evaluate the effect of the risk reduction strategies, and from figure 4.3 it is possible to see how the strategies are implemented to change one RIF. Although no specific action is taken to change other RIFs, some of these may change as a consequence of the actions taken to change the targeted RIF (Rosness, 1998).

4.4.2 Factor Model

A factor model is a qualitative illustration of the interaction between different RIFs and the influence of RIFs on an accidental event. The influence is illustrated by arrows, this means that a factor model describes the causal relationship between RIFs and an associated event (Pettersen, 2012). RIFs are identified by for example the methodology proposed in chapter 4.3, and these RIFs can have both a direct and an indirect effect on the event. A factor model is used for the development of potential indicators for major accidents and to describe potential causes and effects of changes in the status of a RIF (Tranberg, 2013).

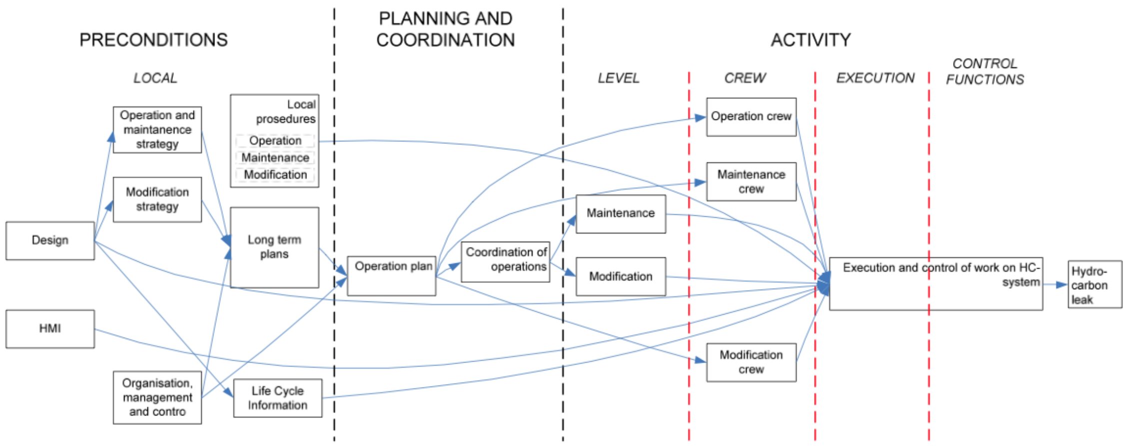


Figure 4.4: Factor model of RIFs influencing the risk of hydrocarbon leaks. Source: Haugen et al. (2012)

Figure 4.4 illustrate how technical, human and organizational RIFs influence the event "hydrocarbon leak", both directly and indirectly through other RIFs. To organize the model the RIFs are structured in three layers: Preconditions, Planning and coordination and Activity. The layers represents the RIFs "distance" from the event. The first layer is Activity and this represents the sharp end. Factors in this layer are controlled or influenced by the operating organization on an installation, and many of these factors have direct influence on the probability of the event (Haugen et al., 2012).

The intermediate and final layer represents Planning and coordination and Preconditions respectively. Both these categories contains factors that are changed infrequently, such as operational planning, maintenance procedures, design, regulations and company policies (Haugen et al., 2012).

In the factor model the arrows describes the relationship between the factors. An arrow from A to B means that the state of factor B is influenced by the state of factor A. Due to this the factor model can be seen as a bayesian network, given that the model satisfies the conditions of a DAG (i.e. no cycles in the network) (Pettersen, 2012).

4.5 Quantitative Analysis of RIFs

A BBN requires nodes to be quantified with conditional probabilities in order to be useful as a risk analysis tool. This section will discuss the quantification process and explain how to develop a conditional probability table (CPT) for nodes in a BBN.

4.5.1 Quantifying RIFs

As discussed previously in this thesis a BBN is a good tool for analyzing risk, especially for non-deterministic relationships such as human and organizational factors. The downside with BBN analysis is the massive amount of conditional probabilities that must be assigned. The number of probabilities, p_n, in a CPT for a discrete variable with n parents, with m states is given by equation 4.1 (Pettersen, 2012):

$$p_n = m^{n+1} \tag{4.1}$$

This equation shows that the number of probability distributions required to populate a CPT in a bayesian network, grows exponentially with the number of parent nodes associated with that table (Das, 2004). Hence, assigning all conditional probabilities directly will be unmanageable for the expert team (Røed et al., 2009). In addition to the substantial amount of work required, the relevant historic data is often limited. This could be a problem when establishing the CPT. Therefore, a mechanistic method for developing the CPTs is wanted. However, a fully mechanized procedure is not desirable, due to the inability to incorporate specific system knowledge. Røed et al. (2009) have proposed a semi-mechanized procedure for developing CPT, without loosing the flexibility of including specific system knowledge. This procedure is explained in chapter 4.5.2 and 4.5.3.

4.5.2 Algorithm for Assigning CPT

In this chapter an algorithm for assigning CPT will be presented. This algorithm is based on the work of Røed et al. (2009) with the HCL methodology. The idea of this algorithm is that with just a few input parameters based on expert judgement, a mechanistic procedure can be developed to assign the conditional probabilities. The procedure utilizes the assumption that a probability assigned for a RIF being in a state that differs considerably from its parents' state should be smaller compared to a state equal to its parents' state (Røed et al., 2009).

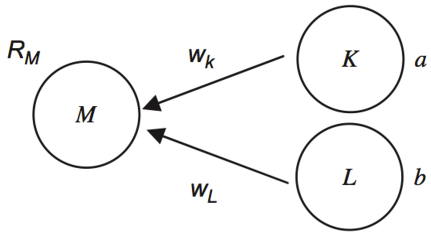


Figure 4.5: Example BBN used in the discussion. Source: Røed et al. (2009)

The assumption stated above is the starting point for determining the CPT. To explain the method for assigning probabilities, the simple BBN in figure 4.5 will be used. The first step is to determine the importance of the parent RIFs relative to each other (Røed et al., 2009). To do this, each parent RIF, i, is given a weight w_i determined by expert judgement. The weights are then normalized so that the sum of all w_i equals 1. The weights are assigned based on a procedure inspired by Sklet et al. (2005), and a scale proposed by Thomassen and Sørum (2002) in the technical condition safety (TTS) project, given in table 4.2.

State	Description
a	Condition is significantly better than reference level
b	Condition is in accordance with reference level
c	Condition is satisfactory, but does not fully comply with reference level
d	Condition is acceptable within the statutory regulations' minimum intended safety level, but deviates significantly from the reference level
e	Conditions with significant deficiencies as compared with "d"
f	Condition is unacceptable

Table 4.2: Definition of states in the TTS project. Source: Thomassen and Sørum (2002)

To assign the weight w_K, with reference to figure 4.5, expert judgement must be used to determine the relative change in expected value $E(M)$ when K is changed from state a to f, while L is held constant in state c, and vice versa for determining w_L (Røed et al., 2009). By performing this estimation, it will become clear which parent K or L that has the most influence over the state of M. When the weights have been determined they can be applied to calculate Z_j, a measure reflecting the distance from the state of the RIF we are considering and the weighted average parents state (Røed et al., 2009):

$$Z_j = \sum_{i=1}^{n} |Z_{ij}| w_i \qquad Z_j \in [0,6] \tag{4.2}$$

where Z_{ij} is the "distance", or the number of states, between the parent i and the RIF we are considering, n is the number of parents and j is the state of the RIF we are considering. Røed et al. (2009) illustrate the use of equation 4.2 with an example: consider the situation where $K = a$ and $L = b$, and we consider the situation where $M = d$ (i.e. $j = d$). The distance between a and d is three states, hence $Z_{Kd} = 3$, correspondingly $Z_{Ld} = 2$. From expert judgement the weights have been estimated to be $w_K = 0.7$ and $w_L = 0.3$. This gives the the weighted distance for RIF M to be in state d to be $Z_d = 0.7 \cdot 3 + 0.3 \cdot 2 = 2.7$. This calculation must be performed for all possible combinations of the states of node K, L and M. This means that $6^3 = 216$ "distances" must be determined.

The next step is to assign the probability of finding the RIF in state j, based on the "distance" Z_j. Equation 4.3 is used to determine the CPT for RIF M. The R in this equation is an outcome distribution index, that distributes the probability mass between the possible outcomes (Røed et al., 2009).

$$P_j = \frac{\mathrm{e}^{-RZ_j}}{\sum_{j=a}^{f} \mathrm{e}^{-RZ_j}} \qquad P_j \in [0,1] \tag{4.3}$$

The value of the R is determined by expert judgment, and a high R express a low probability of the RIF being in a state that is distant from its parents' states (Røed et al., 2009). The determination of R is of course based upon the individual beliefs of the experts, however a method for determining R is suggested by Røed et al. (2009). This method considers the relative difference between a perfect and an average situation. The experts can base their assignment on the following, with reference to figure 4.5, suppose that the parents K and L are in a perfect state a. The question to be asked is then how much higher probability should be assigned for M being in perfect state, a, than for M being in an average state, c? (Røed et al., 2009). If the experts assign a factor 10, then R equals 1.15. This is found from solving the equation $\mathrm{e}^{-0 \cdot R} = 10\mathrm{e}^{-2 \cdot R}$. This equation describes that the probability is 10 times lower in a distance 2 states away from c, and the proper R value can then be determined.

To sum up, by utilizing the suggested method the development of CPT are considerably simplified compared to assigning the probabilities one by one. By determining the weights of the parent RIFs and the distribution index, R, the CPT can be found. This does require some computer software due to the massive amount of calculations necessary to develop the CPTs.

4.5.3 Algorithm to Calculate Probability for Binary Events

In order to introduce the use of this method for binary events, Røed et al. (2009) propose to combine BORA and results from the HCL framework. A three step method is proposed (Røed et al., 2009):

1. Quantify basis probability, P_{basis}

2. Determine by expert judgement maximum deviation from the basis probability

3. Calculate the conditional probability tables.

Step one can often be determined from historical and generic data, and step two is based on the procedure outlined in the BORA method (see for example Haugen et al. (2007)). The goal of this step is to determine a factor reflecting how much the basis probability should be adjusted if the parent RIFs are in the extreme cases a or f (Røed et al., 2009). The adjustment factors are based on the BORA methodology presented in Aven et al. (2006), these are summarized in table 4.3. The adjustment factors marked with superscript a are only valid for basis probabilities $p < 0.1$.

Parent RIF state	Adjustment factor Q
f	10^{a}
e	7^{a}
d	4^{a}
c	1
b	0.55
a	0.1

Table 4.3: Adjustment factors for the basis probabilities. Source: Røed et al. (2009)

The third step is calculating the conditional probability tables based upon the parents RIF states and the adjustment factors Q_i as (Røed et al., 2009):

$$P_j = P_{basis} \sum_{i=1}^{n} w_i \sum_{k=a}^{f} P_{ik} Q_{ik} \qquad P_j \in [0,1] \tag{4.4}$$

Where P_{ik} represents the probability of a parent RIF i being in state $k = a$ to f. Q_{ik} is the adjustment factor from table 4.3. In this case the j represent the possible states of the event considered (ie. success or failure). w_i is the weight of the parent RIF influence on the child, as discussed in chapter 4.5.2.

An example to explain the method is adapted from Røed et al. (2009). Suppose K and L from figure 4.5 reflects two parent RIFs and M reflects a binary event, and K and L have equal weights ($w_K = 0.5$ and $w_L = 0.5$). The probability distribution for K is $a = 0.5$, $b = 0.3$, $c = 0.1$, $d = 0.06$, $e = 0.03$ and $f = 0.01$ and the probability distribution for L is $a = 0.2$, $b = 0.3$, $c = 0.3$, $d = 0.1$, $e = 0.09$ and $f = 0.01$. Then this results in a $P_{failure} = 1.24 \cdot P_{basis}$, or in case the weights are $w_K = 0.1$ and $w_L = 0.9$, we get $P_{failure} = 1.54 \cdot P_{basis}$.

4.5.4 Factors Without Parents

Factors without parents must be established by expert judgement or historical data if possible (Pettersen, 2012). The CPT for the factor represents the probability that the factor is in one of the predefined states a to f, according to table 4.2. This CPT will therefore consist of six elements. These probabilities are prior probabilities, and they represents the belief of the analysts. A prior probability is unconditioned and assigned to variables without parents (Krieg, 2001). Although prior probabilities have been criticized as a source of unwanted bias, they are an integral part of human uncertainty reasoning (Jensen, 1996).

A posterior probability is conditioned on the available evidence. This means that for an event A, a prior probability is assigned, $P(A)$, given that we get information about event B we can update our belief about A, so that $P(A|B)$ represents the posterior probability (Jensen and Nielsen, 2007).

4.6 Generic Data for Factors

To assign the prior probabilities to nodes without parents, one can in some cases use generic data. There are quite a few sources that gives data on human error probabilities and technical reliability data for general cases. For the specific case of offshore operations, the data is more limited. In this chapter a brief explanation of how to obtain and estimate human error probabilities and technical reliability data will be presented.

4.6.1 Human Error Probability

There are a vast amount of different methods for human reliability assessment (HRA) and for estimating human error probabilities (HEP). A comparison of the available methods can be found in HSE (2009). The most applicable and most used method is the technique for human error rate prediction (THERP). THERP was developed for the US Nuclear Regulatory Commission and it is a handbook that includes methods, models and estimated HEPs to enable analysts to make qualitative and quantitative assessments of occurrences of human errors (HSE, 2009). The handbook (Swain and Guttmann, 1983) is indispensable when performing THERP analysis (Rausand, 2011). This handbook contains data tables with nominal HEPs, hereafter called HEP_n. THERP acknowledges that human performance can be influenced by a range of performance shaping factors (PSF) (Rausand, 2011). The PSFs are used to alter the nominal HEPs, according to the analyst's judgement (Miguel, 2006). THERP lists a number of different PSFs, and these are divided into three main groups (Rausand, 2011):

1. External PSFs: i.e. situational and task characteristics, job and task instructions
2. Internal PSFs: i.e. organismic factors
3. Stressors: i.e. psychological stressors, physiological stressors

Nominal HEPs are then altered with the PSFs according to equation 4.5. The basic HEP, HEP_b, is the corrected value of the nominal HEP, that represents a specific action performed under specific circumstances (Rausand, 2011).

$$HEP_b = HEP_n \cdot \prod_{i=1}^{n} PSF_i \tag{4.5}$$

4.6.2 Technical Reliabiltiy Data

There are a wide range of databases containing information on component reliability. Most of the commercially available reliability data sources are based on an assumption of constant failure rates (Rausand, 2011). Examples of such databases includes: Process Equipment Reliability Database (PERD), Electronic Parts Reliability Database (EPRD), Nonelectric Parts Reliability Database (NPRD), but the most important database for applications in this thesis is the Offshore Reliability Data (OREDA).

OREDA contains information from a wide range of components and systems used in offshore oil and gas installations, collected from installations in several geographic areas (Rausand, 2011). An example of data on ballast valves that can be found from OREDA, which was used in the RABL project is presented in table 4.4. More data can be found in the OREDA handbook (OREDA, 2009).

Item	Failure rate (per hour)
Ballast valves, hydr. operated butterfly	
- Critical filure	$1.2 \cdot 10^{-5}$
- Fail to close (per demand)	$2.0 \cdot 10^{-3}$
- Blocked	$1.7 \cdot 10^{-6}$
- Faulty indication	$1.5 \cdot 10^{-5}$
- Internal leakage	$3.0 \cdot 10^{-6}$

Table 4.4: Data on ballast valves from OREDA. Source: Østby et al. (1987)

4.7 Expert Judgement

Expert judgement elicitation is the process for obtaining data directly from experts in response to a specified problem, where data from real applications are scarce or non existing (Rausand, 2011). This has always been an important part in science and engineering, and increasingly expert judgement is recognized as just another type of scientific data, and methods are developed for treating it as such (Cooke and Goossens, 2004). Judgement involves the weighing of available evidence and reaching a balanced conclusion from that evidence (Hora, 2009). It is important to identify all relevant factors that influences the risk in the system. Failure to identify relevant background information can lead experts to conditionalize their uncertainties in different ways and can introduce unnecessary "noise" into the assessment process (Cooke and Goossens, 2004).

Before acquiring expert judgement for an analysis, a number of decisions must be made, including (Hora, 2009):

- Selecting the issues to be addressed by the experts
- Selecting the experts
- Organizing the effort
- Choosing a method for combining multiple judgements, if needed

Generally, an expert is one who has or is alleged to have superior knowledge about data, models and rules in a specific area or field (Hora, 2009; Bonano et al., 1989). Apart from being an expert some important requirements should be satisfied to obtain an as objective as possible result. A judgement is by definition not objective, but it is essential that the judgement is not affected by personal motives. The expert should therefore be free from motivational biases caused by economic, political or other interests in the decision (Hora, 2009). In addition, a choice about using internal or external experts is often raised. A potential expert who is already on the project team may be easier to engage in the judgement process, but questions about their independence of their judgements from project goals may be raised (Hora, 2009).

The expert judgement process may be formal or informal, and may involve one expert or a group of individuals with various type of expert knowledge (Rausand, 2011). There have been suggested several processes for expert judgment, and according to Rausand (2011) some have been proven useful in risk analysis. There have been studies to find the optimal size of a group of experts when working with judgment processes. Experience has shown that the differences among experts can be very important in determining the total uncertainty expressed about a question (Hora, 2009). Clemen and Winkler (1985) concludes that three to five experts are sufficient, whereas Hora (2004) found that three to six or seven experts were adequate, and that there is little benefit from additional experts from that point (Hora, 2009).

A method known as the delphi method is a special procedure for expert judgement elicitation where individual experts answer questionnaires in two or more rounds (Rausand, 2011). A facilitator will then provide an anonymous result of the survey, so that the experts can revise their judgements in the next round. The belief is that the answers will converge to a "correct" answer during the next rounds (Rausand, 2011).

Chapter 5

Technical, Human and Organizational Factors in Marine Systems

QRAs have traditionally been focused on technical systems. During the past decade more effort and research have been aimed at predicting the influence of human and organizational factors (HOF) on risk (Skogdalen and Vinnem, 2011). The trend towards more extensive use of floating production systems, operations in the arctic and deepwater suggests that operational aspects will be more important in the future, in order to mitigate hazards and control risk (Skogdalen and Vinnem, 2011).

According to Bea (2002) experience has shown that the primary hazard for offshore installations is not the ocean environment itself, as the industry has learned how to build, operate and maintain structures that can survive extreme conditions, but the primary hazards are associated with HOFs that develop during the lifecycle of the installation.

It is now widely accepted that the majority of accidents in the industry generally are in some way attributable to human as well as technical factors in the sense that actions by people initiated or contributed to accidents, or people could have acted better to avert them (Skogdalen and Vinnem, 2011). It is therefore important to have a good understanding of HOF, and how these factors work together with technology.

This chapter will explain what is meant by technical, human and organizational factors in general, and describe how they are linked together. Accident and incident analyses will be performed to identify the most common factors of events relating to stability failure of semi-submersibles. Then a list of RIFs for further modeling will be compiled.

5.1 Factors in General

Accident investigation often shows that a combination of factors cause an accident. Human error is often claimed to account for somewhere between 60% to 90% of all accidents (Rausand, 2011). However, as most systems are dependent on human interaction in its entire life cycle, it is often easy to find a human error in the event sequence of an accident. It is therefore necessary to study the interaction between the factors, and find causes of human error. The man, technology, and organization (MTO) concept includes all aspects of the interaction between man, technology and organizational factors (Skaugrud, 2011).

This section defines technical, human and organizational factors, how these factors fails and how they are related to each other. The description of these factors is partly based on Arnhus (2013).

5.1.1 Technological Factors

Technological factors includes equipment, hardware, software and design (Rausand, 2011). When looking at technological factors the term failure and fault is important. A failure is an event where a required function is terminated, and a fault is a state characterized by an item that is unable to perform a required function (Rausand and Høyland, 2004). The system may also malfunction by producing too little or too much. This will also be classified as a failure.

The state of technological factors is largely influenced by how the human and organizational factors are handling technology. For example regular inspection and maintenance intervals contributes to a more reliable technical factor. However, even the best inspection and maintenance factors cannot guarantee a 100% reliable technical system. Safety barriers are then implemented to further increase reliability of a system.

Common technical failures may be due to fatigue and corrosion or it could be due to operating errors, overloads or inadequate maintenance (Rausand, 2011). In any case the degree of failure is classified as critical, degraded or incipient. Rausand (2011) defines the categories as:

- *Critical:* A failure that causes immediate and complete loss of a system's capability of providing its output.
- *Degraded:* A failure that is not critical, but that prevents the system from providing its output within specifications.
- *Incipient:* A failure that does not immediately cause loss of a system's capability of providing its output, but which, if not attended to, could result in a critical or degraded failure in the future.

5.1.2 Human Factors

Human factors or ergonomics is defined as the scientific discipline concerned with the understanding of the interactions among humans and other elements of a system, and the profession that applies theoretical principles, data and methods to design in order to optimize human well being and overall system performance (IEA, 2013).

The term human factor is often confused with human error. Human error is defined by Rausand (2011) as an out-of-tolerence action, or deviation from the norm where the limits of acceptable performance are defined by the system. These situations can arise from problems in sequencing, timing, knowledge, interfaces, procedures, and other sources. While human error is the immediate cause of accidents, human factors are considered as the underlying causes (Gordon, 1998). According to Reason (1990) there are four types of human error that may lead to major accidents (Reason, 1990; Rausand, 2011; Vinnem et al., 2012):

1. *Slip:* an action that is carried out with a correct intention, but a faulty execution. (i.e. pushing the wrong button, reading error etc.)

2. *Lapse:* a failure to execute an action due to a lapse of memory or because of a distraction. (i.e. wrong sequence of action, omitting steps in a sequence etc.)

3. *Mistake:* A correct execution of an incorrect action.. (i.e. inadequate judgement/conclusion due to fatigue, competence, information, time pressure or workload etc.)

4. *Violation:* a person deliberately applies a rule or procedure that is different from what he/she knows is required, even though he/she may do it with good intent.

In addition to the above categories, Reason (1990) also includes sabotage, and defines this as a deliberate action with a prior intention to damage the system. This is not further treated here, as this is outside the scope of this thesis. Reason (1997) distinguishes between three major categories of violations (Reason, 1997; Vinnem et al., 2012; HSE, 2005a):

- *Routine violations:* Behavior in opposition to a rule, procedure or instruction that has become the normal way of behaving within the current context, such as corner-cutting and shortcuts.

- *Optimizing violations:* attempt to realize unofficial goals as part of the activity performed.

- *Necessary violations:* includes inappropriate actions due to failures of the work site, tools and equipment.

Humans factors are characterized as a range of issues including perceptual, physical and mental capabilities, as well as the interactions of individuals with their jobs and the working environments, the influence of equipment and system design on human performance and, above all, the organizational characteristics that influence safety related behavior at work (Skogdalen and Vinnem, 2011).

According to Bea (2002) the primary hazards to offshore structures is human and organizational factors that develop during the life cycle. This view is also supported by the UK Health and Safety Executive (HSE) stating that management of human factors is increasingly recognized as having a vital role to play in the control of risk (HSE, 2003).

Even though humans contribute to risk, they also contribute to safety. By utilizing senses, humans can make decisions based on previous experience and awareness of a situation (Grech et al., 2008). Barriers must be implemented to protect humans, and ensure that they cannot take the wrong decisions and limit their possibilities to make errors.

5.1.3 Organizational Factors

Organizational factors are characterized by the division of tasks, design of job positions, including selection, training, and cultural indoctrination, and their coordination to accomplish the activities (Skogdalen and Vinnem, 2011). The organizational culture shapes the employees view on safety. Organizational safety performance factors include leadership, culture, rewards, manning, communication and coordination, social norms and pressure (Bellamy et al., 2008).

The organizational factors influences whether the organizational culture is strong or weak. A strong culture is one where employees align with the organizational values, conversely in a weak culture the employees do not adhere to the organizational values (Vulchi, 2011). The organizational culture is a product of the organizational safety performance factors.

In organizational factors it is distinguished between active and latent failures. Performance of frontline personnel is usually associated with active failures, whereas latent failures are those that lie dormant for varying periods of time (Reason, 1997). To distinguish between active and latent failures, the time and originator of the failure must be determined. Active failures are performed by persons on the operational side and usually results in immediate failure. Latent failures may lie dormant for long periods prior to triggering an accidental sequece of events (Grech et al., 2008).

The performance of an organization is a result of combined effects of influencing or causal factors. It may create circumstances where none of the individual factors have any problems, but where the interactions may result in accidents (Mohaghegh and Mosleh, 2009). Thus, it is not necessary to find a series of failures that need to line up to lead to an organizational failure, as implied by Reason's swiss cheese model (Reason, 1990, 1997; Mohaghegh and Mosleh, 2009). This means that accidents rooted in organizational factors may happen, even though the factors themselves have not failed.

5.1.4 The Interaction Between Technical, Human and Organizational Factors

The interaction between a technical system and an organization is the personnel that is responsible for the operation and maintenance of the system, this is illustrated in a simple model in figure 5.1. The model captures most paths of influence during the operational phase of the life cycle. Arrows at interface points run in both directions, symbolizing the interactive and often dynamic nature of influences. (Mohaghegh and Mosleh, 2009).

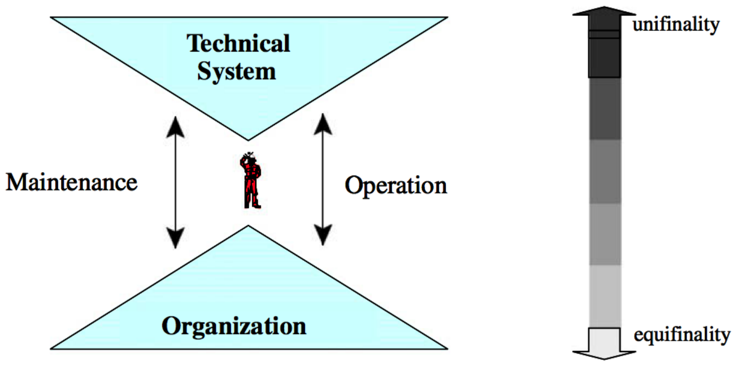


Figure 5.1: Operation and maintenance actions as links between organization and technical systems. Source: Mohaghegh and Mosleh (2009)

The model suggest a scale from unifinality to equifinality (Katz and Kahn, 1978; Sharit, 2000). Unifinality refers to a situation where there is only one way for the system to yield its product, whereas equifinality characterizes the case where the product of the system can be brought forth in different ways (Mohaghegh and Mosleh, 2009). A technical system usually has a specified operating procedure which limits the possible ways of obtaining the final output, hence technical systems tends to be at the unifinality side of the scale. On the other side of the scale, we can find the organization. This means that there are many different ways in which an organization can achieve its desired output. Bier (1999) elaborates on this and points out that the study of management and organizational factors is difficult because there is no one correct management style, corporate culture or organizational structure. This means that several different combinations of the states of organizational factors and different structures may produce the same organizational output (Mohaghegh and Mosleh, 2009).

Some of the major challenges in including organizational factors in a risk analysis is because of the equifinal properties of the output from organizational factors. When considering a technical factor it is often easy to identify errors by the state of the output. This, in addition to the argument that organizational factors do not need to fail as the swiss cheese model implies (as discussed in chapter 5.1.3), suggests that the modeling of organizational factors can be challenging. Mohaghegh and Mosleh (2009) therefore suggests that a shift from traditional models that focuses on errors, such as the swiss cheese model, to models that focuses on actual performance would be an improvement. In this thesis, it is suggested to use a BBN model to overcome this challenge. One of the advantages of using a BBN is that it is able to model non-deterministic relationships and it is updatable and hence capture the actual performance.

5.2 Accidents

Information from accidents and near misses is an important source for prevention of accidents in the future. Details from these accidents and events are found in investigation reports, however a number of incidents are not reported (PSA, 2011a). Some of the most serious major accidents occurred decades ago. Vinnem (2014b) states that a drawback with this is that important experience gained from these occurrences may be forgotten and not be brought forward to future generations. This is supported by statistical evidence which shows that the damage frequency has not improved over the last decade (Kvitrud, 2013). With an average number of semi-submersible units of 150 in the world during the period 1980-2010, the stability accident frequency has been observed to about $19 \cdot 10^{-4}$ per unit-year (PSA, 2011a). According to PSA (2011a) this number is higher than acceptable.

A short description of some of the most serious accidents relating to loss of stability and buoyancy is included in this thesis for the purpose of understanding why the accidents occurred (see table 5.1). A list of less serious incidents is given in appendix A. The accidents and incident are used as a basis for establishing RIFs and RIF structures in the BBN modeling process. The accidents that are considered in this context are the ones that would fall into the category of DFU8, according to the RNNP (2014) report. This category includes incidents and accidents relating to structural and maritime systems. Most emphasis is placed on marine systems, and the distinction between the two scenarios depends on what constitutes the major accident potential in the event. Loss of stability due to a fault in the main structure is classified as a structural event, whereas an accident due to aftereffects from water ingress is classified as a marine event (RNNP, 2014). Other events such as loss of stability due to collision with ships (DFU5), floating objects (DFU6) or field related traffic (DFU7) are important factors that can contribute to the risk, but these are not treated further in this thesis, because these are defined as separate DFU categories (RNNP, 2014).

5.2.1 MTO-Analysis of Selected Accidents and Incidents

A man, technology and organizational (MTO) analysis is a technique developed for investigation of accident and incidents (Vinnem, 2014b). This technique uses event and cause diagrams to structure the analysis and to describe the accident sequence, as well as the deviations from normal practice and the barriers that were breached (Rausand, 2011). MTO is a qualitative analysis, which is practical when analyzing accidents where a chain of events rooted in technical, human and organizational factors are the causes of the accident. The reason why it is included in this thesis is because it gives a good foundation for the identification of RIFs for the

Unit, year	Description
Ocean Ranger, 1982	Windows in one of the columns broke due to wave impact. Short circuit of ballast system due to sea water ingress caused ballast valves to open and close uncontrollably. Ballast operators unable to rectify the situation and the rig assumed a forward list. Ballast system was not designed to operate under these conditions. A major accident cased by capsizing of the rig. Loss of 84/84 crew members and loss of the rig.
Ocean Developer, 1995	An inexperienced operator used a complex ballast in system. The operator is assumed to have "pushed the wrong button", resulting in the sinking of the rig during tow outside Angola, Africa (COWI, 2003).
P-36, 2001	A gas leak leading to an explosion caused a collapse of the starboard emergency drain tank and a rupture of a sea water outlet pipe. This caused flooding of one of the columns, and open manholes allowed water ingress into pontoon on the starboard aft side. To reduce the tilt, water was allowed into the opposite ballast tank, however this only accelerated the undesirable increase in the platform's draft until it sank. Loss of 11 crew members.
Thunder Horse, 2005	The semisubmersible platform was evacuated due to Hurricane Dennis. When the crew returned they found the platform with a 20° heel. An error in the hydraulic control system caused ballast and bilge valves to open. Several check valves were installed backwards allowing water to migrate into the column and pontoon. Reserve buoyancy in the deck saved the platform and allowed it to be restored.
(...), 2010	Semi-submersible under construction. A short circuit and program error caused the control unit to open ballast valves in part of the platform. This gave an unintended non critical heel of 3° and manual deballasting corrected the error.
Aban Pearl, 2010	A leak occurred most probably due to significant water inflow to machine room in a pontoon and on into a column. Flow exceeded the capacity of the ballast pumps. The rig gained a 45 degree list and sank.
Jupiter 1, 2011	The unit began to take in water, due to failure of a mechanical valve. Water inflow exceeded bilge pumps. The unit eventually sank (in 38 m of water).
Scarabeo 8, 2012	The semi-submersible developed a 5.7° list due to wrongful operation of ballast system by an unqualified control room operator. The situation was restored right after without serious consequences. (Eni and Saipem, 2012)
Island Innovator, 2013	The rig developed a 4° list in a yard stay in Hanøytangen, Norway. All workers were evacuated. Seawater entered the pump room instead of the ballast tanks due to a rupture in the rig. (Offshore Energy Today, 2013)

Table 5.1: Summary of the most relevant incidents and major accidents. Sources Vinnem (2014b), Kvitrud (2013) and Tinmannsvik et al. (2011). (...) refers to the name of a semi-submersible, where the name is kept secret.

development of a BBN. Some of the most relevant accidents and incidents, that are caused by a combination of MTO factors, are analyzed. The MTO diagrams are included in appendix B, and are based on accident investigation reports.

According to the RIF identification and selection method outlined in chapter 4.3, an important step in selecting RIFs is to first identify possible event sequences that can lead to accidents. The MTO perspective shows how different factors contributes to accidents, and possible event sequences. In the following analyses only the root causes relevant for stability is considered. In this thesis the focus is on the operational issues that can lead to loss of stability or buoyancy. Evacuation and post accident issues are therefore not considered in this context.

Ocean Ranger, 1982

The Ocean Ranger accident happened more than 30 years ago and operational conditions have improved a lot since then. The immediate causes for this accident is the broken porthole, that allowed sea water to flow into the ballast control room. This is believed to have short circuited the ballast control console, which then causes the forward ballast tanks to open (NASA, 2011). The uneven ballast conditions lead to a list and eventually the capsizing of the rig.

Looking at the underlying causes in the MTO analysis, it is clear that this situation was further escalated by human and organizational issues. The control room operator (COOP) did not have any formal training, only two weeks on-the-job training, and on each shift only one COOP was on duty (NASA, 2011). The COOP also had limited knowledge of the ballast system as a whole. This was evident when the control unit was out of operation and manual intervention was needed. The COOP did not have sufficient understanding of how the system worked, this led to further worsening of the situation for each attempt to manually override the system (Price, 2013). The only qualified stability operator on board the Ocean Ranger was the rig master, but he had no experience with the system and hence could not help in the situation.

The operating procedures were not good. Former crew members testified that the operating manual had been produced with the primary goal of fulfilling regulatory requirements (NASA, 2011). As the procedures were lacking, the crew based their actions on previous experience. The rig was, at the time, the largest mobile offshore unit and it was designed to withstand storm conditions, which it had been exposed to more than 50 times before (NASA, 2011). Since it had never experienced any problems with ballast control during storms, no actions were taken to prepare this system for the storm. This is a typical case of overconfidence in the system, the same that could be seen in the Macondo disaster in 2010 (DHSG, 2011).

The MTO diagrams in appendix B, pages 114-116, illustrate a chain of the most important events leading to the capsize, and it is based on NASA (2011), Price (2013) and COWI (2003).

Thunder Horse, 2005

The Thunder Horse was initiated by valves that opened while the platform was abandoned as a precautionary measure, due to an incoming hurricane (Vinnem et al., 2006c). The hydraulic power unit (HPU) that controls the ballast and bilge valves was isolated before the evacuation. No operating procedures existed for this scenario, and the crew based their decisions on previous experience (MMS, 2005). Isolation of the HPU was not successful and multiple valve movements were recorded after the rig was abandoned. This allowed for water migration to take place, causing the initial listing (SINTEF, 2011). In addition, three check valves were found to be installed in the wrong position and one was inoperable after maintenance work on the system (MMS, 2005). Also, improper installation of cables through watertight bulkheads were found to have contributed to escalate the rate of water migration. This shows that human error in maintenance and construction, and organizational errors in third party inspection failed.

The operator, BP, did not perform a hazard and operability (HAZOP) study of the HPU, nor did they confer with the manufacturer to identify hazards created by improper operation of the HPU system (MMS, 2005). This resulted in incomplete operating procedures, and this is considered by the Mineral Management Service (MMS) to be a contributory factor in the incident. The reserve buoyancy in the deck saved the platform from a complete capsize. This was a measure introduced after the Kielland accident in 1980. The MTO diagram in appendix B, pages 117-118, is based on MMS (2005), Vinnem et al. (2006c) and SINTEF (2011).

Scarabeo 8, 2012

In this incident, the initiating event was operator error. The COOP was inexperienced as he only had six weeks in total of ballasting experience. Internal guidelines at Saipem requires three years of familiarization and experience to be a COOP. At the time of the incident, this COOP was the only operator on duty (Eni and Saipem, 2012). According to the guidelines to section 31 of the activities regulations, of which Scarabeo 8 had to comply with, there shall be at least two persons in the central control room on permanently manned facilities (PSA, 2014b). It is clearly an organizational barrier that has failed with regards to followup on regulations and internal guidelines. In the investigation of this incident it was discovered that the lack of qualified personnel in the market forced Eni and Saipem to employ unqualified personnel (Dybvig et al., 2012). This is a general concern for the entire industry, not only for this specific company.

The COOP made an error in the ballasting operation, by unintentionally opening a sea chest and hence allowing water to flow into a ballast tank. Due to limited experience the COOP cannot understand what is wrong and became stressed (Dybvig et al., 2012). The stability section leader (SSL) and platform manager (PLM), both with considerable experience, arrives at the control room, but they cannot understand what causes the rig to list (Eni and Saipem, 2012). In the investigation, it was discovered that the personnel could not identify that the sea chest valve was open, this is due to a non-optimal human machine interface (HMI) on the ballast control (Dybvig et al., 2012).

The Scarabeo 8 incident was caused by human error and rooted in organizational and technical factors. In this case relevant documentation and guidelines were available, but not used properly. The MTO diagram of this incident is given in appendix B, pages 119-120, and this is based on Eni and Saipem (2012) and Dybvig et al. (2012).

(...), 2010

This incident happened while the rig was at a norwegian yard for construction. A short circuit in the ballast control unit caused the system to fail, and needed a manual restart. This restart could only be performed by personnel from the manufacturer of the ballast system (Restricted 1, 2010). During the short circuit, a software error caused all valves to all ballast tanks in the N21 quadrant to open. Whenever the system fails, the standard is to close all valves. The ballast system was recently installed so the operator was not familiar with all parts of the system (Restricted 1, 2010).

During emergency situations, a panic button should be pushed to stop all pumps, and close all valves. This button was not yet installed, however a software option existed (Restricted 1, 2010). The ballast operators did not know about this function, and the operating procedures did not specify to use this function in emergency situations, hence the ballast operators did not perform an emergency stop of the system. The MTO diagram is given in appendix B, pages 121-122, and this is based on (Restricted 1, 2010) and (SINTEF, 2011).

Comments

The MTO diagrams in the appendix and the descriptions about the accidents and incidents given above shows that small and perhaps insignificant events can lead to potentially hazardous situations. It is also clear that technical, human and organizational factors contributes to the event sequence. By investigating the root causes of an accident it is often identified that organizational factors such as operating procedures, training and selection of personnel and management of changes are involved. This further lead to human errors, and technological malfunction. The list of RIFs that contributes to the loss of stability and buoyancy should therefore include technical, human and organizational factors, and as evident from the MTO analyses, root causes are especially important and should therefore have a major focus.

The results from the MTO analyses shows evidence that the two theoretical theories “Man-Made Disasters” (Turner and Pidgeon, 1997) and “Drift into Failure” (Dekker, 2011) applies. Turner and Pidgeon (1997) concluded that serious accidents often had long “incubation periods” where the conditions developed in a negative direction until an accident occurred (RNNP, 2014). A central point in this theory is that it was almost always a single person or a part of the organization that knew about the negative development (RNNP, 2014). This can be seen in Scarabeo 8 and Ocean Ranger, where someone in the organization must have known that unqualified personnel were operating the ballast system, and in the Thunder Horse where the lack of risk assessment may have contributed to the accident.

The "Drift into Failure" theory (Dekker, 2011) is concerned with development that is slow enough to not cause attention, because the personnel get used to the small changes without noticing that this affects the risk level in a negative direction (RNNP, 2014). This can also be seen in all the accidents, due to the negative trends that are allowed to develop without being stopped. These are theories that should be bared in mind when analyzing accidents and incidents. In addition it is worth mentioning the problem discussed by Rasmussen (1997) about the risk development as a competition between different targets, such as safety vs. cost, safety vs. work progress, and how one must alway be aware of these differences (RNNP, 2014).

5.3 Causes of Accidents and Incidents

The RIF identification and selection method described in chapter 4.3 suggests to identify possible causes of accidents and incidents. Table 5.2 and 5.3 lists a set of initiating events, the units that experienced these events and a list of possible root causes. This list of initiating events is based on Tinmannsvik et al. (2011), PSA (2011a), Kvitrud (2013), Vinnem (2014b), and accident investigations and descriptions in appendix A. The root causes reflects the author's interpretation of the incidents/accidents and personal beliefs.

Causes are defined as events or conditions that affects the consequences of a hazardous event, or that increases the probability of occurrence of such event (RNNP, 2014). This is in accordance with how Reason (1997) use the term in the "energy-barrier perspective" and the swiss cheese model. Reason (1997) also points out that causes can be either active or latent, in terms of where the cause appears in the accident sequence. PSA (2013a) presents a similar view of how barriers are designed. This means that when analyzing the causes of an accident, it is not sufficient to focus on the immediate causes that have a direct effect on the accident, but an emphasis should be given to the root causes. RNNP (2014) acknowledges that the links between causes and effects can be somewhat weak and unclear when root causes are considered. It is, however, suggested that as far as one can logically argue that there could be a link between a root cause and an effect, this root cause should be included in the analysis (RNNP, 2014). This view is adopted in the analysis in this thesis.

An interesting result is that many of the root causes seems to be present in many of the initiating events. Examples includes operating procedures, training and experience. This was also evident from the MTO investigations performed in chapter 5.2.1. In addition, many of the units seem to be linked to many initiating events. These results strengthen the conclusion given above that small and perhaps insignificant events can lead to potentially hazardous situations.

Initiating causes of stability incidents and accidents	Unit	Root causes
Improper ballasting caused by lack of expertise or training	- Scarabeo 8 - Ocean Ranger - Ocean Developer	- Operating procedures - Training - Experience - Personel selection
Changes in center of gravity	- West Gamma	- Communication - Operating procedures
Collisions can puncture holes close to or below the water line	- Åsgard B - Floatel Superior	- Communication - Alarm management
Grounding during transit	- Deep Sea Driller	- Experience - Training - Equipment - Weather
Valves, either internal or towards the sea, can be opened, wrongly installed, malfunctioning or removed for repair or maintenance	- Thunder Horse - Polar Pioneer - Transocean Arctic - Jupiter 1 - Transocean Searcher - COSL Rival	- Maintenance - Inspections - Technical condition - Maintenance procedure - Experience
Openings in bulkheads	- Thunder Horse - P-36 - Henrik Ibsen	- Structural condition - Work practice - Inspections - Operating procedures
Damaged piping	- West Venture - COSL Innovator	- Structural condition - Maintenance procedures
Wrong or misleading indications from systems	- Ocean Ranger - Scarabeo 8 - Polar Pioneer - Transocean Wildcat - Transocean Prospect	- HMI - Technical condition - Experience - Knowledge of the situation
Programming errors in ballast system computer software	- Transocean Prospect - Transocean Arctic - (...) 2010 - P-34	- Testing procedures - Technical condition of control and logical unit
Environmental loads or inadequate structural capacity	- (...) 2002 - (...) 2008 - Alexander Kielland - Ocean Ranger - COSL Rigmar	- Structural condition - Operating procedures - Maintenance procedures - Inspections - Weather

Table 5.2: Initiating and root causes of stability incidents and accidents (1/2)

Initiating causes of stability incidents and accidents	Unit	Root causes
Firewater from ships can cause water to flow into and migrate through the hull	- Deepwater Horizon	- Communication - Operating procedures - Knowledge of the situation
Short circuit or faults in the electrical system may cause ballast system to malfunction	- Ocean Ranger - (...) 2010	- Structural condition - Technical condition - Training - Inspection and testing - Operating procedures - System knowledge - Weather
Lack of risk assessment	- Deepwater Horizon - P-36 - Thunder Horse	- Work practice - Supervision - Operating procedures - Training - Experience - 3rd party inspection - Internal inspections
Lack of understanding of the ballast system	- Ocean Ranger - Scarabeo 8 - P-36 - Ocean Developer	- Personnel selection - Operating procedures - Experience - System knowledge - Training
Undetected errors	- Thunder Horse	- Condition of tech. system - Operating procedures - Work practice - Weather
Wrongful or unintended movement of water	- Ocean Ranger - (...) 2010 - Transocean Winner - Henrik Ibsen	- Communication - Condition of tech. systems - Operating procedures - Experience - Work practice - Weather
Initiating damage due to wrong handling of flammable liquids	- Deepwater Horizon - P-36	- Operating procedures - Work practice - Training - Supervision
Deluge and firewater may be activated and cause water to flow into the hull and migrate through openings	- Snorre B - Visund - (...) 1999 UKCS	- Operating procedures - Knowledge of the situation

Table 5.3: Initiating and root causes of stability incidents and accidents (2/2)

Tinmannsvik et al. (2011) have concluded that uncontrolled water flow and migration is the most common cause of incidents and accidents relating to stability. It was also found that on an overall level, most of the accident scenarios listed in appendix A were covered by existing regulations (applicable to operations on NCS), such that the incidents should not have occurred (PSA, 2011a). A list of the areas of the regulations that need closer attention and improvement to prevent similar events in the future are among others (PSA, 2011a):

- Safety relating to capsize and sinking
- Competence of stability leader
- Requirements for watertight integrity
- Handling of snow and ice with respect to stability
- Capacity and performance requirements for bilge system
- Requirements for watertight transitions through bulkheads
- Requirements for firewater system

Results from a survey and interviews given to various industry experts on marine systems are presented in the "trends in risk level" report (RNNP, 2014). This report has given valuable knowledge into the potential risks and possible root causes of stability loss. This survey revealed that the lack of knowledge, lack of operating procedures and incorrect use of existing procedures were the most important causes that could lead to incidents relating to marine systems.

5.4 Identification and Selection of RIFs for Stability Operations

In this chapter the most relevant RIFs will be identified and selected. The RIFs will be listed according to the barrier functions (BF) that they influences. The BFs are defined according to the results from the accident investigations. It was found that most accident and incidents are rooted in events that relates to three different situations, namely during normal operation, during abnormal situations, or occur due to technical malfunction. The barrier functions to prevent loss stability (and buoyancy) are proposed to be as follows:

- **BF 1:** Conducting normal operation
- **BF 2:** Response to abnormal situation
- **BF 3:** Condition of technical systems

The next step in the process is to identify the RIFs that influences the BFs. Based on the accident investigations and causes listed in the previous chapters, the RIFs in table 5.4 are found to affect the ability of the BFs to function. A detailed explanation and exemplification of the RIFs can be found in appendix C.

BF	RIF
BF1: Conducting normal operations	Training of ballast crew Experience and system knowledge Operating procedures Fatigue HMI Personnel selection Stress Condition of technical systems Communication Work practice Simultaneous activities Supervision Weather
Response to abnormal situations	Operating procedures Tools and equipment availability Experience and system knowledge HMI Fatigue Stress Communication Simultaneous activities Emergency drills Alarm management and responses Condition of technical systems Normal operations Knowledge of the situation Weather
Condition of technical systems	Operating procedures Training of tech. crew Training of ballast crew Experience and system knowledge Spare parts and equipment availability 3rd party inspection Routine inspections and testing Personnel selection Work practice Supervision Workload Condition of valves Condition of pumps Condition of logical and control unit Condition of structure

Table 5.4: Identified RIFs for further risk modeling in BBN

There are many RIFs and other scenarios, than the ones identified in this thesis, that also can influence and affect stability of a semi-submersible. Only the most frequent RIFs have been included here, this is based on the accidents and incidents that have occurred in the past. However, as stated by Haugen et al. (2007) there will often be many RIFs that may have an effect, but by selecting the 3-5 most important ones, good coverage is achieved in most cases.

From table 5.4 we can see that concurrent RIFs exits. A concurrent RIF is a RIF that influences more than one event. For example simultaneous activities influences BF1: Normal operation and BF2: response to abnormal situations. It is important that the RIF is represented only once in the BBN (Røed et al., 2009), this is to avoid dependency within the BBN. It is therefore necessary to identify all the concurrent RIFs to make sure they are modeled only once in the network. A note on concurrent RIFs is that for example training of ballast crew and training of technical crew are two independent RIFs, hence not concurrent. This means that they are treated as two separate RIFs in the BBN.

5.5 Comments

This chapter explained how technical, human and organizational factors are understood and used in this thesis. Further, a comprehensive list of all major accidents and incidents have been compiled and used in the identification of accident scenarios and as initiating causes for hazardous events. MTO-analyses have been performed for some accidents where the causes were rooted in all of the MTO factors. As a result of the identification of causes, a list of the most common RIFs have been established. This list will be used in the next chapter when the BBN is modeled. It is interesting to notice how this RIF identification analysis compares to the results of the RNNP (2014) survey. These two analysis were done simultaneously and hence not influenced by each other, and the results are very similar. Both analyses emphasizes the importance of competence and knowledge for the crew, HMI problems, maintenance and inspections. In addition, both analyses recognizes that most of the problems are rooted in organizational factors.

The main focus in this thesis is the operational issues regarding loss of stability and buoyancy of semi-submersible units. This means that only the events that affects stability is considered. Evaluation of the consequences beyond loss of stability or buoyancy, such as evacuation and loss of life, have not been treated in this analysis. This is an important and related topic that is recommend for further research.

The selected RIFs are considered as the root causes for events that can lead to loss of stability. As a comparison to the RABL program, that was conducted in the late 1980's, the RIFs listed in table 5.4 are more focused on root causes, whereas RABL focus more on technical and operational factors (Standing, 2003). RABL report no. 2 (Østby et al., 1987) notes that the history of ballast system failures includes numerous examples where human operational failures have caused significant loss of buoyancy, but does not consider human error as an initiating event (Standing, 2003).

One of the conclusions in the RABL project is that human maloperation, combined with a single component failure was probably the most critical combination of failure events (Østby et al., 1987). The final recommendations suggested that efforts should be made to identify system failures that might lead to critical ballast operator errors (Standing, 2003). It was also considered important to prepare procedures and establish a sound understanding of how to handle system failures during critical operations (Standing, 2003).

From the accident investigations presented in this chapter it is clear that the recommendations given by RABL more than 25 years ago are still valid today. By utilizing the BBN approach to describe the risk of loss of stability and buoyancy, it is possible to describe root causes in a more refined way than the RABL project could do. In this way, a more thorough risk analysis with focus on technical, human and organizational factors can be performed.

Chapter 6

Modeling of Stability Risk

In this chapter a model of the proposed BBN will be presented. The rationale behind the model, assumptions and simplifications are discussed. The quantification process is also explained and exemplified. The model is implemented into two different software tools for quantitative analyses. Last, some general comments about the model and the modeling process is presented. A more thorough evaluation is given in chapter 7.

In the development of a BBN to model stability risk the most applicable level of modeling is on a macro level [1]. This model will then treat stability in a general picture. More specific modeling may be required for the sub-systems or sub-tasks encountered in ballast operations. The challenge is then that this model has to fulfill the requirements of both being reasonable complete and the same time practically usable, which means to balance two conflicting requirements, but above all, it has to fit the purpose (Øien, 2001a). The purpose of this model is to describe the operational risk level of a semi-submersible with regards to stability.

Øien and Sklet (2001) states that it seems to be an increasingly intrusive problem to say something about how the safety or the risk level is developing in the North Sea, both for individual installations and for the industry as a whole. Øien and Sklet (2001) also claims that if the risk level is not systematically monitored during operations, then we cannot say anything about how the risk is developing, not whether it increases or decreases, and we can definitely not say anything about how much it increases or decreases. The model presented in this chapter address this issue by suggesting a framework that can be used to estimate the development the operational risk level, and also give a quantitative interpretation of the development.

The RNNP (2014) survey found that 55.5% of the persons asked claimed that marine systems is an area of risk analysis that does not get the attention that it requires. One representative from an engineering company said that "ballast and bilge is not as hot as process – where the values are created" (RNNP, 2014). More attention have been placed on hydrocarbon leaks, than on marine systems in the past. This view is also expressed by PSA, which states in the RNNP

[1] Please refer to chapter 4.3 for the definition of the different levels

(2014) report that it is necessary to increase the attention and status to marine systems. The method presented in this chapter is a suggestion for how to answer the statements raised by PSA and the industry.

6.1 Structure of the Bayesian Belief Network

The proposed BBN in this thesis is built on the defined barrier functions and the RIFs identified in chapter 5.4. The BBN is first modeled separately for each barrier function, then a combined model is presented. It is believed that this is a structured way of presenting the RIFs and illustrates how the different RIFs influences the risk of failure for the barrier functions. Description of RIFs can be found in appendix C

The nodes in this network are color coded. The colors represents factors and events and are set up in the following structure:

Yellow:	Organizational factors
Green:	Technical factors
Blue:	Human factors
Purple:	Non controllable factors
White:	Clusters for grouping related RIFs
Orange:	Status of a barrier function
Red:	Stability condition

Since the BBN consists of three separate parts with a number of concurrent RIFs (i.e. the same RIF influences more than one barrier function), the complete model presented in chapter 6.5 should be regarded as the core of this model.

6.2 Normal Operations

From investigations it has been seen that failure to conduct normal operations is a contributing factor to incidents and accidents. The node normal operations refers to any situation that is initiated by factors that should have been avoided by conducting operations in line with regulations and guidelines. Figure 6.1 shows a BBN with the identified nodes that can contribute to the failure of normal operations.

Figure 6.1 is based on investigation of incidents and accidents, as described in chapter 5. The rationale behind this model is that all controllable factors (such as training, operating procedures and communication practice) can have weaknesses that in some cases can lead to events that results in hazardous situations. An example of this is Scarabeo 8. This incident would probably not occur if the control room operator would have the required experience to perform ballasting operations.

Figure 6.1: RIFs affecting normal operations

The “communication”, “supervision” and “work practice” nodes are included here to control how human factors are working, with regard to slips, lapses, mistakes and violations as discussed in chapter 5.1.2. Communication is of particular interest when looking at how the development of risks are treated. According to Turners “man-made disaster” theory single persons or parts of the organization often knows about risk developments. The challenges lies in communicating and correcting these risks (RNNP, 2014). Problems with communication can arise when many different actors with different experiences are present, or with personnel from different countries with different cultures works together. RNNP (2014) also states that it is necessary that the control room *team* works well, and have good cooperation relations. These nodes are yellow, representing organizational factors, this is because it is the responsibility of the organization to make sure the human factors are functioning correctly. An argument for why these are not represented as human factors lies in results presented in Lotsberg et al. (2004), where data from a study by Matousek and Schneider (1976) shows that the following human errors could have been detected in time before an incident or accident:

- 32% by a careful review of documents by the next person in the process
- 55% by additional checks, if one had adopted the right strategies

Many errors are difficult to detect by self checks, therefore many errors can only be detected by independent additional checks or by independent analysis (Lotsberg et al., 2004). Matousek and Schneider (1976) concluded that 13% of all errors could not be detected in advance. This shows that even though we can say that slips, lapses mistakes and violations are human factors, the risk for the system lies in how well the organization is set up to detect and correct these errors.

The direct human factors “fatigue”, “stress” and “experience”, represented as the blue nodes, are personal characteristics of the crew. One can argue that these are also organizational factors because it would be an organizational responsibility to design tasks that reduces stress and fatigue, and to train the personnel so that they gain the required experience and knowledge. However, as people can gain different experiences from the same training sessions, and people handle stress and fatigue in different ways, these nodes are attributed to human factors in this model.

“Training” and “experience” are important factors. According to RNNP (2014) 26% of the respondents in the survey said that lack of competence is the most important factor that can cause incidents with marine systems. A concern was expressed, especially by offshore crew, that familiarization to unit specific systems is a part of the training that is often limited. The familiarization process includes learning the control room systems and other technical solutions, how the work is organized and get to know the colleagues. This is especially a challenge in today’s market where scarcity of qualified personnel is a concern for all companies in the industry. The turnover rate is high, due to the lack of qualified personnel. This means that the personnel holds their positions for a shorter time, and often gets promoted with less experience than the situation was a few year ago (RNNP, 2014). This development is believed to contribute to increasing the major accident risk, as it is a valid assumption to say that the lack of experience affects the ability to avoid and handle critical situations (RNNP, 2014). This is supported by evidence from the survey, where 70% believed that lack of experience involves an increase in risk of major accidents (RNNP, 2014).

HMI is concerned with how well the technical systems and human factors work together. The RNNP (2014) survey found that 44.4% of the industry experts believes that marine systems (ballast and DP-systems) are easy to understand and use whereas 25.9% thinks these systems are difficult to use. Accident investigations have shown that factors in the form of poor design of work space and HMI, in terms of colors and lighting etc. are root causes in marine systems incidents (RNNP, 2014). This combined with the state of the technical system, represented as the barrier function “condition of technical system”, are believed to be the only two technical factors that could disrupt normal operations. The only RIF that cannot be categorized into either of the factors is the weather. This is obviously not possible to control, and it has been an important facto in many incidents and accidents. The weather RIF includes all the environmental effects that can be expected offshore, such as wind, waves, current, temperature etc.

Investigations have shown that some event sequences starts out as a failure to conduct normal operations, then moves over to a failure to respond to abnormal situations scenario (see chapter 6.3). Examples of this include: Scarabeo 8, Ocean Developer and (...) 2010. This indicates that there could be a link between normal operations and respond to abnormal situations. This is further treated in chapter 6.5.

6.3 Response to Abnormal Situations

Response to abnormal situations includes any situation that is not experienced on a regular basis, and that could lead to harm if not properly treated. This could be for example unintentional filling of tanks and void spaces, collision with ships and other objects, or unintended water migration within the hull. Common for these situations is that they must be treated in a correct manner to avoid the situation to escalate.

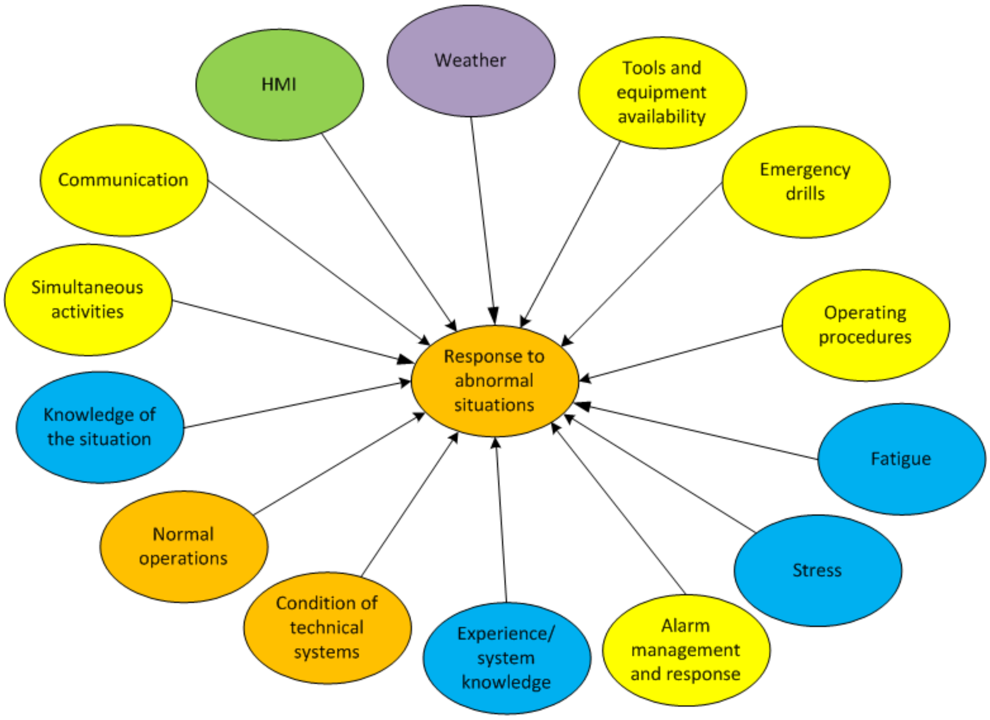


Figure 6.2: RIFs affecting response to abnormal situations

In order to treat these situations a set of RIFs have been identified. These RIFs take a general view of the response scenario, focusing on the root causes. This means that the RIFs covers general concepts such as experience and system knowledge, equipment availability, and training, as opposed to specific factors such as what to do in the event of unintentional water filling. This is done in order to make the model as general as possible, so that it covers most scenarios. Another reason for why RIFs are as general as possible is that it is easier to find indicators and measure these generalized RIFs.

Figure 6.2 illustrates the BBN covering the response scenario. According to investigations done in chapter 5, the failure of this barrier function is the most frequent scenario that leads to incidents and accidents. The Ocean Ranger disaster is an example of a failure to respond situation. This accident had weaknesses in almost all the RIFs shown in figure 6.2.

The nodes “knowledge of the situation” and “alarm management and response” represents how the operating personnel are informed about the situations and how easy information is obtainable. In the Ocean Ranger accident the crew had no functioning indicators of what was going on and how their actions affected the situation. And in the P-36 accident 1723 alarms were triggered, and there were no system in place to prioritize these alarm entries or aid control operators in addressing the overwhelming number of alarms (NASA, 2008). Both these nodes have a bit of technical, human and organizational factors in them, but for this BBN “knowledge of the situation” is considered as a human factor, and “alarm response” is an organizational factor. The reason for this choice is that in “knowledge of the situation” human interpretation would be the dominating decision factor, whereas in “alarm management and response” procedures and priority can and should be decided in advance.

“Emergency drills” are not mentioned in any of the accident investigations. However, it is the personal belief of the author that drills have a direct and important effect on the state of the emergency preparedness, and in turn this affects how well response to abnormal situations are treated. “Tools and equipment availability” was an issue in the Ocean Ranger accident, and this does not only refer to the tools that are needed, but also tools that are not need or intended to be on board. In the Ocean Ranger accident there were some bras rods on board that were used to manually override the ballast system during testing and approval at the ship yard (NASA, 2011). Not only did the rods remain on board after testing, they were still installed in the ballast control unit, such that the personnel believed that their function was to open and close valves during electrical failure (NASA, 2011). This caused confusion due to the lack of system knowledge and enabled the crew to override the system in a fatal way.

6.4 Condition of Technical Systems

Failure to maintain technical systems is found to be a contributing factor in some of the incidents and accidents investigated in chapter 5. The condition of technical systems scenario in this thesis refers to situations where the technical systems are not functioning and hence cannot perform its tasks. The role of technical systems is obviously important in stability operations. Without functioning equipment stability operations could be next to impossible. Most technical systems have some kind of redundancy, or manual backup alternatives that increases the reliability of the systems. However, even though the technical systems functions as intended, it is found in chapter 5 that the human and organizational factors behind the systems are often the factors that fails the most with regard to situations that have the potential to become serious.

Figure 6.3 illustrates the RIFs that influences the condition of this barrier function. It can be observed that 8 out of 12 of the RIFs are human or organizational, and only 4 are technical

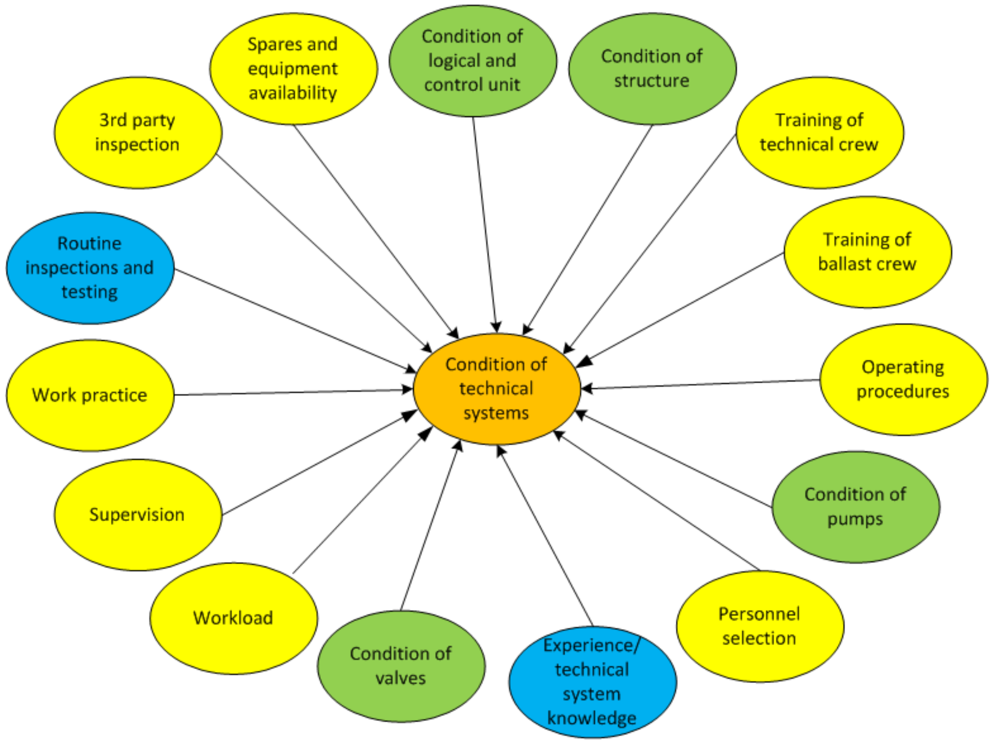


Figure 6.3: RIFs affecting the condition of technical system

RIFs. This shows that human and organizational factors are important for technological factors to work. A study of two technical factors, valves and watertight doors, was done by Arnhus (2013), based on results from the RNNP project (RNNP, 2012). This study showed that valves were malfunctioning in 0.50% of the inspected cases, and watertight doors did not function as intended in 0.35% of the cases. This can be incorporated into the RIFs "condition of valves" and "condition of structure" respectively. However, even with such a high failure rate, it has not been any incidents with accident potential, solely due to these technical failures. Organizational or human factors are often the initiating or escalating factor in the accidents investigated in chapter 5.

The "routine inspection and testing" and "3rd party inspection" nodes are similar, but handle two different cases. "Routine inspections and testing" refer to how well and often routine inspections and testing are conducted. One must here take into account how humans can do mistakes, violations, slips and lapses. The "3rd party inspection" refers to how inspections are conducted, documented and followed up. The name "3rd party" is more of a description to distinguish this node from the "routine inspection", than an actual 3rd party. It could refer to the next person in the process, supervisors or in fact a 3rd party such as classification societies or law enforcing agencies.

The role of maintenance is also addressed in the RNNP (2014) survey. The questions are related to anchoring systems, but some aspects can be used as an indication to ballast systems. In the survey 41% answered that lack of maintenance, inspections and condition monitoring are the most frequent causes of failure, and 37% answered lack of competence and experience. Even though these results are for anchoring systems, they still suggest that these are areas that may be should have a focus in ballast systems as well.

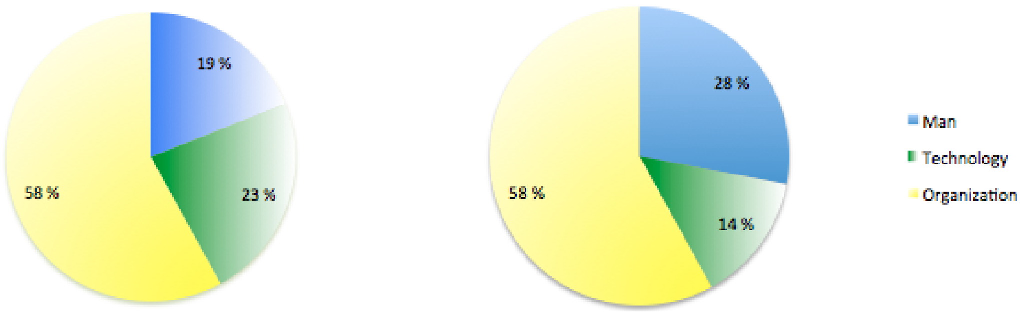
The reason for why both training of technical and ballast crew is part of the condition of technical systems is that the handling of the system is done by the ballast crew, and wrongful handling can cause errors or failures to the system.

6.5 Complete BBN for Stability Operations

The core of this thesis is the BBN presented in figure 6.4. This network illustrates how the RIFs influences the barrier functions which again influences the loss of stability of a semi-submersible. The three BBNs presented in chapter 6.2 to 6.4 are combined into one network. The strengths of combining the three networks are to be able to analyze scenarios that are affected by the failure of more than one barrier function. An example of this is the Thunder Horse incident where a failure to respond to abnormal situations, combined with technical errors produced the resulting incident. To make the analysis more understanddable the RIFs have been grouped into smaller clusters. This is inspired by the factor model presented in chapter 4.4.2 and developed by Haugen et al. (2012). This clustering of RIFs does not only contribute to clarity, but it also makes the quantification process considerably easier. This is due to the exponential growth of conditional probabilities to the amount of parent RIFs.

In combining the networks, all concurrent RIFs are identified and represented only once in the network, and the condition of d-separation is also fulfilled when analyzing the BBN with regards to the center node. The BBN is modeled with the RIFs on the outer perimeter, and nodes representing the barrier functions in the middle circle and the "stability condition" is placed in the center. From the figure it can be observed how "normal operations" have a causal influence over "response to abnormal situations", and that "condition of technical systems" have a causal effect on the functioning of the two other barrier functions. This is a probabilistic causality, meaning that if A happen then B may happen, as explained in chapter 3.1.1. The fact that "condition of technical systems" may influence both of the other barrier functions shows that it is important to have a functioning and reliable system. On the other hand, it is interesting to notice that only 5 out of 27 RIFs in the complete network represent technical factors, and more than half of the RIFs are organizational factors. This suggests that the root causes for maintaining stability of a semi-submersible is rooted in organizational factors. A comparison to the RNNP (2014) study shows similar percentage distribution of root causes between human, technical and organizational factors in figure 6.5. It is interesting to notice that these two studies were done simultaneously, meaning that they are not influenced by each other.

Figure 6.4: Complete BBN including all RIFs



(a) – Research by author (b) – Research by RNNP (2013)

Figure 6.5: Distribution of human, technical and organizational factors as root causes for loss of stability

To make use of this BBN as a risk analysis tool, it is assumed that the RIFs can capture the real world by assigning them a state on the scale $a - f$. There are no connections in the BBN that leads to dependencies among the RIFs, and there are no RIFs that leads to conditional independence that do not hold for real world scenarios. This means that the BBN satisfies the conditions for being a BBN, so the question is: how well does the RIFs describe the real world, and is this BBN suited for risk analysis? This question is further evaluated in chapter 7.

6.6 Quantification and Probability Calculations

So far the BBN has illustrated a qualitative description of the risk. For quantitative risk analysis the nodes must be quantified with a conditional probability table (CPT). An algorithm for assigning CPTs is described in chapter 4.5. Other algorithms also exists, some more mechanized than others. The reason for using this specific method for quantification purposes is that it was initially intended for use with offshore risk analysis, and it simplifies the quantification process while maintaining the flexibility needed (Røed et al., 2009).

The amount of conditional probabilities to be assigned is large, take the BBN in figure 6.2 as an example. With 14 nodes, each with six states, the number of probabilities that must be established is[2]:

$$p_n = m^{n+1} = 6^{14+1} = 470\ 184\ 984\ 600 \tag{6.1}$$

It goes without saying that manually assigning more than 470 billion probabilities for only a small section of the complete BBN would be impossible. The RIFs have therefore been grouped into clusters to reduce the amount of parents, and to make the BBN more intuitive. To further reduce the work load, some way of automating the process is required. The algorithm can then be incorporated in an excel spread sheet, MATLAB script or similar methods. A simple MATLAB

[2]For reference and explanation of this equation, see equation 4.1 on page 37

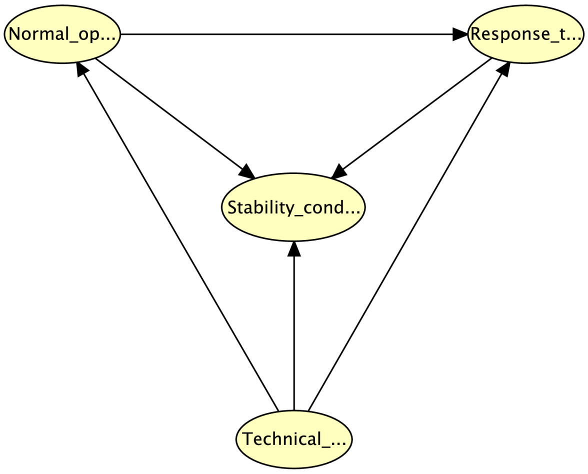


Figure 6.6: Part of the complete BBN selected for analysis with HUGIN

code is included in appendix D to illustrate how to do this for a node of three states with two parents.

6.6.1 Analyzing the Risk

In order to analyze the risk, find the likelihood of failure and to update the beliefs about the risk level, the BBN with associated CPTs must be implemented into a bayesian network software tool. There are a number of different software tools available, such as HUGIN and GeNIe. The generalized stepwise procedure for these tools is to:

1. Add the nodes
2. Select the states for each node
3. Add links (arrows) between the nodes
4. Input the CPT

This works well for smaller networks, for large networks it may be useful to use the open source gRain package for R (Højsgaard, 2012; R Development Core Team, 2011). This package allows the user to write the BBN in code, rather than graphically developing the BBN.

For illustrative purposes a part of the network, see figure 6.6, is analyzed with the use of HUGIN Lite. This is a free version of the HUGIN software that allows the user to analyze small networks. The drawback with using the Lite version is that there is a limitation to how many nodes and states that can be used. Therefore, only the middle circle, and center node of the complete network is analyzed with the use of HUGIN. In addition, in stead of six states, $a-f$, only three states, $a-c$ will be used. In chapter 6.8, a full implementation of the BBN in GeNIe is presented. The HUGIN analysis is thoroughly explained, and all accompanying CPTs are presented.

The first step is to develop the BBN, by inserting the nodes, specifying the possible states for each node and drawing the links between the nodes. The network in figure 6.6 includes the same dependencies and links as the middle circle in the complete network in figure 6.4. A check of the network must be performed to confirm that the d-separation criteria is fulfilled and that there are no circles in the network. Both point are in order for this network.

The next step is to assign conditional probabilities by use of the previously described algorithm. The resulting CPTs are given in tables 6.1 to 6.4. For nodes without parents the conditional probabilities must be assigned based on expert judgement or statistical data. For the case of the maintenance node, these probabilities are assigned by the author of this thesis, based on personal beliefs. The maintenance node does not have any parents, and hence the probability table is developed manually. This is shown in table 6.1. The states $a-b-c$ represents condition good, average and bad respectively.

State	Probability
a	0.3
b	0.65
c	0.05

Table 6.1: CPT for the technical node in figure 6.6

For the normal operations node, the resulting CPT is shown in table 6.2. To develop these results the input values are $R = 1.5$ (chosen by subjective belief of the author) and since the only parent node is the maintenance node, the weight is $w_m = 1$. The state of the normal operations is given in the first column, and this is conditioned on the state of the maintenance, given in the first row.

Maintenance	a	b	c
a	0.786	0.154	0.039
b	0.175	0.691	0.175
c	0.039	0.154	0.786

Table 6.2: CPT for normal operations node in figure 6.6

The response to abnormal situations node has two parents. This means that the state of the response is conditioned on the state of the normal operations (given in row one) and the state of the maintenance (given in row two). For this calculation the input values are $R = 1.5$ and $w_{normal} = 0.4$ and $w_{maintenance} = 0.6$ (chosen based on subjective belief of the author).

Normal	a			b			c		
Maintenance	a	b	c	a	b	c	a	b	c
a	0.786	0.377	0.240	0.525	0.154	0.087	0.437	0.114	0.039
b	0.175	0.509	0.324	0.389	0.691	0.389	0.324	0.509	0.175
c	0.039	0.114	0.437	0.087	0.154	0.525	0.240	0.377	0.786

Table 6.3: CPT for response to abnormal situations node in figure 6.6

The center node represents the stability condition, and this is conditioned on the three surrounding nodes. With three parents the number of probabilities to be determined is $p_n = 3^{3+1} = 81$. The resulting CPT is shown in table 6.4. We can see how the tables increase in size when more parent nodes and states are added. The input for this calculation is $R = 1.5$ and $w_{normal} = 0.3$, $w_{response} = 0.3$ and $w_{maintenance} = 0.4$.

Maintenance	Response	Normal	a	b	c
a	a	a	0.786	0.175	0.039
a	a	b	0.598	0.328	0.073
a	a	c	0.541	0.297	0.163
a	b	a	0.598	0.328	0.073
a	b	b	0.377	0.509	0.114
a	b	c	0.324	0.473	0.240
a	c	a	0.541	0.297	0.163
a	c	b	0.324	0.437	0.240
a	c	c	0.240	0.324	0.437
b	a	a	0.525	0.389	0.087
b	a	b	0.310	0.564	0.126
b	a	c	0.262	0.477	0.262
b	b	a	0.310	0.564	0.126
b	b	b	0.154	0.691	0.154
b	b	c	0.126	0.564	0.310
b	c	a	0.262	0.477	0.262
b	c	b	0.126	0.564	0.310
b	c	c	0.087	0.389	0.525
c	a	a	0.437	0.324	0.240
c	a	b	0.240	0.437	0.324
c	a	c	0.163	0.297	0.541
c	b	a	0.240	0.437	0.324
c	b	b	0.114	0.509	0.377
c	b	c	0.073	0.328	0.598
c	c	a	0.163	0.297	0.541
c	c	b	0.073	0.328	0.598
c	c	c	0.039	0.175	0.786

Table 6.4: CPT for the loss of stability node in figure 6.6

After determining and implementing the CPTs in a software tool, the overall risk can be determined, and changes in the risk can be estimated easily. A screenshot from the HUGIN program is shown in figure 6.7. From this analysis, given the CPTs above, it is found that it is about 60% probability that the stability condition is is in state *a*, or in other words a good condition. Conversely, it is found that the probability of the stability condition being in state *c* is about 10%.

One of the major advantages of using BBN in risk analysis is the possibilities of updating the belief about risk by giving evidence into the analysis. In figure 6.8 a screenshot taken from HUGIN is shown. Evidence is here provided that the state of normal operations is in state *c*, meaning

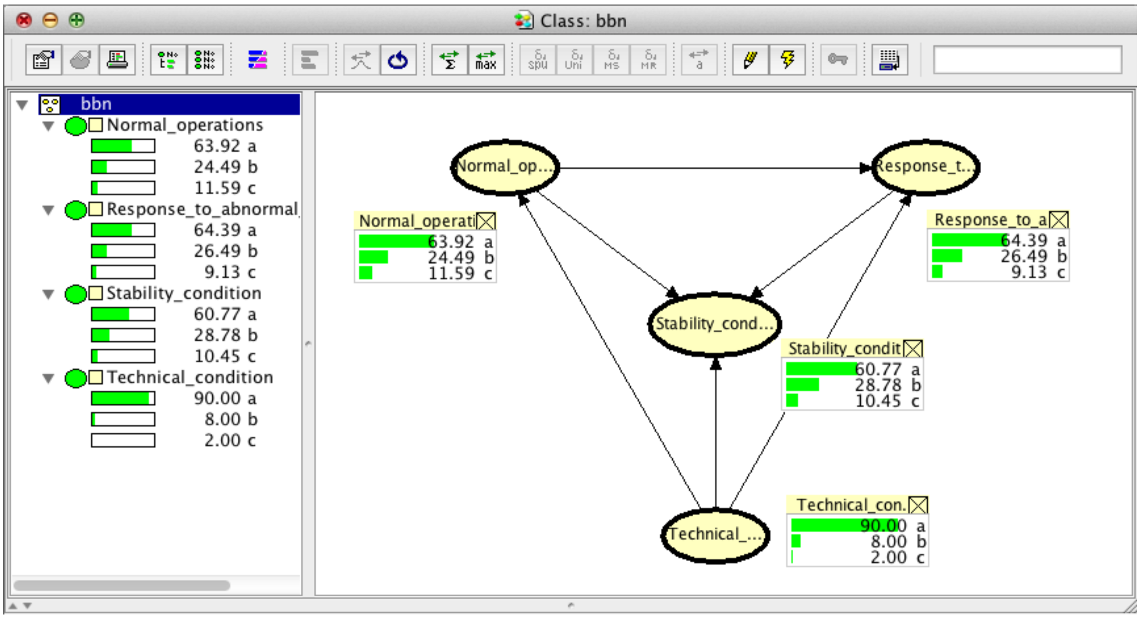


Figure 6.7: Screenshot from HUGIN with results of the analysis

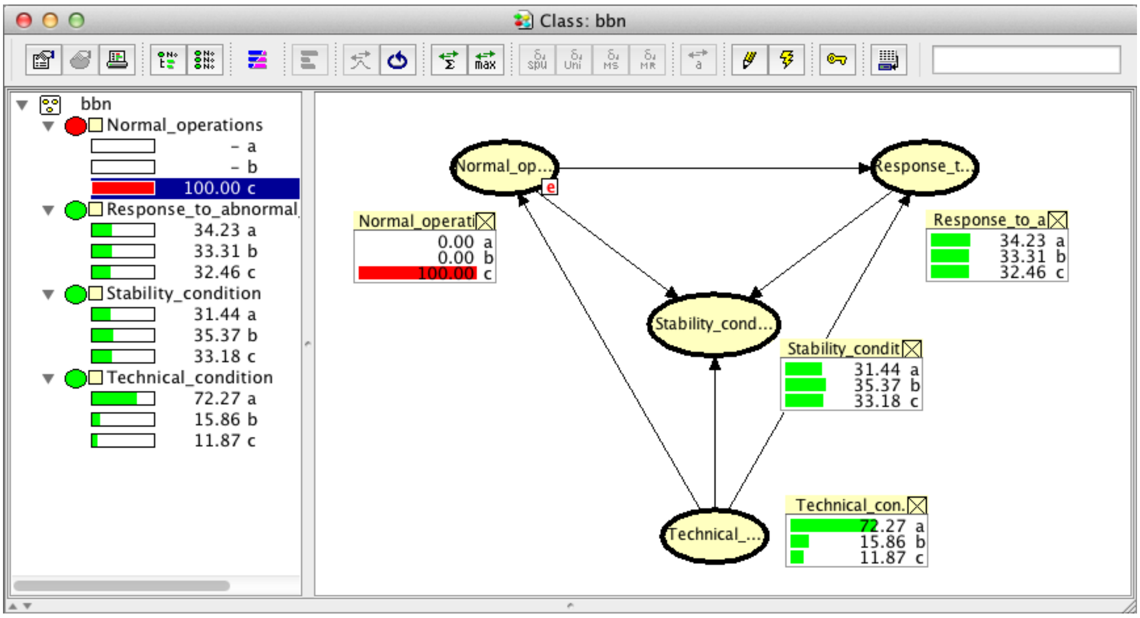


Figure 6.8: Screenshot from HUGIN with results of the analysis, given evidence

that normal operations are conducted in a worse than average manner. For the stability condition, it is now clear that this node has about 33% probability of being in state c, compared to 10% when evidence was not provided.

Giving evidence is the same as instantiating the nodes. One or more nodes can be instantiated at the same time. Updating the analysis by instantiating nodes gives a real time update about the change in risk. One important thing to notice is that when nodes are instantiated, the CPTs are not changed. The only change is the conditioned probabilities given the instantiated nodes (Charniak, 1991).

With HUGIN and other software tools it is possible to do a range of different analyses, for example finding the most likely combination of states. Other possibilities is to get specific probabilities for a combination of states given evidence.

Now that the risk is analyzed, a question to be raised is: what does it mean to be in the different states? For example, the analysis showed that for the stability condition being in state c has a 10% probability. This is obviously not the probability of experiencing a loss of stability and in worst case capsizing and sinking the semi-submersible. The analysis only shows the probability of being in a state that is less than average. For calculation of the probability of having an accidental event with regards to loosing stability we must consider the center node as a binary node and use the formulas explained in chapter 4.5.3.

From the analysis in figure 6.7, the probability of each node being in each state $a-c$ is determined. This information is used in the calculation of the event loss of stability, and it is summarized in the table 6.5.

P_{ik}	Normal	Response	Maintenance
a	0.6392	0.6439	0.900
b	0.2449	0.2649	0.080
c	0.1159	0.0913	0.020

Table 6.5: Probability of node i being in state k

To determine the probability of the event loss of stability, we use equation 4.4 given on page 40, this is repeated below.

$$P_j = P_{basis} \sum_{i=1}^{n} w_i \sum_{k=a}^{f} P_{ik} Q_{ik} \qquad P_j \in [0,1] \tag{6.2}$$

The weights, w_i are the same as used above $w_{normal} = 0.3$, $w_{response} = 0.3$ and $w_{maintenance} = 0.4$. The basis probability, P_{basis}, is difficult to determine since these accidents does not happen very often and are often conditioned on some very specific events that may not be modeled in this analysis. However, Kvitrud (2013) states that the observed accident frequency world wide where the unit sank or had a list of more than 17° is about $27 \cdot 10^{-4}$ per platform year. This is based on accident statistics from year 2000 to 2013. This number will therefore be used as the basis probability for the calculation of accident risk. This probability is based on eight reported accidents in 13 years, so the uncertainties associated with this number is of course a big disadvantage. The lack of conclusive data is a general problem when looking at statistics for major accidents, but since this is the number available to us we need to work with this. The result should then be treated as an indication of the risk, rather than a firm conclusion.

The values of Q_{ik} are given in table 4.3, but because these values are intended for a six-point scale, the table is amended slightly. Table 6.6 shows the new adjustment factors for the three-point scale. This table is based on the TTS states given in table 4.3, the only changes is that the original states b, d and e are removed and the remaining states are named a, b and c respectively.

Parent RIF state	Adjustment factor Q_{ik}
a	0.1
b	1
c	10

Table 6.6: Adjustment factors for basis probabilities

The probability of experiencing an accident with loss of stability can then be calculated. From equation 6.2 it is found that the probability of loosing stability per platform year is:

$$\begin{aligned} P_{\text{loss of stability}} &= 0.961 \cdot P_{basis} \\ &= 0.961 \cdot 27 \cdot 10^{-4} \\ &= 25.9 \cdot 10^{-4} \end{aligned} \tag{6.3}$$

As seen from equation 6.3 the probability of loosing stability is slightly reduced. This corresponds well to the results from the HUGIN analysis, which showed that the most likely combination of states is when all nodes are in state a. When all nodes are in a state above average it is reasonable that the probability of loosing stability decreases compared to the world average.

6.7 The Model

The proposed model is built on previous research and existing models. The core of this model is the BBN and the quantification method. The completed model can then be used for operational risk analysis and it is also proposed to use this model as a decision support tool and as a tool for observing how the risk level develops. In the following paragraphs it will be given a short description of how existing models have been used to develop this model. Common for most of the existing models is that they all focus on hydrocarbon leaks, and they approach this problem in different ways. It is believed that by using parts of and concepts from the existing models, a new model for marine systems can be developed. This is illustrated in the following and applied to operational risk analysis of stability operations.

The structure of the BBN is inspired from the RIA methodology. RIA is a method used for decision support and its structure is built to show how risk reduction strategies influences RIFs, and then how these RIFs affects the risk contribution to specific accident types. At last all the risk contributions adds up to the total risk. The differences between “the model” and RIA is that in stead of modeling how specific risk reduction strategies influences the risk level, a state is given to the RIFs, and this state must be updated if a risk reduction strategy is implemented. Rather than modeling how RIFs influences the risk contribution to accidents, “the model” determines how the state of the RIFs influences the barrier functions. The state of the barrier functions then adds up to the total risk level. The advantage of using this structure is that it is possible to assess the effect on the total risk whenever a RIF is changed.

The method for quantifying the results is based on the HCL algorithm. This is a method combined from the BORA and TTS projects and outlined in chapter 4.5.2. This method simplifies the assignment process of the CPTs without loosing the flexibility that is needed to properly reflect the phenomena that are being considered (Røed et al., 2009).

Just as the ORIM project, “this model” is also aimed at developing a method for updating the information about the risk level of an offshore installation. This is done by monitoring the root causes through risk indicators. The difference between ORIM and “this model” is that ORIM focuses only on organizational factors and it is updated about every third month. “This model” should be updated more frequently, and this can be achieved through only a few simple steps. The main similarity between these models is that the purpose of both models is to monitor how the risk level is changing, and to determine a quantitative measure of the change.

“This model” is distinguished from the other models first of all by the area of application. There has been limited previous research in the field of risk analysis of stability operations (Vinnem et al., 2006b), therefore this model should be regarded as a starting point for further research. However, by utilizing models and methods that are already published and accepted by the industry, it is hopefully easier to accept the model presented here.

6.8 Using the Model as a Decision Support Tool

This model is developed with the main aim of analyzing the operational risk. Once developed, this model has the advantage of being easily updatable, meaning that it can be updated on a day by day basis to estimate the current risk level with regards to stability of the semi-submersible. The proposed use of this model is for stability crew and onshore support staff to monitor the risk level, by conditioning the RIFs on the available evidence of the day.

To further explain, a complete model has been developed by the use of the GeNIe software tool. All the RIFs, nodes and barrier functions are modeled with six states $a - f$, and the center node "stability condition" is modeled with three states, *good, average* and *bad*, respectively. The reason for only using three states at the center node is because it is believed to be easier for the user to interpret the results in this way. All the nodes can be instantiated by supplying evidence of the condition of the RIFs. If the condition is unknown, no evidence has to be provided. The result from the analysis is a probability distribution of finding the center node in any of the three states. The weights and R-values used in the development of the CPTs, are given in table 6.7. These input data should be determined by expert judgment, for this example case the input values are determined by the author based on personal beliefs about how the RIFs will influence the risk. The total amount of individual probabilities needed to complete this BBN analysis is 181 170.

Now, to make use of this result, a predefined acceptance criteria should be established. This criteria should define the actions that must be taken, based on the probability distribution of the center node. For example, if there is more than 30% probability of finding the center node in state *bad*, then immediate action should be taken to reduce this probability. Or, another criteria could be that more than 25% probability of being in state *bad*, requires close attention by control room operator of the stability of the semi-submersible until the risk level is reduced to a state that is as low as reasonably practicable (ALARP). The percentage criteria presented above are only intended as an example, the real criteria must be established when the model is developed. These criteria must be calibrated to fit the model, based on the input parameters used in developing the CPTs. Further research on the acceptance criteria is recommended.

Comparing this model to the factor model presented in chapter 4.4.2, the same principle applies with regards to RIFs on the soft and sharp end of the system. This means that some of the RIFs are quite stable and does not need to be updated on a daily basis. These RIFs includes for example operating procedures, personnel selection, HMI etc. Other RIFs are frequently changing and must be updated daily, for every work shift or even on an hourly basis (i.e. weather). The assignment of states for the RIFs can in some cases be challenging or influenced by the subjective belief of the person doing the assignment process. To reduce the possibilities of personal interference it is suggested that a set of risk indicators should be developed to describe the risk in an objective way. The ORIM model (Øien and Sklet, 2001) proposes a way of describing organizational risk indicators. An example of risk indicators can be "ratio of employees with formal training" or "average number of years of experience". Similar risk indicators should be developed to describe the RIFs in this model. Here we can see the advantage of using general and generic RIFs, it is easier to establish indicators, and hence it is easier for the crew to choose the best state to describe the system.

The purpose of this model is to use it as a decision support tool. It can be difficult for the ballast operations crew to know when an operation is conducted within an accepted level of risk or not. This tool, with corresponding acceptance criteria, can help the management to

Node	Weight	R-value
Pre conditions	$w_{\text{Personnel selection}} = 0.3$	2
	$w_{\text{Supervision}} = 0.15$	2
	$w_{\text{Work practice}} = 0.25$	2
	$w_{\text{Training}} = 0.3$	2
Planning and coordination	$w_{\text{Simultaneous activities}} = 0.3$	1.8
	$w_{\text{Operating procedures}} = 0.45$	1.8
	$w_{\text{Communication}} = 0.25$	1.8
Activity	$w_{\text{HMI}} = 0.2$	2
	$w_{\text{Fatigue}} = 0.2$	2
	$w_{\text{Stress}} = 0.2$	2
	$w_{\text{Experience}} = 0.2$	2
	$w_{\text{Weather}} = 0.2$	2
Emergency preparedness	$w_{\text{Tools and equipment}} = 0.15$	2
	$w_{\text{Alarm response}} = 0.2$	2
	$w_{\text{Emergency drills}} = 0.35$	2
	$w_{\text{Knowledge of the situation}} = 0.3$	2
Technical condition	$w_{\text{Valves}} = 0.35$	2.5
	$w_{\text{Structure}} = 0.0.15$	2.5
	$w_{\text{Logic and control}} = 0.2$	2.5
	$w_{\text{Pumps}} = 0.3$	2.5
Maintenance work	$w_{\text{Experience}} = 0.3$	1.5
	$w_{\text{Training}} = 0.2$	1.5
	$w_{\text{Spares and equipment}} = 0.1$	1.5
	$w_{\text{Workload}} = 0.15$	1.5
	$w_{\text{Operating procedures}} = 0.25$	1.5
Inspections	$w_{\text{Routine}} = 0.6$	1.5
	$w_{\text{3rd party}} = 0.4$	1.5
Normal operations	$w_{\text{Cond. of tech. systems}} = 0.25$	2
	$w_{\text{Pre conditions}} = 0.3$	2
	$w_{\text{Planning and coord.}} = 0.2$	2
	$w_{\text{Activity}} = 0.25$	2
Response to abnormal situations	$w_{\text{Normal operations}} = 0.15$	2
	$w_{\text{Cond. of tech. systems}} = 0.15$	2
	$w_{\text{Planning and coord.}} = 0.15$	2
	$w_{\text{Activity}} = 0.3$	2
	$w_{\text{Emergency preparedness}} = 0.25$	2
Cond. of tech. systems	$w_{\text{Pre conditions}} = 0.15$	1.5
	$w_{\text{Technical condition}} = 0.3$	1.5
	$w_{\text{Maintenance work}} = 0.3$	1.5
	$w_{\text{Inspections}} = 0.25$	1.5
Stability condition	$w_{\text{Normal operations}} = 0.3$	2
	$w_{\text{Response to abnormal sit.}} = 0.4$	2
	$w_{\text{Cond. of tech. systems}} = 0.3$	2

Table 6.7: Weight and R-values used in the development of the CPTs for the complete BBN model. These values are based on subjective beliefs of the author.

decide what to do and when to take actions to reduce the risk level. Another use of this model is to anticipate changes in the risk level in the future. This is explained by an example where maintenance work is planned on the pumps in the ballast system: When maintenance work is executed, one pump is taken out of operation, reducing the RIF “condition of pumps” to state d and the operation is expected to take four hours. In addition the weather is forecasted to be at state e in two hours. The model can then be used to predict whether or not the maintenance operation is safe, based on the available evidence on the state of the pumps and the weather, and other RIFs.

Furthermore, the model can be used to simulate “what if” scenarios. This can be done by keeping all the RIFs at a constant state c, and varying one or a combination of RIFs to analyze how the risk level is affected. If, for example, it is found that the RIF “stress” affects the risk level to a high degree, then more focus should be placed on stimulating stress in practice drills.

The advantage of this model (once it is developed) is that it is easy to use and it does not require any previous knowledge in risk analysis. Simply, insert the available evidence and compare the result to a predefined acceptance criteria. The development of the model is however a more challenging task. The analysts should have some knowledge in risk analysis and BBN, and a team of experts must be used to determine the weights of each RIF and the associated R values. In addition, the acceptance criteria and appropriate risk indicators must be established to make this a useable model for operational risk analysis.

6.8.1 Case Study

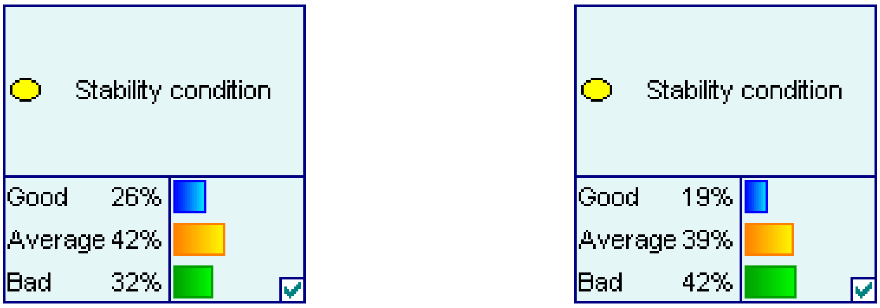
In the interviews conducted with the RNNP (2014) study, one of the persons described a scenario that could be experienced, and that causes challenges for the control room operators. The scenario was as follows (Vinnem, 2014a): During normal operations, only one crew member is present in the control room and the other crew member is “somewhere” doing “something else”. Even though the guidelines to the Activity Regulations, section 31, indicates that there should be at least two persons in the control room (PSA, 2014b), this is seldom the case. The one crew member that is present in the control room is then responsible for the ballasting operations. The scenario starts out with a counter ballasting operation to compensate for some heavy lifting, for example lifting of casing pipes onto the platform from a supply vessel. During this operation a ballast valve breaks down and no immediate redundancy is available, causing the ballasting operation to stop. It was indicated that this causes a lot of stress for the control room operator. The question now is, how does these events affect the risk of loosing stability?

To analyze this scenario, the states are given to the affected RIFs is shown in table 6.8. With no additional information about the remaining RIFs, these are not instantiated. The analysis results in a probability of being in state *bad* of 42%, compared to 32% without evidence.

RIF	State	Description
Stress	f	It was indicated that this was one of the most stressing scenarios encountered, and hence estimated to be state f.
Simultaneous Activities	d	A situation where two operations that affects stability are conducted simultaneously.
Work Practice	d	The practice of not following the guidelines to the activities regulations, by only employing one control room operator
Valves	f	A breakdown in a component with no redundancy causing the ballasting operation to stop is considered to be state f

Table 6.8: Evidence provided to the model to analyze the case study

Figure 6.9 shows how the probability of being in the three states changes when evidence is provided.



(a) No evidence

(b) Evidence provided

Figure 6.9: Probability distribution of center node with no evidence and evidence according to case study

Figure 6.10 shows the BBN and the specified RIFs that are instantiated. All the RIFs that are not given any evidence have a probability distribution equal to the communication RIF as illustrated in figure 6.10. The resulting probability distributions for the three barrier functions in the middle circle can be used to estimate the probability of loosing stability according to equation 4.4 given on page 40. Again, the result here is as compared to the world average.

$$\begin{aligned} P_{\text{loss of stability}} &= P_{basis} \sum_{i=1}^{n} w_i \sum_{k=a}^{f} P_{ik} Q_{ik} \\ &= 2.85 \cdot P_{basis} \\ &= 2.85 \cdot 27 \cdot 10^{-4} \\ &= 7.70 \cdot 10^{-3} \text{ [per platform year]} \end{aligned} \tag{6.4}$$

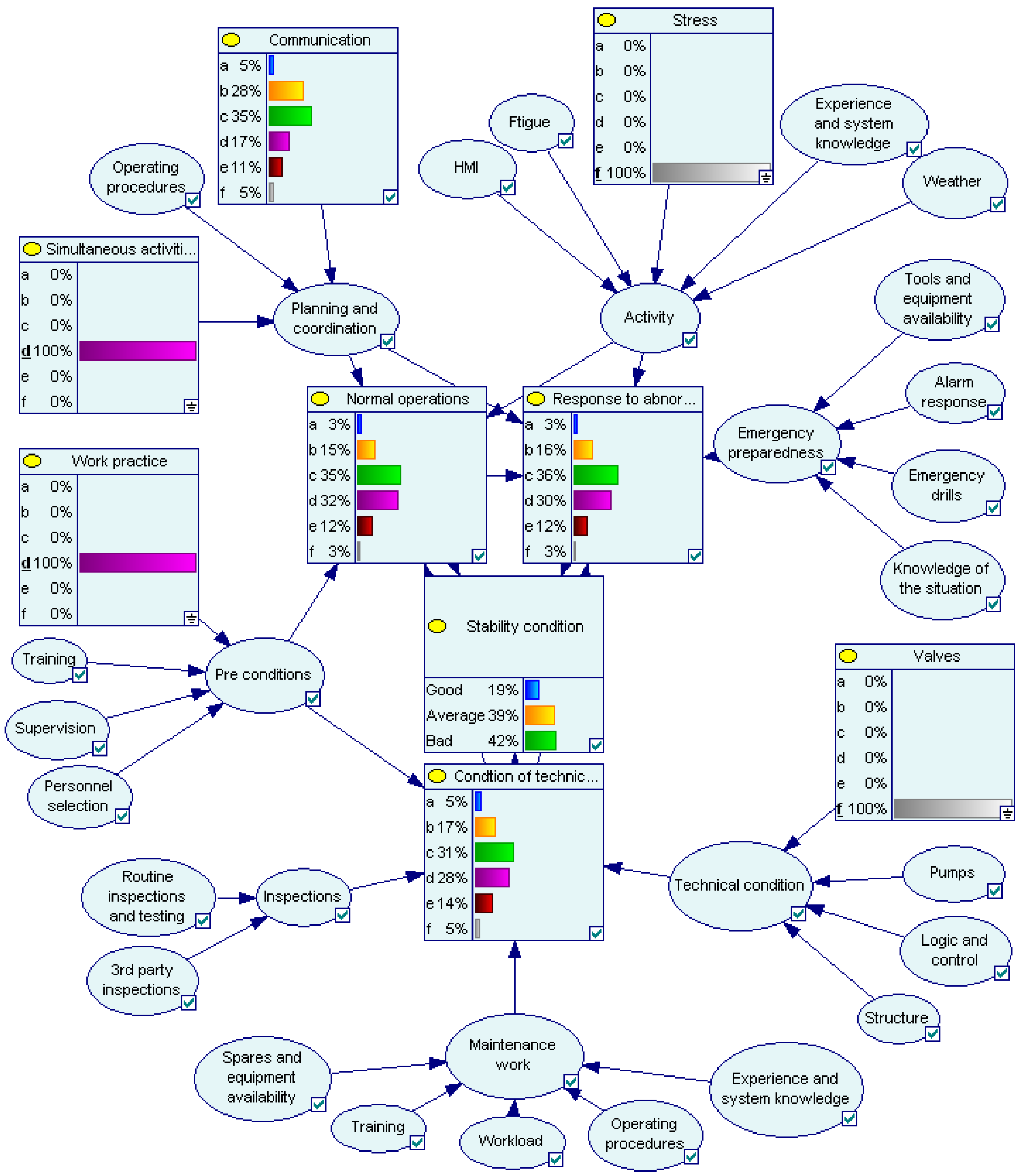


Figure 6.10: Screenshot from GeNIe illustrating the analysis when evidence is provided

From equation 6.4 we can see that the probability of loosing stability is almost three times higher when the situation explained above occurs. This result is very high, and this is due to the evidence that is used. Since only four nodes were instantiated, and these were all in a condition worse than average, this will cause the result to be far worse than what it realistically is. If all the other RIFs also were instantiated the result would be better, but since the condition of the other RIFs are unknown in this case, they are not taken into consideration in this analysis. However, it may be reasonable to assume that the other RIFs are in an average state, c. An analysis was performed to find the probability of loss of stability with the RIFs as specified in table 6.8, and all other RIFs in state c. The result was $P_{\text{loss of stability}} = 2.12 \cdot P_{basis} = 5.73 \cdot 10^{-3}$ per platform year. This is a more valid result, because all RIFs are instantiated, hence reducing the uncertainties involved. The assumption here is that all other RIFs are in state c, which is unknown in our case. This does however show the strengths of how BBNs are capable of handling uncertainties, but the result must also be treated thereafter. When some RIFs are uninstantiated, it is clear that the result from the model will be conservative, this is shown as a higher probability of loosing stability.

A similar analysis has been done for the cases studied in the MTO analyses in chapter 5.2.1. The $P_{\text{Loss of stability}}$ is given in table 6.9, and screenshots from the GeNIe analysis can be found in appendix E. These analyses are based on the information provided by the accident reports, and the author has used subjective interpretation to assign RIF states based on the available information. The column of “only affected RIFs instantiated” shows the probability of loosing stability when only the RIFs that were not in an average state are given evidence, whereas the “all RIFs instantiated” shows the probability when RIFs without a specified state are given evidence of being in state c.

	Probabilty for loss of stability	
Unit	Only affected RIFs instantiated	All RIFs instantiated
Ocean Ranger	$3.48 \cdot P_{basis} = 9.40 \cdot 10^{-3}$	$2.84 \cdot P_{basis} = 7.68 \cdot 10^{-3}$
Thunder Horse	$3.55 \cdot P_{basis} = 9.57 \cdot 10^{-3}$	$3.13 \cdot P_{basis} = 8.45 \cdot 10^{-3}$
Scarabeo 8	$3.33 \cdot P_{basis} = 8.98 \cdot 10^{-3}$	$2.85 \cdot P_{basis} = 7.70 \cdot 10^{-3}$
(...)	$2.83 \cdot P_{basis} = 7.66 \cdot 10^{-3}$	$2.26 \cdot P_{basis} = 6.10 \cdot 10^{-3}$

Table 6.9: Results from BBN analysis of MTO cases

As for the case study analysis, the probabilities in the MTO cases are also quite high, and a similar argumentation must be considered for these cases. By providing evidence for the remaining RIFs, assuming that they are in an average condition, c, the probabilities of stability loss are reduced. It is interesting to notice that the Thunder Horse accident results in a higher probability than the Ocean Ranger, even though the Ocean Ranger was more severe in terms of loss of lives and assets. In a way we can say that the Ocean Ranger (and Alexander Kielland) accidents saved the Thunder Horse, due to new design regulations.

6.8.2 Comparison of Results with Statistics

Accidents involving loss of stability does not happen very often, and hence the basis for statistical analysis is limited. There have been some attempts to determine a statistical figure for loss of stability and some of these attempts are given in table 6.10. From the table it is clear that it is difficult to establish a single probability for loss of stability.

Frequency	Location	Time period	Description	Source
$2.5 \cdot 10^{-3}$	NCS	1977-2011	Total loss	Vinnem (2014b)
$1.3 \cdot 10^{-3}$	Worldwide	1970-2001	Total loss	Lotsberg et al. (2004)
$2.7 \cdot 10^{-3}$	Worldwide	2000-2013	Unit sinking or list > 17°	Kvitrud (2013)
$1.9 \cdot 10^{-3}$	Worldwide	1980-2011	Unit sinking or list > 17°	Kvitrud (2013)
$1.5 \cdot 10^{-3}$	UKCS	1990-2007	Unit capsize	Oil and Gas UK (2009)
$3.2 \cdot 10^{-3}$	UKCS	1980-2005	Unit capsize	HSE (2007)

Table 6.10: Statistics for loss of stability. All frequencies are measured as per unit years

The reason for why there are some differences in the frequencies given in table 6.10 are obviously due to the different in time periods and locations of which the statistics is based. However, it is also based on how accidents are classified. For example the P-36 accident may be classified as an explosion by some and as a stability accident by others. It can also be claimed that statistics from other parts of the world is not comparable to Norwegian conditions, due to differences in regulations and operating conditions. Furthermore, statistics based on old data may also be incomparable due to new regulations, for example it may be possible to assume that the Ocean Ranger and Kielland disasters may not occur today because of improved design regulations. Even so, one general conclusion can be drawn from this table, and it is that the order of magnitude is the same for all stability accidents worldwide.

The general concept of the BBN model presented here is that it modifies a general probability, given that some evidence is presented. The frequencies given in table 6.10 can all be used as basis probabilities. In the calculation of $P_{\text{Loss of stability}}$ in the case study, the basis probability used is the result from Kvitrud (2013). This is because it takes into account the most recent cases, and it fits with the requirements set by the Norwegian Maritime Directorate that the heel angle should never exceed 17°. However, as seen from table 6.10, this is one of the highest estimates for probability of stability loss.

The data given in table 6.10 must be considered as the average frequency in the industry, i.e. that all RIFs are in state c. But as the situations in the case study and MTO cases are not average, due to the RIFs that are given evidence of being in a state less than c, one should expect the result to produce a higher probability of loosing stability. The question then is: by how much should the probability increase? The case study gives two results, one where only the affected RIFs are given evidence and one where all RIFs are given evidence. It is not surprising that the result with all RIFs instantiated gives a lower probability than the one with only four RIFs instantiated because less uncertainties are involved.

Interpreting the results, either with or without all RIFs instantiated, still brings up the question of whether the modification factor is correct. The modification factor is the number that should be multiplied with the basis probability to obtain a modified probability for the loss of stability. For the case study when all RIFs are instantiated, $P_{\text{Loss of stability}} = 2.12 \cdot P_{basis}$, whereas the case where only the four RIFs are given evidence is $P_{\text{Loss of stability}} = 2.85 \cdot P_{basis}$. This means that the modification factor is either almost 2 or 3. This is quite an increase in probability of loosing stability. To determine whether these are reasonable results or not, an assumption is made that stability accidents are Poisson distributed. A Poisson distribution is also known as "the law of rare events", and it is good for describing events that occurs with a known average rate, and independent of the time since the last event (Ubøe, 2008). With a 90% prediction interval (P.I.), and with the raw data obtained from Kvitrud (2013), it is estimated from equation 6.5 that the 5% "worst cases" of stability accidents have a probability of loosing stability $> 8.1 \cdot 10^{-3}$ per unit year. In other words, the modification factor for the 5% worst cases should be greater than 8.1/2.70=3. In equation 6.5 $\hat{\lambda}$ refers to the average rate of stability accidents, and n is the average amount of semi-submersibles in the world during the time of which the statistics is based. A similar estimation was done by Vinnem (2014b), where it was found that the upper 95% limit is $9.8 \cdot 10^{-3}$ per unit year.

$$\begin{aligned} 90\%\ \text{P.I.} &= \hat{\lambda} \pm 1.64 \cdot \sqrt{\frac{\hat{\lambda}}{n}} \\ &= 2.7 \cdot 10^{-3} + 1.64 \cdot \sqrt{\frac{2.7 \cdot 10^{-3}}{250}} \\ &= 8.1 \cdot 10^{-3} \end{aligned} \tag{6.5}$$

It is not known where the case study would be on the scale from best to worst, but certain assumptions can be made. Since the RIFs are given state *c* or worse, we would expect the result to produce a probability higher than average. Furthermore, it was indicated that the described scenario is one of the most stressful scenarios encountered, but still possible to handle without loosing total control. This suggests that the case study should be somewhere in the middle, between average and the 5% worst cases. And by comparing the results from the case study and statistics we can see that the results fit, and are in the range of what should be expected.

Further, one can also argue that the Ocean Ranger and Thunder Horse accidents should be amongst the worst 5%, because it resulted in total loss and severe damage respectively. Comparing the prediction interval with the results in table 6.9 shows that it also fits here into the range of expected results. This shows that from a statistical point of view, the results obtained from the model are within the range of valid results. It is however still difficult to argue that the results are precise, due to the lack of statistical data in the generation of CPTs and the uncertainties involved in the basis probabilities from table 6.10.

6.8.3 Risk Reducing Measures

After a quantitative risk level has been established, and the result is compared to the criteria to evaluate whether the risk is acceptable or not, one may need to perform actions to reduce the risk. An obvious starting point is to take actions to increase the state of the RIFs that are in the worst conditions. However, that may not be possible. Let us say that the weather is bad, or a valve is broken, these RIFs may be impossible to change or repair at any given time. Another option is then to perform a sensitivity analysis to determine which of the RIFs that contributes the most to the risk, and then apply proper risk reducing measures.

Figure 6.11 shows which RIF are most sensitive in the case study. The RIFs are arranged according to the brightness of the red color. The brighter the color, the more sensitive the final result is to a change in the RIF. The RIF that are instantiated will per definition not contribute more to the sensitivity, and are therefore grey in color. In the scenario of the case study we can see that the final result is most sensitive to a change in operating procedures. This means that to reduce the risk, a change in the operating procedures gives the greatest effect. This is of course only if the operating procedures are improved, a worsening of the operating procedures would result in a greater increase in risk, as compared to for example a worsening of the RIF workload.

Table 6.11 shows the sensitivities of the remaining RIFs in the case study scenario. The calculation is performed by GeNIe, when the “Stability condition” node is selected as the target. The numbers express the change in posterior probability of the target when the RIF state is changed (Wang et al., 2002). The numbers illustrates the minimum, maximum and average change on the stability node, when the RIF is changed. Whether the change is minimum or maximum depends on the state RIF is changed to, but the expected change to the stability node will be an increase of 0.012 percentage points when the Operating procedures are changed.

RIF	Max	Average	Min
Operating procedures	0.05	0.012	0
Routine inspections and testing	0.052	0.011	0
Training, Personnel selection	0.045	0.011	0
Weather, Experience, Fatigue, HMI	0.047	0.01	0
Pumps	0.045	0.009	0

Table 6.11: Sensitivity analysis of the most influential RIFs in the case study scenario

The same sensitivity analysis can be preformed without inserting evidence. The result will then show which RIF that contributes most to the risk. Table 6.12 shows the five most and least sensitive RIFs in a general case where no evidence is provided. The RIFs are arranged from most to least sensitive. This sensitivity analysis shows that the most influential RIF is the operating procedures. This also corresponds well to the accident analyses in chapter 5, which proved that operating procedures, or rather the lack of these procedures, were an important part of the event sequence leading to the accident. It must be mentioned that this sensitivity analysis is

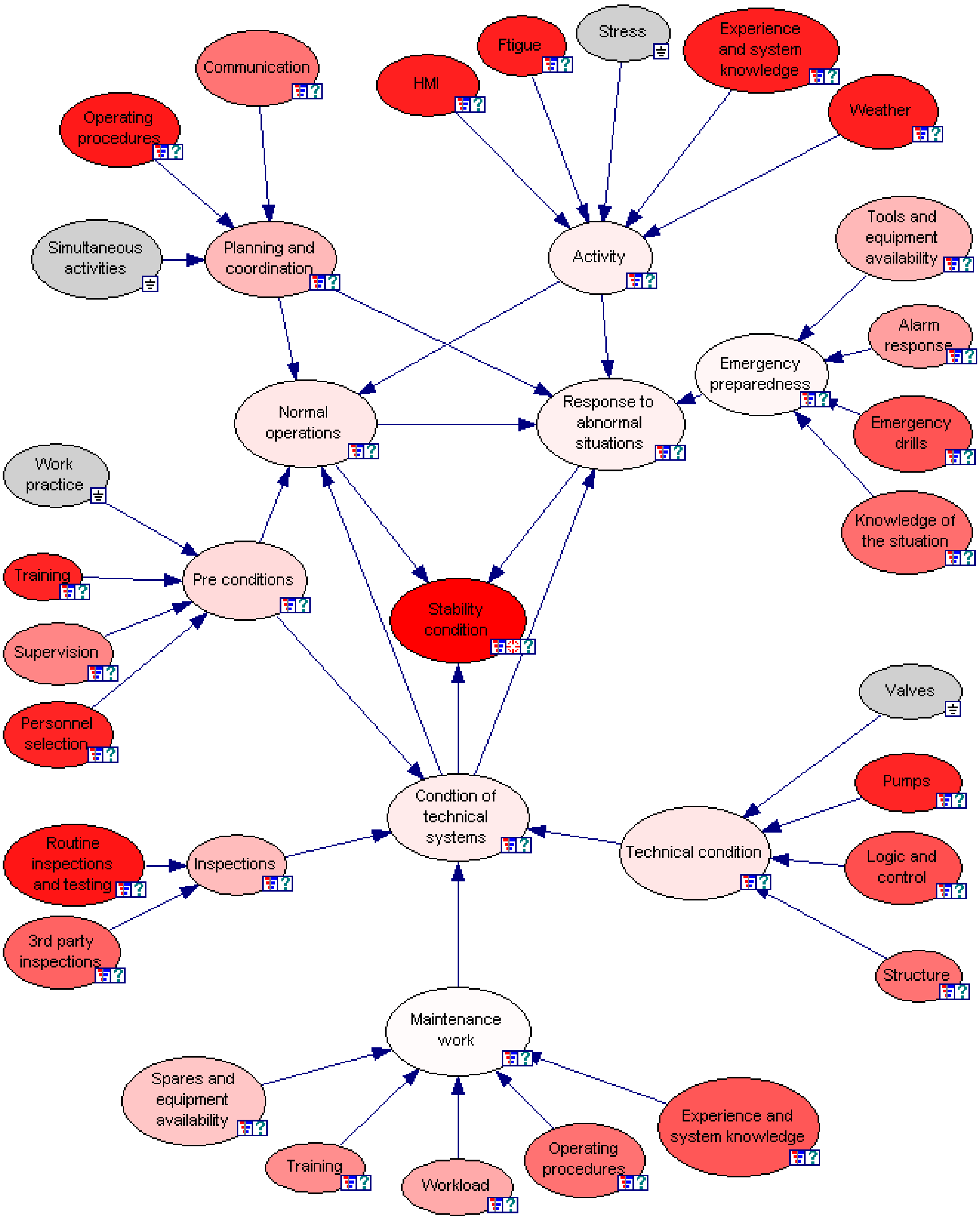


Figure 6.11: Sensitivity analysis of the case study

based on the CPTs that were developed on subjective judgment by the author. The result would probably be different if the CPTs were developed by expert judgment. This means that in the real world, operating procedures may not be the most important RIF influencing the stability of a semi-submersible.

RIF	Max	Average	Min
Operating procedures	0.047	0.011	0
Routine inspections and testing	0.047	0.010	0
Training, Personnel selection	0.041	0.010	0
Valves	0.037	0.009	0
Weather, Experience, Fatigue, HMI, Stress	0.033	0.008	0
...			
Alarm response	0.014	0.004	0
Structure	0.013	0.003	0
Workload	0.012	0.003	0
Tools and equipment availability	0.010	0.003	0
Spares and equipment availability	0.008	0.002	0

Table 6.12: Sensitivity analysis of the most and least influential RIFs on the stability condition, in a general scenario

A more in-depth sensitivity analysis can be preformed for each RIF to evaluate how sensitive the result is to a change to a specific state of the RIF. An example is given for the RIF operating procedures, as shown in table 6.13. This table shows quantitative influence of each state of the RIF on the specific state of the stability condition. This analysis assumes that all other RIFs remains the same.

Stability condition:	Good	Average	Bad
a	0.0369	-0.0042	-0.0328
b	0.0327	$-2.028 \cdot 10^{-5}$	-0.0327
c	0.0027	0.0113	-0.0086
d	-0.0226	0.0043	0.0269
e	-0.0306	-0.0115	0.0421
f	-0.0329	-0.0143	0.0472

Table 6.13: Sensitivity of the state of operating procedures on the stability condition

6.9 Comments

The BBN model has been developed on the basis of incidents and accidents that have happened. The accidents have been grouped into three categories that refers to the barrier functions for maintaining stability, as defined in this thesis. To each category a set of RIFs have been identified. These RIFs are identified as the most common causes for the accidents and incidents that were analyzed in chapter 5. A basic assumption for all BBNs is that the probability distribution of a node is only dependent on the parent nodes, meaning that all relevant

RIFs must be identified in order to get a comprehensive picture of the risk. It is obviously not possible in practice to take all possible RIFs into account for the analysis, but it is the belief of the author that the most frequently occurring and most influential RIFs are taken into account in the BBN presented.

The complete BBN in figure 6.4 shows that more than half of the RIFs are yellow, meaning that they reflect organizational factors. This is not surprising because the foundation for functioning technological and human factors is a functioning organization. In addition, as discussed in chapter 5.1.4, the organization is on the equifinality side of the scale. This means that there are many ways in which an organization can achieve its output. Further, organizational factors does not necessarily need to fail as implied by Reasons swiss cheese model, meaning that the factors themselves may be working, but the interaction between them can cause hazardous situations. This implies that the study of organizational factors should have a great focus. These are arguments for why the majority of the RIFs in the analysis should be organizational factors.

Even though most RIFs are assigned to either technical, human or organizational factors in the BBN in this thesis, it is debatable whether or not they are in the “correct” group. The factors represent the subjective belief of the author, and it is recognized that certain RIFs, for example fatigue, can be both a human and an organizational factor. One could also argue that some RIFs may belong to all three groups. Take the condition of a valve as an example. This is at first glance seen as a technical factor, however, it may be influenced by maintenance work (human factor), and the maintenance work can again be influenced by organizational factors such as time pressure or lack of maintenance routines.

The quantification process in this analysis has certain strengths and weaknesses. As mentioned before it is an easy method for establishing the CPTs. The only input to the calculation is a weight that determines how important one parent RIF is compared to other parent RIFs, and a R-value that determines the distribution of the probability of the different outcomes. However, since this method does not take into account statistical data, the result cannot be an exact description of the real world. It is therefore difficult to argue that the CPT assignment algorithm can be used in an analysis to find the probability of an event or to determine the risk level. Pettersen (2012) states that one could, based on the assumption that the RIFs have an influence on the risk level, argue that the development of the calculated probability of an event, could say something about the trend in the actual development of the risk level.

If the analysis was based on real data, rather than on the assigned data, the probability of an accidental event could be established with a higher degree of confidence. For example, let us say that the model was used to analyze the Scarabeo 8 incident, and that it was based on real data. From this analysis a good approximation to the probability of an accidental event could be obtained. However, if we were to analyze the same situation based the CPT assignment algorithm, we could not be as confident in the probability of an accidental event, but what we could do is to calculate the change in probability when the state of some RIFs are changed.

Take for example the nodes "training", "HMI", and "system knowledge and experience". In the Scarabeo 8 incident it was these RIFs that were in a rather bad condition at the time of the incident. Then we could calculate how much the risk is reduced in the model by employing trained and experienced personnel in stead. This is where the model should have been used as a decision support tool. Depending on the acceptance criteria and calibration of the model, it may have been revealed in advance that employing unqualified personnel would result in an unacceptable risk level.

Building this model and BBN networks in practice is somewhat more challenging than fault and event tree analysis. The first step is to master the BBN methodology, and understand the concept of conditional probabilities. When working with the amount of conditional probabilities that could be encountered in BBN analysis it is also important to treat the data correctly, so that it is conditioned on the correct set of nodes or evidence. The development of the CPT, either with or without the algorithm, requires the establishment of some kind of spreadsheet or script that can store and handle the data. Once the CPTs are imported into a software tool, and presented graphically, it is reasonably easy to determine risk levels and insert evidence to condition the analysis, and it is in this part of the analysis where BBN reveal its real advantages. The interpretation of the results is worth mentioning again. If the analysis shows that there is a 10% probability of being in the worst state, this does not necessarily mean that an accident is going to happen with a 10% probability. Being in the worst state increases the probability of experiencing an accident, but by how much is more challenging to say. Attempts to determine the specific probability for loosing stability have been done by applying the binary node formula, equation 4.4. This is however based on a high degree of assumptions and uncertain statistical data. The BBN model, combined with this equation, results in a modified risk estimate. This risk estimate is based on average conditions in the industry, P_{basis}, and modified to account for installation specific conditions. These conditions are implemented into the calculation through giving each RIF a specific state.

Chapter 7

Evaluation of the BBN Method used in Risk Analysis

This thesis is built based on the statement that BBN is a better than traditional risk analysis methods to analyze non-deterministic causal relationships, such as human and organizational factors, and hence a more suitable way to analyze operational risk. An important question to be raised in this context is: how can we say that the statement above is true? This chapter seeks to evaluate and discuss this statement. In addition, a discussion and evaluation of the development, validity and use of the model is performed.

7.1 Development of a BBN

A BBN approach to risk analysis is a twofold process. The first step is to build and quantify the model, the next step is to analyze the risk, by providing evidence. The first step is by far the most challenging step in terms of work load and the competence required. In the development of a BBN, some basic assumptions are made (Vinnem et al., 2012):

1. All relevant RIFs are identified
2. The RIFs are "measurable"
3. The relationship between the RIF and the risk is known

This list of assumptions literally fails on the first item. It is practically impossible to guarantee that all relevant RIFs are identified. A more precise statement is that the most important RIFs that are believed to be relevant should be included. The measurability of the RIFs refers to how the RIF should be quantified in the analysis. In order to make use of the RIF in a calculation, it must be possible to assign a state to it, based on some measurable value. In general it is suggested to use one or more indicators to measure the state of each RIF. Indicators can be

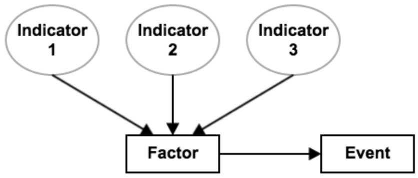


Figure 7.1: Relationship between indicators, factor and event. Source: based on Haugen et al. (2012)

modeled directly into the BBN model, as illustrated in figure 7.1. This gives the opportunity to instantiating the RIFs by using the indicators (Pettersen, 2012).

However, in this thesis another method is chosen to incorporate indicators into the BBN. The suggested method is to develop a set of predefined tables to confer when choosing the states for each RIF. An example of such decision criteria is presented in table 7.1. This is for the RIF weather, and similar decision criteria should be developed for all the other RIFs in the BBN. The important thing to bear in mind when determining the criteria for the states is that they should be graded compared to the industry as a whole.

RIF: Weather	
State	Criteria
a	Wind speed: < 2 m/s Wave height: $H_s < 0.2$ m
b	Wind speed: 1-2 m/s Wave height: $H_s < 0.5$ m
c	Wind speed: 2-10 m/s Wave height: $H_s < 1$ m
d	Wind speed: 10-20 m/s Wave height: H_s = 1-5 m
e	Wind speed: 20-40 m/s Wave height: H_s = 5-15 m
f	Wind speed: > 40 m/s Wave height: $H_s > 15$ m

Table 7.1: Example of decision criteria for weather RIF

The reason for choosing this solution, compared to the more fancy way of including the indicators in the BBN, is due to the complexity of the model, and the additional work required to develop CPTs. It is believed that this solution gives the same advantages, but with less modeling work. The disadvantage is that there are more documents to deal with, and that possible errors in reading the tables or instantiating the RIFs may occur.

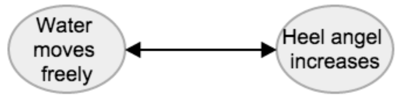


Figure 7.2: Cyclic connection in a BBN

A general limitation of a BBN is that it is unable to model factors that influences each other. This is best explained by an example. Consider the free surface effect, the semi-submersible can gain a heel if water is allowed to move freely. As more water moves, the heel becomes greater which agin causes more water to move. This causes a cyclic connection, which is impossible to model in a BBN.

7.1.1 Comparison of HUGIN and GeNIe

In the modeling of this BBN two software tools were used. HUGIN and GeNIe. These tools are very similar, both in the graphical interface and how to build a BBN. HUGIN is a renowned program, and the costs to obtain a full license for this tool is quite expensive. Therefore, in this comparison the HUGIN test is done by the use of HUGIN Lite, which is free of charge, but has some restrictions in terms of the allowed number of nodes and states in the BBN. GeNIe is on the other hand free, and has received wide acceptance within both academia and industry (GeNIe, 2014).

The most time consuming task when developing a BBN is the quantification of the nodes. Even for small networks the amount of conditional probabilities can reach thousands (Wang, 2004). With such a substantial amount of probabilities to handle, a good feature is that the software tool can easily import these data from other files, if necessary. For the case with quantifying the nodes in this BBN, Excel was used to run the quantification algorithms and the results were simply copied from Excel to GeNIe without problems. The HUGIN help manual states that this should be possible in HUGIN Lite as well (HUGIN, 2014), but the author could not succeed to do this in practice. Another option exists, and that is to convert the completed CPTs into a .dat file and import the file directly into HUGIN. This does however require knowledge in handling .dat files and a very specific structure of the file.

Both programs have similar graphical user interface, which is easy to understand and use. The output from the analyses can be given as numerical answer, or as a graphical interpretation with a variety of plotting tools. For the analysis conducted with the work of this thesis, no difference was found in the time it takes for running the analyses. Both programs used less than a second to complete the analyses.

7.2 Evaluation of the Quantification Method

The method for quantifying the CPTs is based on an assumption made by Røed et al. (2009) that a probability for a RIF being in a state that differs considerably from its parents' states should be smaller than compared to a state equal to its parents' states. For the quantification to be valid, this assumption must hold for the real world that is being analyzed in the BBN. Another important assumption is that the RIFs are only influenced by their parents. This means that all relevant RIFs, and connections between the RIFs must be identified before the quantification process begins, and hence as stated by Pettersen (2012), the quality of the model is therefore very important for how good the quantitative model becomes.

Røed et al. (2009) states that there are some weaknesses of this quantification model. Firstly, it is resource intensive, and secondly there are several simplifications in the method. However, the author of this thesis would agree to disagree to this statement. For the first part, the quantification process is resource intensive in the sense that risk analysts and experts must be summoned to conduct the development and judgements required to perform the analysis. But, as compared to a process of manually assigning all the conditional probabilities, this method is quite resource un-intensive. One can of course say that compared to other risk analysis methods this BBN model is still a resource intensive tool, but by saying this one would also imply that the benefits gained from using BBN is not worth the resources spent. For the second part of the statement, that there are several simplifications to this method, it is of course easy to say that "yes, this is a weakness". However, a certain degree of simplifications must be accepted in order to simplify the quantification process. The questions to be asked is then is: to what extent does the simplifications affect the accuracy of the results? This is a difficult question to answer, as there are no way of validating the results, in the sense that you can check the results are accurate relative to some true probabilities (Røed et al., 2009). The confidence in the model should be based on the fact that a team of experts are making the decisions. Experts can of course be wrong in their judgment, but this is a problem in all kinds of risk analyses, not only for BBN. A further evaluation of this question is done in the next chapter.

What should in fact be regarded as a weakness with this model is that it is to a small degree based on real data. This makes it difficult to argue that the model can be used to calculate the actual probability of an event (Pettersen, 2012). This means that it is difficult to find the actual risk level, however, by using this method it is possible to estimate the changes in the risk level. This is based on the assumption that the RIFs in the model have an effect on the risk level, and therefore says something about how the risk develops when the RIF state changes. Pettersen (2012) states that the calculated probability of an event can be seen as an indicator that summarizes the condition of the organization. In this way it is possible to say something about the trend in the risk level, which is difficult to determine if all the RIFs were considered individually.

In selecting states for the RIFs we can see from table 4.2 that there is a misalignment of the states (i.e. a and b better than average and d, e and f worse than average). This is because the existing safety level in the industry is so high that the potential for declining in the status is greater than the improvement potential (Aven et al., 2006). The treatment of this scale is also a source of error in the quantification process. There may be correlations between RIFs. The following example is taken from Røed et al. (2009), and refers to the small BBN illustrated in figure 4.5. Let us say that K refers to the competence of the personnel and L reflects the safety focus of the management and M reflects the safety focus of the personnel on the installation. If both K and L are considered to be in the best state a, the probability of M being in the worst state can be assigned and it will in most cases be a low value. Now, let us consider the opposite case where K and L is in the worst state f, what probability should then be expressed for M to be in the best state a? And should the probabilities in the two examples be equal? It is easier to believe that the two examples should have different probabilities, and that the probability in the example in the latter case should be lower than in the first case. Røed et al. (2009) states that this quantification process does not reflect such correlations between RIFs.

One issue that must be confronted when dealing with large CPTs is the amount of probabilities that is generated. The example on page 70 that showed the number of probabilities to estimated for a part of the whole BBN, found that more than 470 billion probabilities must be estimated. There is no problem in using the quantification process to perform such a generation, however the issue that presents itself is the capacity of the computer. A simple estimation gives that a table of 470 billion probabilities, stored as a float number with a precision up to six decimal places, will require 1750 GB of storage capacity. This is quite a lot of storage, and quite impossible for regular computes. It is however important to bear in mind the storage capacity, as the number of probabilities increases exponentially with the amount of parent RIFs. To reduce the storage requirements it is possible to store the numbers as other data types, reduce the amount of states or the amount of parent nodes. This problem is not treated any further in this thesis, but suggested for further research and as a note for analysts to keep in mind when designing BBNs.

7.2.1 Expert Judgement in Risk Analysis

The whole quantification process is based on the use of experts to determine the weights, w_i of the RIFs and the outcome distribution index, R. The weighing of the RIFs is an assessment of the effect (or the importance) the RIF has on the probability of the event (Vinnem et al., 2009). This is an assignment that should be based on the experts beliefs about how the probability distribution will change when the state of the RIF changes from a to f. All the weights that affects the same child RIF should then be normalized such that $\sum_{i=1}^{n} w_i = 1$.

The R-value on the other hand says something about what the probability distribution should look like. Figure 7.3 illustrates how the R-value influences the resulting probability distribution in the CPT. In this case the BBN in figure 4.5 is analyzed to find the probability distribution when node M is in state j, given that both K and L are in state c. As we can see from figure 7.3, the assigned R-value clearly influences the probabilities generated by the quantification algorithm.

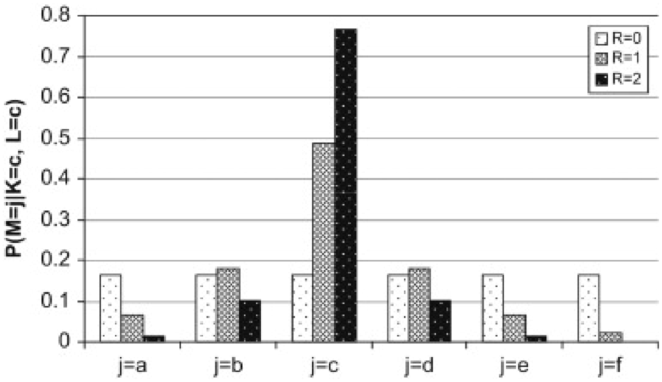


Figure 7.3: Example of probability distribution with different R-values. Source: Røed et al. (2009)

The above discussion suggests that the generation of CPTs is highly influenced by the judgment of the experts, even though it is a rather mechanized procedure as a whole. This brings us back to the question stated in chapter 7.2 about how the simplifications affect the accuracy of the model, or in other words how can we trust the results from this model? The simple answer that was given, was that the confidence of the model should be based on the experts that are making the decisions. The problem of expert judgment is that it is by definition a subjective measure. Hora (2009) states that because subjective probabilities are personal and vary from individual to individual and from time to time, there is no true probability that one might use as a measure of the accuracy of a single elicited probability. This means that expert judgments are vulnerable for errors.

According to Slovic et al. (1979), typical problems associated with experts, when judging risks, are (Skjong and Wentworth, 2001):

- Failure to consider all probabilities with respect to human error affecting technological systems
- Overconfidence in current scientific knowledge
- Insensitivity to how a technological system functions as a whole
- Failure to anticipate human response to safety measures

In order to reduce the potential errors in expert judgment, it is important to know about heuristics. Heuristics are used by people in everyday life and experts consulted when performing risk assessments (Skjong and Wentworth, 2001). Heuristics may be structured as follows:

- **Structural biases**: involves the situation in which individuals are influenced by the manner a problem has been structured before it is presented to them (Haimes and Lambert, 1999; Skjong and Wentworth, 2001)
- **Motivational biases**: occurs in cases where an individual has a stake in the outcome of an analysis (Skjong and Wentworth, 2001)
- **Representativeness**: probability is often evaluated based on the degree of representativeness or similarity to the prototype of a category (Glass and Holyoak, 1986; Skjong and Wentworth, 2001)
- **Availability**: involves basing judgments on the ease with which relevant instances can be retrieved from memory (Glass and Holyoak, 1986; Skjong and Wentworth, 2001). This means that strong associations to the event, leads to a conclusion that the event is frequent. How perceptually available a parameter is, may depend on the following factors (Skjong and Wentworth, 2001):
  - Distinctiveness
  - Ease of visualization
  - Obviousness
- **Anchoring**: is the phenomenon that subjects, when asked to estimate a probability, sometimes fix on an initial value and then adjust this value (Cooke, 1991; Skjong and Wentworth, 2001)
- **Simulation**: the perceptions or decisions are based on examples or scenarios that are constructed by the reasoner (Skjong and Wentworth, 2001)
- **Belief biases**: are biases to accept arguments that results in conclusions believed to be true, and reject arguments that results in conclusions believed to be false (Skjong and Wentworth, 2001)

The heuristics concept suggests some factors that may influence the accuracy of an expert judgment process. Some of these factors can be controlled, but errors may still occur, or as Bazermann (2006) states "professionals are not stupid, but they are human". Kirkebøen (2009) suggests three strategies for debiasing the results. (1) Taking an outsiders view, (2) Considering the opposite and (3) Make the decision in a group. These are strategies that can help in making the expert judgment less biased and should therefore be used. Skjong and Wentworth (2001), however, argues that point (2) is not alway applicable as opposite situations are not always symmetrical. Glass and Holyoak (1986) exemplifies this by stating that Poland may be perceived to be more like Russia, than Russia is to Poland (perhaps more valid in 1986 than today, but the example still shows how opposite situation may not always be symmetrical).

Making the decision in a group is recommended by Hora (2009). The size of the group can vary, but a suggested size is in the range of three to six or seven (Hora, 2009). The example that follows was described by Kirkebøen (2009), and shows how a group may give a better result than one single expert. In 1906, the scientist Francis Galton visited a cattle show where a bull was being exhibited. The visitors were invited to guess the weight of the bull, and a prize was put up for the best guess. The average guess was a weight of 1197 pounds, and the real weight was 1198 pounds. Most of the bets were far off from the real weight, but this example shows how a combination of independent estimates can improve the judgment (Kirkebøen, 2009). It is of course not suggested in this thesis that assembling a large group of experts will result in a good average answer, but this example illustrates that a group can reach a better conclusion than individuals on their own. This example is directly transferrable to the process where experts should decide the weights of the RIFs in the BBN model. Methods, such as the delphi method, have been developed to facilitate expert judgment in groups.

To answer the question of how we can rely on the accuracy of risk analyses that are based on expert judgment, the answer is that we must trust it, due to the lack of a better alternative. It is shown in this chapter that there are several ways for experts to be biased, but as long as one is aware of these biases, and the heuristic factors are controlled to the extent possible, an expert judgment made by a team of experts can result in reasonable conclusions. Skjong and Wentworth (2001) argues that risk assessment, even with the use of expert judgment, is at least better than the alternative of not having any assistance in the decision making process.

7.3 BBN as a Risk Analysis Tool

BBN is mainly seen as a tool allowing the analyst to exploit different information, deterministic or probabilistic, emerging from the real world, under the conditions of complex relations between a large number of variables (Trucco et al., 2008). Increasingly, BBN models are used for the construction of system reliability models, risk management and safety analysis based on probabilistic and uncertain knowledge (Khakzad et al., 2011). The ability of BBN models to handle uncertainty is one of the main reasons for using this model in risk analysis. The prior probabilities are updatable and based on evidence a higher degree of certainty can be achieved in the model. The posterior probabilities (the updated probabilities) are more specific to the situation studied and hence reflect the characteristics better (Khakzad et al., 2011).

Friis-Hansen (2000) states that the real advantage of a BBN is that the model may be built in a way that focuses on a causal relationship between physical phenomena. This results in a model that is easily understood by the involved parities. In a list format, Bayesian networks offer the following advantages over existing methods with respect to risk analysis (Friis-Hansen, 2000):

- Qualitative and quantitative variables can easily be combined in the same model
- Consistent dependence/independence statements
- Nodes are not restricted to binary states as is the case for fault trees

- Compact representation
- Insertion of evidence and subsequent updating of the model
- Identification of requisite and irrelevant information
- Sensitivity analysis

A downside of BBN is the exponential growth of the number the conditional probabilities and thus of the size of CPTs. However, as Friis-Hansen (2004) points out, neither Fault Tree Analysis (FTA) nor Event Tree Analysis (ETA) offer any better alternatives (Trucco and Leva, 2012). Another weak point of BBN is that there is no specific semantic to guide the model development and to guarantee the model coherence (Weber et al., 2010). This means that it is necessary to verify the models in accordance to the system reality. A BBN model is, on the other hand, based on causal relationships so that it shows explicitly the conceptual assumptions, hence it is easier for a third party to verify a BBN as compared to a fault or event tree.

7.3.1 BBN vs. Other Risk Analysis Tools

There have been developed many different tools for risk analysis. The most common are FTA and ETA. Although conventional methods have been used effectively for the purpose of risk analysis, they suffer limitations in their static structure and uncertainty handling (Khakzad et al., 2011). The use of BBNs in risk analysis provides a specific advantage with respect to other modeling approaches. This is because a BBN is structured as a knowledge representation of the problem, including the probabilistic dependence between the main elements of the model and their causal relationship (Trucco and Leva, 2012; Friis-Hansen, 2000).

BBN are similar to FTA in many respects, however, the distinct advantages making BBN more suitable for risk analysis than FTA, is the ability to explicitly represent the dependencies of events, updating probabilities and coping with uncertainty (Khakzad et al., 2011). A FTA is based on binary representation of events, which results in an efficient and exact method for calculation of probabilities of, for example, the failure of a safety barrier. In FTA it is also possible to consider dependencies between events, and to integrate different kind of knowledge in the form of technical, human and organizational aspects (Weber et al., 2010). However, there are multiple limitations of a FTA compared to BBN. First of all, a FTA can only consider one top event. In contrast, a BBN possesses the same capabilities as FTA, but has the advantages of a multi state variable modeling, and the ability to have several output variables in the same model (Weber et al., 2010). The use of multi state variables allows the BBN model to assess failures that have multiple consequences on the system.

In a FTA it is common to use minimal cut sets to find the importance of events. The equivalent procedure in a BBN analysis would be the determination of the most likely scenario. This is easily found by use of software, such as HUGIN. Khakzad et al. (2011) states that unlike minimal cut sets, the most probable configuration provides information of both occurrence and non-occurrence of primary events, and hence BBN can produce a more reliable measure of importance than FTA.

A fault tree can always be represented as a BBN, but BBN is not necessarily possible to represent in a fault tree. This is due to the multi state variables that can be modeled in BBN. A study conducted by Khakzad et al. (2011) analyses the common features of a BBN and FTA. The result was that both methods gave similar results for accident occurrence probability, but the BBN was able to update prior probabilities by taking new information into account. And the study concluded that a BBN in general has a more flexible structure than fault trees and therefore more useable to a wide range of accident scenarios. In addition, it was found that BBN is more suitable for real time accident analysis and for the design and evaluation of safety measures due to its ability for abductive reasoning and uncertainty handling. Bayesian networks may thus be seen as a unifying tool because of their large flexibility and modeling power (Friis-Hansen, 2000).

The compactness of a BBN makes it easier for a third party to verify that the dependencies are correctly captured, compared to several pages of FTA and ETA (Friis-Hansen, 2000). This is due to the causal representation of events. A fault and event tree, on the other hand, illustrates sequential dependent failures. This can be interpreted with regards to the swiss cheese model, where sequential failures of barriers may lead to a hazardous event. However, as described in chapter 5.1.3, organizational factors does not necessarily need to fail as described by the swiss cheese model (Mohaghegh and Mosleh, 2009). This implies that FTA and ETA may not be the best way to describe organizational factors. Following the same line of arguments, one can say that FTA and ETA are better at describing technical factors, as these factors usually have a sequential failure mechanism. The hybrid causal logic framework (HCL) utilizes the advantages of BBN to model organizational and human factors, and fault trees to model technical factors in a combined model. Hybrid methods are recognized as an effective way to deal with the multidisciplinary nature of organizational safety and corresponding assessment frameworks (Mohaghegh et al., 2009). The reason for why this method has not been utilized in the model presented in this thesis is further discussed in chapter 7.4.

Friis-Hansen (2000) states that the modeling power of traditional risk analysis methods such as FTA and ETA is clearly surpassed by that of bayesian networks. This view is also supported by other authors such as, but not limited to: Weber et al. (2010), Khakzad et al. (2011) and Trucco and Leva (2012).

7.4 Evaluation of "the model"

This model is developed as a response to the industry's need for a better tool for operational risk analysis for marine systems. PSA (2011b) states that it is necessary to initiate an ambitious investigation and development work with the goal of developing a better tool for controlling major accident risk. Furthermore, DNV (2014) states that most accidents results from inadequate operational safety. The model presented in this thesis is intended to treat major accident risk from an operational perspective. PSA (2011b) further states that a tool is needed to analyze, evaluate and understand the risk associated with large and small changes (organizational and structural changes on the one side to changes/deviations in plans for performing activities on the other side) in a better way than today's practice.

The work of PSA has for many years involved a great focus on barriers (PSA, 2011b). However, this model has omitted most of this specific barrier focus. The goal of this work has been to place emphasis on the factors that causes the accidents, rather than the factors that prevents accidents. The assumption here is that the risk can be described equally good by looking at the state of the root causes, as by looking at the state of the barrier elements. Another reason for why barriers are not included in this model is that this is intended as a general model, that can be used for a variety of different scenarios. This is also the reason for why a hybrid model was not developed. As described in chapter 7.3.1, the HCL methodology has some strengths that could have been useful in this model as well. However, it is believed that by including a fault tree in this model, the analysis becomes too specific and sequential, hence loosing its flexibility. Further arguments for not including barriers in the model is that most operators would already have a system in place to monitor the state of the existing barriers. This information could then be used to determine the state of the RIFs, therefore indirectly representing the barriers, without explicitly modeling them in the BBN.

A limitation of this model is that the state of the center node is based on the probability distribution of the barrier functions. This means that in the scenario where half of the RIFs are in state a, and the other half is in state f, the real seriousness of this situation would not be sufficiently covered by looking at the probability distribution for the stability node. Figure 7.4 shows the probability distribution of the center node when half of the RIFs are in state a and the other half in state f. The situation would probably be more severe than what the probability distribution suggests. The reason that the bad state has a higher probability than the good state is due to the misaligned scale where c, represents average conditions, with a, b better than average and d, e, f worse than average.

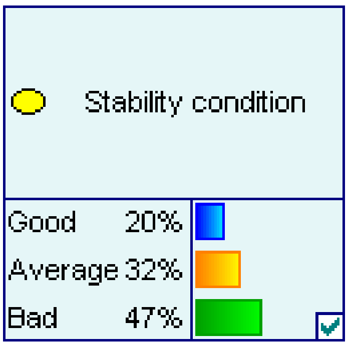


Figure 7.4: Half of the RIFs in state a, the other half in state f

Another issue regarding this model is best explained by an example. Let us say that we are faced with the scenario described in the case study in chapter 6.8.1. By providing evidence of some other RIFs, for example weather that is in state a, this results in a reduction in the risk level. The question is then, does the risk level reduce as much as the model suggests by providing evidence that some RIFs are in a good state, while some other factors are in a bad state? Or in other words, can we say that some obvious defects (RIFs in a bad state) are cancelled out by some other RIFs in a good state? One possible solution to this issue is to use a non-linear "distance" scale. In the quantification process for this model the "distances" (refer to equation 4.2), or the numerical values, of the states are used as suggested by Røed et al. (2009): $a = 3, b = 2, c = 1, d = 0, e = -1$ and $f = -2$. By using the TTS approach (Thomassen and Sørum, 2002), the numerical values are $a = 3, b = 2, c = 1, d = 0, e = -2$ and $f = -5$. The advantage of using this scale is based on the assumption of the quantification method: a probability assigned for a RIF being in a state that differs considerably from its parents' states should be smaller than compared to a state equal to its parents' state (Røed et al., 2009). This non-linear scale further enhances results of this assumption. The implications of using such scale is that if evidence is provided as described above, the good weather would be in a state "further" from the other states, and hence contribute less to the overall probability distribution of the result.

The results gained from this analysis need some evaluation. An obvious weakness of the result is that it does not give any indication of fatal accident rates (FAR) or individual risk per annum (IRPA). This is mainly due to the limitation of the model as a whole, that it does not take into account what happens after an accident, but only the factors leading up to an accident. Further research on accidental scenarios and individual risk is recommended. However, the results from the model can still say something about the operational risk level of the semi-submersible. The probability distribution of the center node must be compared to a predefined acceptance limit. This limit can for example be calibrated using the results from the BBN analyses of the MTO cases, as given in table 6.9. The strengths of the model is that it can be used to determine and quantify the risk of the operation as compared to the industry average. This result can also be used to determine how the risk level develops over time. This is the exactly what Øien and Sklet (2001) identified as a problem, quote: a more intrusive problem is to say something about how and how much the risk level is changing for a single unit and for the industry as a whole. In addition, this model is easy to use and to interpret the results, as long as clear acceptance criteria have been developed. This is identified by the RNNP (2014) report, that it can be a challenge to communicate and explain the interpretation of the results from a risk analysis to all the personnel involved. This model keeps the input simple and presents the results in a way that the personnel can understand the risk and act thereafter.

Attempts are made to quantify the risk level by using a basis probability that is determined from worldwide incidents between 2000-2013, based on Kvitrud (2013). Other basis probabilities, also based on statistics, are presented. A conclusion drawn from looking at statistics is that it is difficult to determine a single "correct" probability of loosing stability. Because it depends on time period and location from where the data is collected, and how the accidents are defined.

And due to the small amount of accident cases that are registered, the statistics are sensitive and one accident less or more will make a big impact on the result. The only conclusion is that the probability of loosing stability is in the low range of order of magnitude 10^{-3} per platform year. The results from the analysis, does on the other hand illustrate probabilities in the upper range of order of magnitude 10^{-3} per platform year. The reason for this is that the basis probabilities, such as those given in table 6.10 are average probabilities. This could be interpreted as all RIFs being in state c. The results from the model is however not in state c, hence cannot be expected to be equal to the statistics. The statistical analysis of the data shows that the results given by the model is within the predicted interval, and that it corresponds well to the expected results.

One of the strengths of a BBN is that it is able to handle uncertainties. This is illustrated in the analyses of the case study and the MTO cases. The problem with including uncertainties in the calculation is that the final result also becomes uncertain. This model produces a conservative result, in the form of a higher probability, when it is confronted with uncertain (non-instantiated) RIFs. This can be seen as the probability of loss of stability is higher when less RIFs are instantiated. The reason for this conservative result is due to the misaligned scale of the states. As there are more possibilities of being in a state worse than average vs. better than average (d, e, f vs. a, b), the model predicts a slightly worse outcome than average when no evidence is given.

A comparison between the analyses presented here and the accidents they are based on, combined with the 90% prediction interval gives an indication of whether the model produces a valid result or not. As the results shows, the most severe accidents have the highest probability of loosing stability, and are also represented close to the 5% worst cases that should be expected. It can also be seen that the Scarabeo 8 incident has a higher probability than the case study from the RNNP report, which also corresponds well to expectations. It is reasonable that the probability of loosing stability is higher in Scarabeo 8 because in this case the crew lost control of the stability for a while, whereas the case study indicates that control was not totally lost. That being said, it is not such that the highest probabilities results in the most severe accidents, it is only an indication of the probability of experiencing a loss of stability. One comment should be made, it is suggested, based on calculations made in this thesis, that the model gives results that are within the prediction interval. This statement is based on the five analyses that have been done in this thesis, and the assumption that Ocean Ranger and Thunder Horse are amongst the 5% worst cases. It is not known, however, whether this is a functioning model or a lucky coincident that the results are within the prediction interval. A series of tests, on different scenarios, should be done to find out what the distribution of the results are in order to evaluate this statement.

The model presented here is by no means perfect, but it is considered as a starting point for risk analysis of marine systems. It is also necessary to acknowledge that the suitability of the model has to be judged by its ability to represent the real world, but also to simplify the real world into a model (Røed et al., 2009). Even if the model cannot describe the risk to a full extent, it can still be useful. As Røed et al. (2009) points out, no approach is able to meet the expectations with regards to all aspects.

To answer the question stated at the end of chapter 6.5, how does the RIFs describe the real world, and is this BBN suited for risk analysis? The conclusion is that based on the available information in terms of accidents and incidents that have occurred, and subjective interpretation by the author the RIFs that were identified are representative for a risk analysis. There are of course other factors that may also influence the risk, but since the identified RIFs are the most commonly occurring factors, these are considered representative. For the second part of the question, the conclusion is that the model can be used as a tool for monitoring the development of the risk level as compared to the industry average.

Chapter 8

Conclusion and Recommendations for Further Work

8.1 Conclusion

The goal of this thesis has been to model how and to what extent technical, human and organizational factors influences the risk involved in stability operations on a semi-submersible. In order to achieve this, the work of this thesis has been focused on root causes, as opposed to immediate causes and barrier failures, of stability incidents and accidents. The model presented in the is thesis is based on incidents and accidents that have happened all over the world. It was found that most of the incidents and accidents were related to the failure of conducting normal operations, failure to responding to abnormal situations or failure of a technical system. The ballast system is the main system used to conduct stability operations, both in normal and emergency situations. Hence, the ballast system is considered to be a barrier system to prevent loss of stability. Based on the accident categories, the following three barrier functions have been defined for the ballast system in this thesis:

- **BF 1:** Conducting normal operations
- **BF 2:** Response to abnormal situations
- **BF 3:** Condition of technical systems

The risk modeling is in this thesis concentrated on how technical, human and organizational factors influences these barrier functions. The factors that influences these barrier functions are defined as risk influencing factors (RIF). A set of 27 RIFs have been identified and implemented into the risk model presented in this thesis.

The RIFs represents the root causes of incidents and accidents. An interesting result is the distribution of the RIFs: 58% are organizational, 19% are human and 23% are technical factors. This corresponds well with a similar study presented in the RNNP (2014) report. This means that most of the root causes of stability incidents and accidents are rooted in organizational factors.

The technique for modeling how RIFs influences the barrier functions, and hence the stability condition of the semi-submersible, is known as bayesian belief networks (BBN). Through literature reviews, it has been concluded that BBN is a very well suited method for modeling non-deterministic causal relationships such as human and organizational factors. This is due to the ability of BBN to handle uncertainty and to model non-sequential event chains. The view adopted in this thesis is that the technical system operates on the unifinality side of the scale, whereas organization is on the equifinality side, and human factors are somewhere in between. The meaning of this is that technical systems have more or less on way of yielding its products, and organizational factors can work in a wide variety of ways, and still yield the intended products. This is why BBN is a good tool for modeling organizational and human factors. The power of BBN is clearly surpassed by traditional risk analysis methods such as fault and ever trees (Friis-Hansen, 2000), the same view is supported by other authors such as Weber et al. (2010), Khakzad et al. (2011) and Trucco and Leva (2012).

The quantification process used for this model is based on expert judgment, and a mechanized algorithm. It has been found that there are a lot of factors that can influence and bias the expert judgment process. The solution is that by controlling the identified biases, and using a group of experts and a recognized expert judgment method, such as the delphi method, the judgment process is made as objective as possible. This is not a perfect solution, but the conclusion is that this method should be used, and we must trust these results, due to the lack of a better alternative.

However, since the quantification in this thesis is to a limited degree based on real data, a question is raised about whether or not the result is applicable to the real world. The answer is that the results should not be used as a firm conclusion to the risk of loosing stability. The results can, however, be used to indicate how the risk level is developing over time, and when RIFs are changed. The results must be interpreted as compared to the industry average.

There are no difficulties in pointing out weaknesses with the model, and some of these have been discussed and evaluated in this thesis. As stated by Røed et al. (2009), no approach is able to meet the expectations with regards to all aspects, and a set of different approaches are needed for modeling risks. This model is developed as a response to the limited amount of work that has been done in this area, and the industry's request for more thorough risk analysis tools for marine systems (RNNP, 2014). As suggested by Mohaghegh and Mosleh (2009), the modeling is shifted from the traditional focus on errors, to a focus on actual performance. This is seen as an improvement, due to the equifinal properties of organizational factors. Traditional techniques that focus on sequential errors, such as Reasons swiss cheese model (Reason, 1990), are not sufficiently flexible to model organizational factors, because these factors does not need to fail sequentially. Even if the factors themselves does not fail, the interaction between them can fail (Mohaghegh and Mosleh, 2009). It is recognized that the model presented in this thesis is not fully adequate for industry applications yet, however, this is intended as a starting point for further development.

8.2 Recommendations for Further Work

Throughout the work with this thesis there have been uncovered some areas that needs further work. The list illustrates the areas that the author suggests to develop or test, in order to enhance the quality of the model.

- Use experts in the development of CPTs. This model has been based on the authors personal beliefs about how the RIFs influences the the total risk level.
- Further develop the model to include evacuations and loss of life scenarios. At the present the is model treats only the causal side of stability loss, and does not have any focus on the consequences of such loss. It is suggested to implement a decision node into the BBN in order to determine FAR or IRPA values.
- Test the model and compare the results to other models or analysis tools. This is to evaluate how the results of this model compares to other models.
- Implement indicators directly into the model. This eliminates the need for external decision criteria that are being used to instantiate the RIFs in this model.

Appendices

Appendix A

Selected Incidents and Accidents

Unit, year	Description
Transocean Arctic, 1995	Personnel discovered that ballast pump no. 7 pumped water towards a closed valve.
Tranocean Arctic, 1995	Ballast pump no. 1 stops after operating for 60 sec.
Transocean Arctic, 1995	Level indicator for ballast tanks are unreliable. Shows 400-600 tons less than actual level.
Transocean Wild-cat, 1996	Alarm for water level in engine room sounded. Leak discovered in sea valve. Valve to sea chest closed.
Transocean Prospect, 1998	Malfunctioning level indicator in ballast tank no. 6. Tank assumed to be almost empty, but in reality it was full.
Transocean Prospect, 1998	Ballast computer monitor froze, changes in ballast level not displayed
Polar Pioneer, 1999	Ballast tanks 3 and 16 was overfilled during ballasting, water came out on deck through vents
Åsgard B, 2000	A tug collided with the installation and punched a hole below the water line. $150m^3$ of water ingress gave a 1.5 degree list

Table A.1: Summary of incidents on the NCS (1/3). Source: adapted and translated from Vinnem et al. (2006c) and Kvitrud (2013)

Unit, year	Description
Transocean Arctic, 2000	Unintended autostart of ballast pumps
Transocean Wildcat, 2001	Water ingress to ballast tank. 20 m^3 of water flowed in through indicated closed valve. Tank emptied and inspected, valve was good, but garbage was flung in ballast tank. This could have prevented the valve to close properly
Polar Pioner, 2001	Water ingress through valve indicated as closed
Transocean Prospect, 2001	Windows in mess room and port anchor room broken by waves
Transocean Arctic, 2001	Remote operated ballast valve broke during testing
Bideford Dolphin, 2002	Cracks discovered on port side column 4. Water ingress, rig closed down and taken to shore for repairs
Polar Pioner, 2002	400 m^3 of water flowed through a valve that was indicated to be closed
Snorre B, 2003	Fire alarm sounded and deluge activated. All activities suspended, no fire detected, but water from deluge caused an imbalance of weights. 200 tons of ballast water moved to rectify situation
West Alpha, 2003	Water ingress through sea valve into ballast tank 24 starboard side
Transocean Leader, 2004	Sea water from pit. 8 entered into trip tank
Bideford Dolphin, 2004	Leak of $6/m^3$ per hour into ballast tank. A rope was tangled into butterfly valve. Rope removed and leak stopped
Ocean Vanguard, 2004	Loss of anchor lines caused a 10 degree list
West Venture, 2004	Firewater pipe leaking water into a ballast tank, causing a list of 2-3 degrees. Pipe was sealed, and ballast tank emptied
Visund, 2006	Gas blowout cased activation of deluge. Gave a 3 degree list to the installation
Transocean Winner, 2006	Flooding in port pump room with drill water from the starboard aft drill water pumps in the amount of 70 - 75 m^3
Polar Pioner, 2007	Small structural damage damage causes seawater to flow into ballast tank bb3. Inflow rate of 10 -20 m^s per hour
COSL Rival, 2009	80 m^3 of water leaked into ballast tank PT-6 and PT-7 through faulty valve
Veslefrikk B, 2011	60 m^3
Åsgard A, 2011	Corrosion in sub-sea drain pipe caused water inflow to space in column

Table A.2: Summary of incidents on the NCS (2/3). Source: adapted and translated from Vinnem et al. (2006c), Kvitrud (2013) and PSA (2014a)

Unit, year	Description
Transocean Winner, 2011	Filling of 75 m^3 void space due to open manhole
COSL Innovator, 2013	Leak of brine line caused the filling of three void spaces
COSL Rigmar, 2013	Corrosion between two tanks caused unintended filling
Transocean Searcher, 2013	Defect valve caused leak between WBT and pump room

Table A.3: Summary of incidents on the NCS (3/3). Source: adapted and translated from PSA (2014a)

Year	Description
1986	Malfunctioning control system caused rig to list 9 degrees
1990	Electrical failure of power supply to ballast control system and UPS not able to keep system running. Three separate operating stains were without power for 8 min. System went into failsafe condition preventing loft of trim and stability.
1990	Rig was under tow when it started to take in water and developed a list. Normal situation successfully restored the next day.
1990	Pump room flooded causing list
1999	A high gas alarm was initiated, causing GT shutdown any deluge activation in a number of zones. A list of 5 degrees to starboard developed due to free flow of ballast due to open valves in the system
2000	Control of the starboard ballast desk was lost and all the remote operated valves vent to open position. Manual closing of valves was done, total list of 6 degrees.
2000	Anchor chain failure led to a 2 degree list of an installation
2000	A water line burst over starboard emergency ballast control panel, causing a list of 3 degrees.
2003	Ballast system failure detachment of motor and pump top from pump bowl housing

Table A.4: Summary of incidents on the UKCS. Source: adapted from Vinnem et al. (2006c)

Unit, year	Description
Alexander L. Kielland, 1980	Loss of one out of five legs of the platform, due to fatigue in one of the bracings. The loss of this leg caused the rig to gain a severe listing for about 20 minutes following a complete capsize. The rig had not been designed with respect to damage stability. A loss of 123/212 crew members (Vinnem, 2014b).
Henrik Ibsen, 1980	The incident occurred 10 days after the Kielland disaster. Ibsen was a floatel and at the time of the incident it was docked in Tananger. Maintenance work was done on the lower bracings, and the maintenance crew asked to get the platform trimmed in order to reach the bracings easier. Water was filled into one column in order to obtain the intended trim. An error in communication resulted in hatches in the water filled column being left open and water flowed to other parts of the platform. Within minutes the semi-submersible gained a 20° list. The investigation concluded with human error, but also a too high center of gravity (Kulturminne-Ekofisk, 2014).
P-34 (FPSO), 2002	Loss of electric power caused ballast valves to open resulting in a 32° listing of the vessel. Deballasting operations brought the vessel back under control, just before it capsized. All crew members survived. (Vinnem et al., 2006c)
(...), 2002	Three full depth cracks were discovered in the horizontal bracings on the rig, initially by leak detection system later by visual inspection. The rig was taken to shore immediately after a safe weather window was obtained, and the BOP was left at the sea bottom, to save time and reduce dynamic forces on the rig. Incident had Kielland potential. (Restricted 3, 2002)
(...), 2008	Leak to port engine room through hole in the bottom. This hole was caused by rust, and other holes in the beginning stage was discovered. The hole was fixed and the whole hull section was filled with concrete (Restricted 2, 2008)
Deepwater Horizon, 2010	MODU that caught fire after a blowout and explosions. The rig was totally damaged by the fire, but surrounding vessels tried to put out the fire by pumping massive amounts of fire water on to the rig. It is believed that the rig capsized and finally sank due to the uncontrolled fire fighting. A list developed before the capsize, possibly caused by the free surface effect of the fire water. (DHSG, 2011)
Floatel Superior, 2012	An unsecured anchor created eight holes in the hull of the rig, causing water to enter two tanks. The heel of the platform was 5.8° and no personal injuries were reported (PSA, 2013b).
Deepsea Aberdeen, 2013	A norwegian owned semi-submersible gained a heel and then sank during maintenance work at Daewoo shipyard in South-Korea. The reason is not known yet. (Offshore.no, 2013)

Table A.5: Related incidents and accidents

Appendix B

MTO-diagrams

The following MTO-diagrams is the result of MTO-analyses of some of the accidents and incidents that have happened with regards to stability and buoyancy. These diagrams are based on investigation reports, and only takes into account the events relating to loose of stability and buoyancy, no focus is put on the evacuation and other life saving events, as these are not considered to be of interest in this context.

The diagrams are listed as follows:

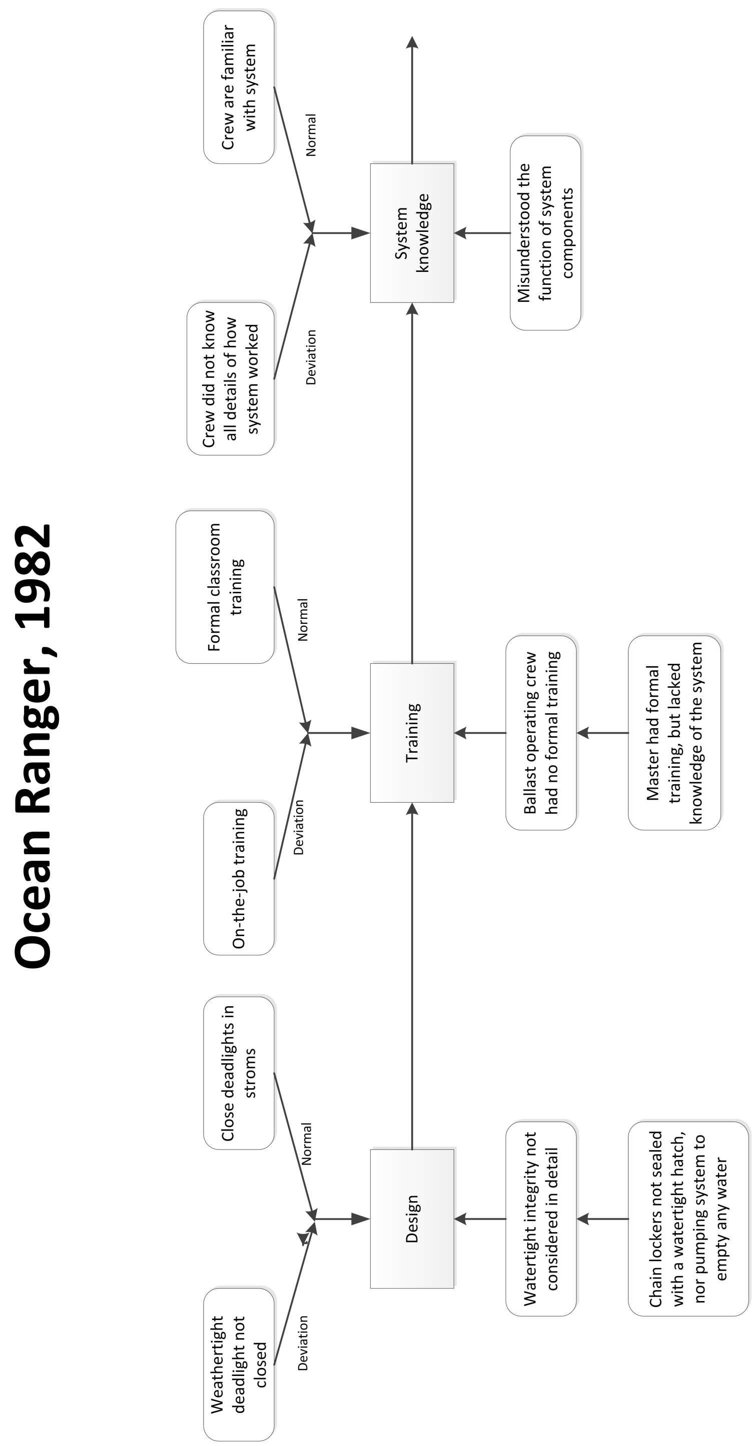


Figure B.1: MTO-diagram Ocean Ranger (1/3)

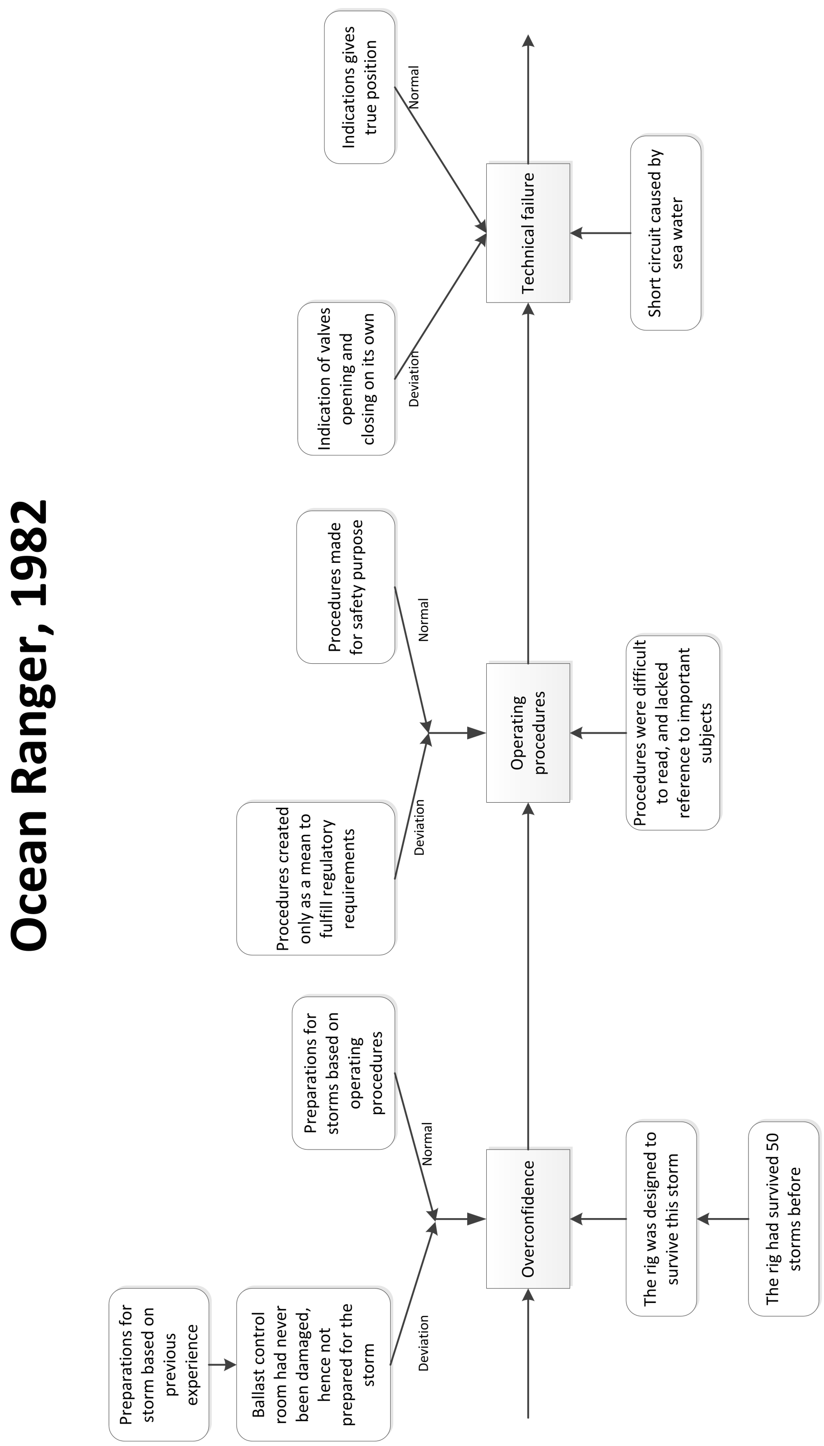


Figure B.2: MTO-diagram Ocean Ranger (2/3)

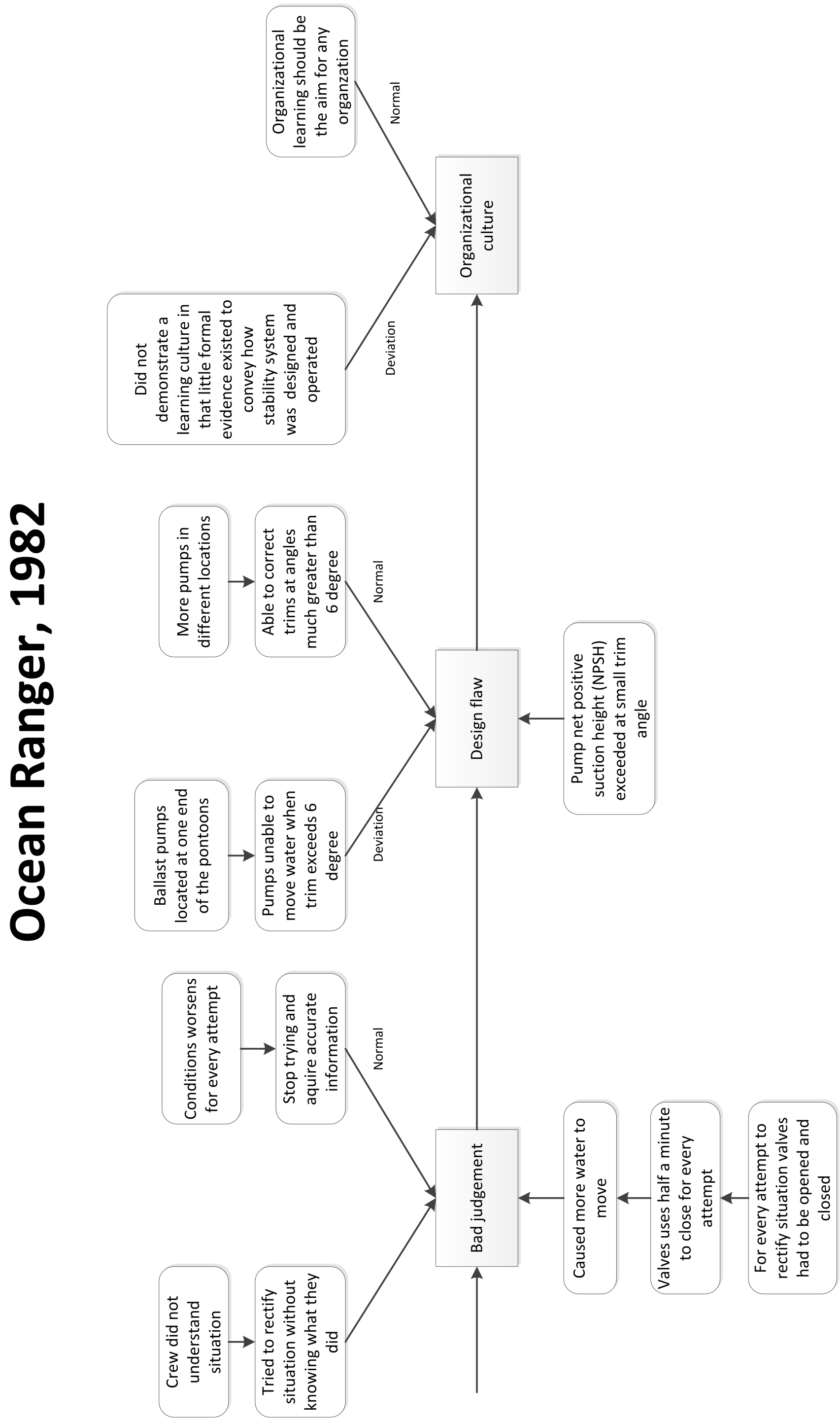


Figure B.3: MTO-diagram Ocean Ranger (3/3)

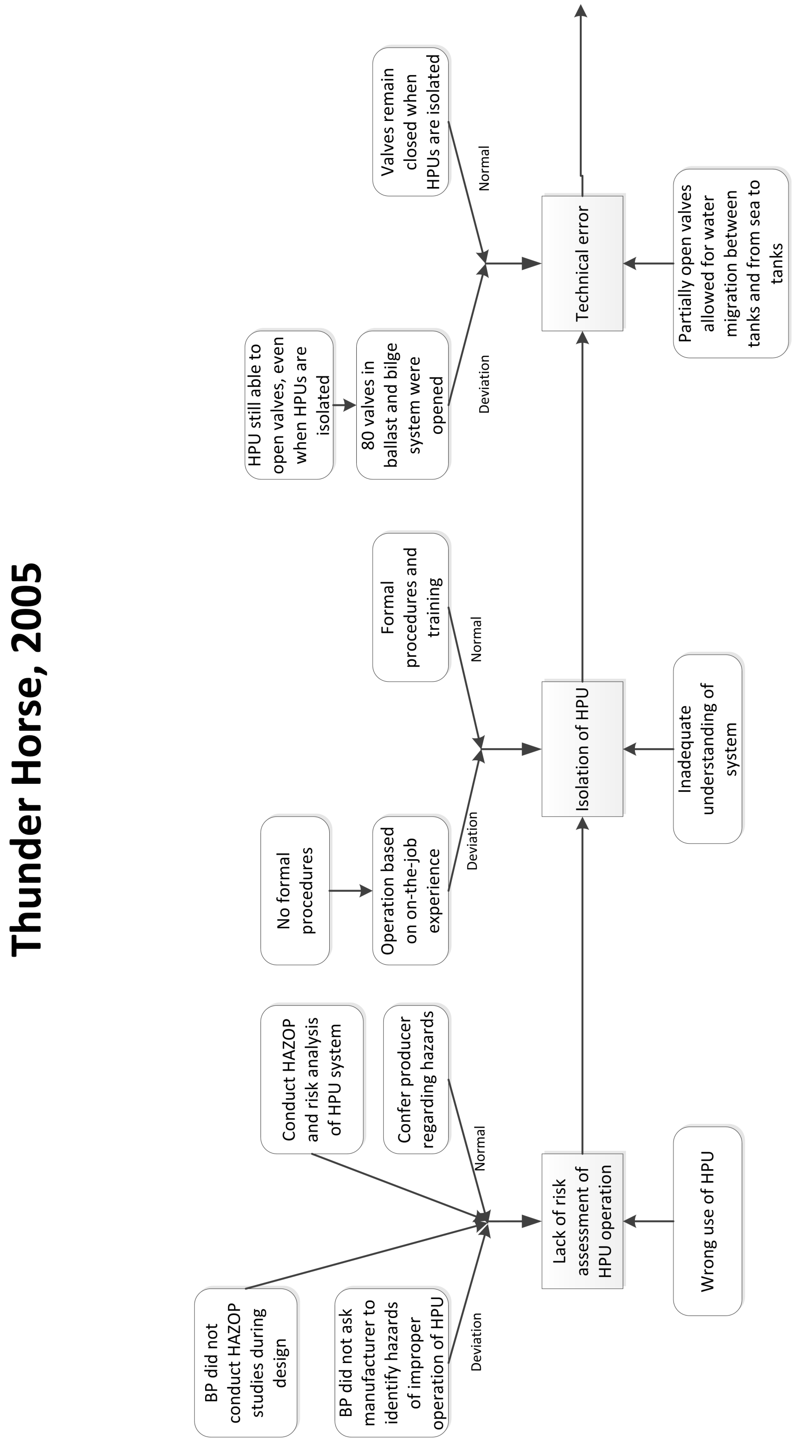


Figure B.4: MTO-diagram Thunder Horse (1/2)

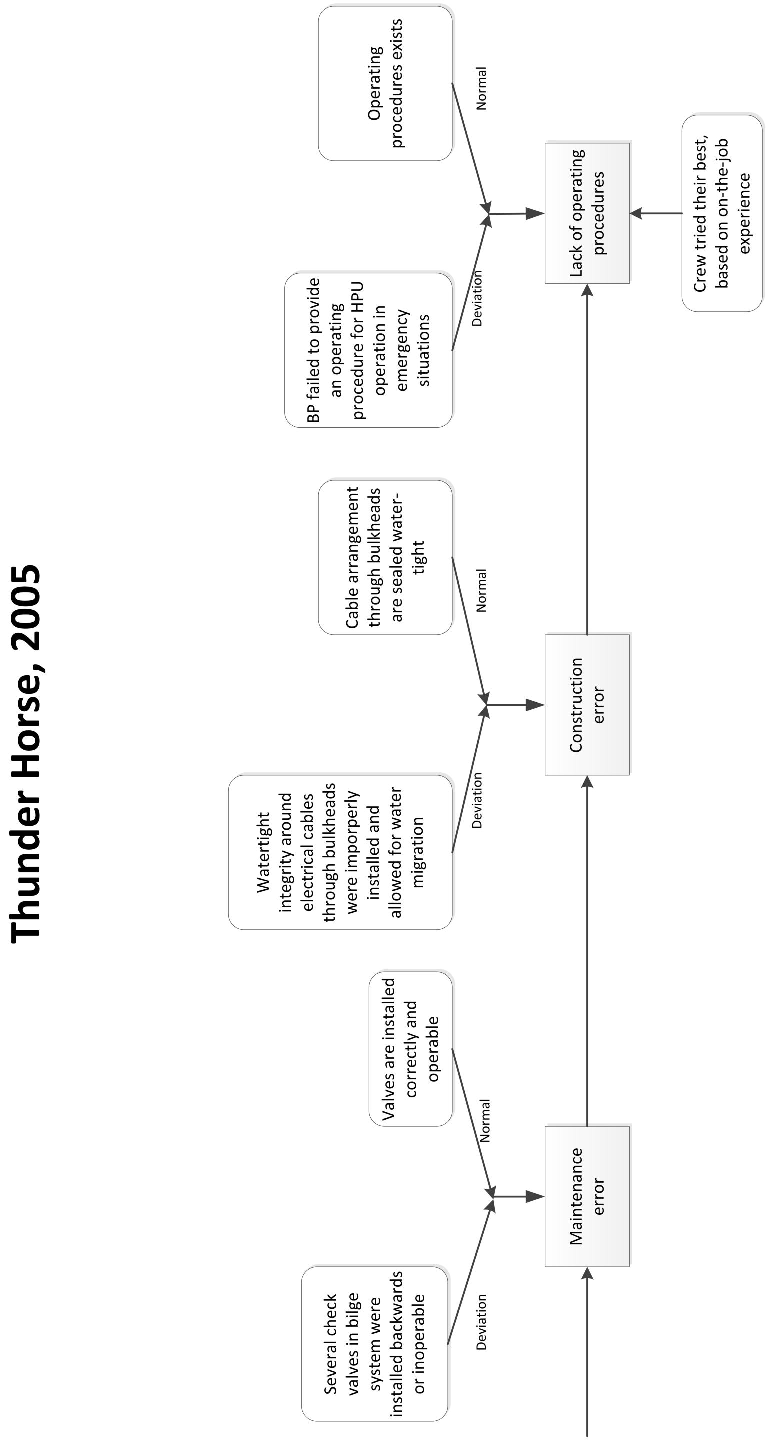


Figure B.5: MTO-diagram Thunder Horse (2/2)

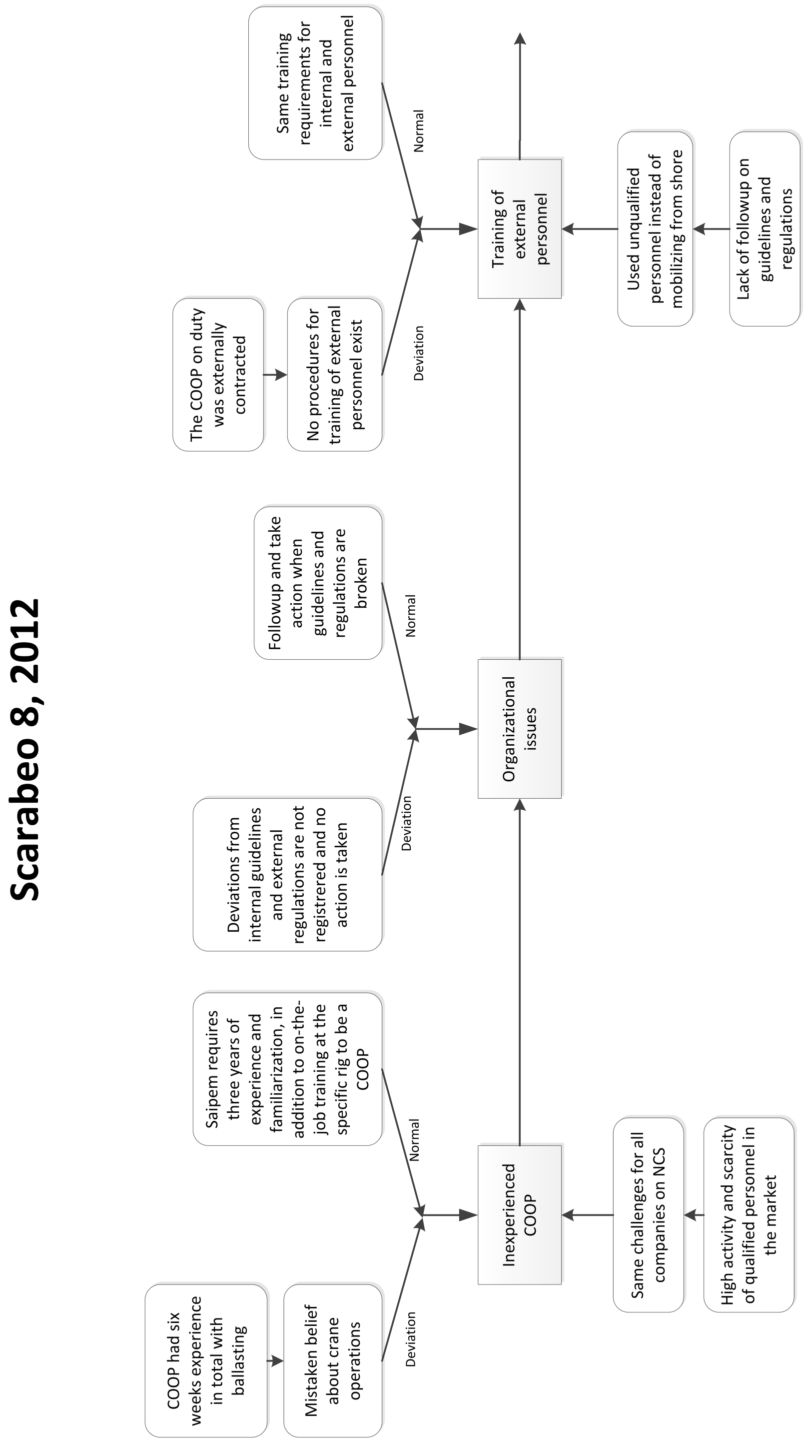


Figure B.6: MTO-diagram Scarabeo 8 (1/2)

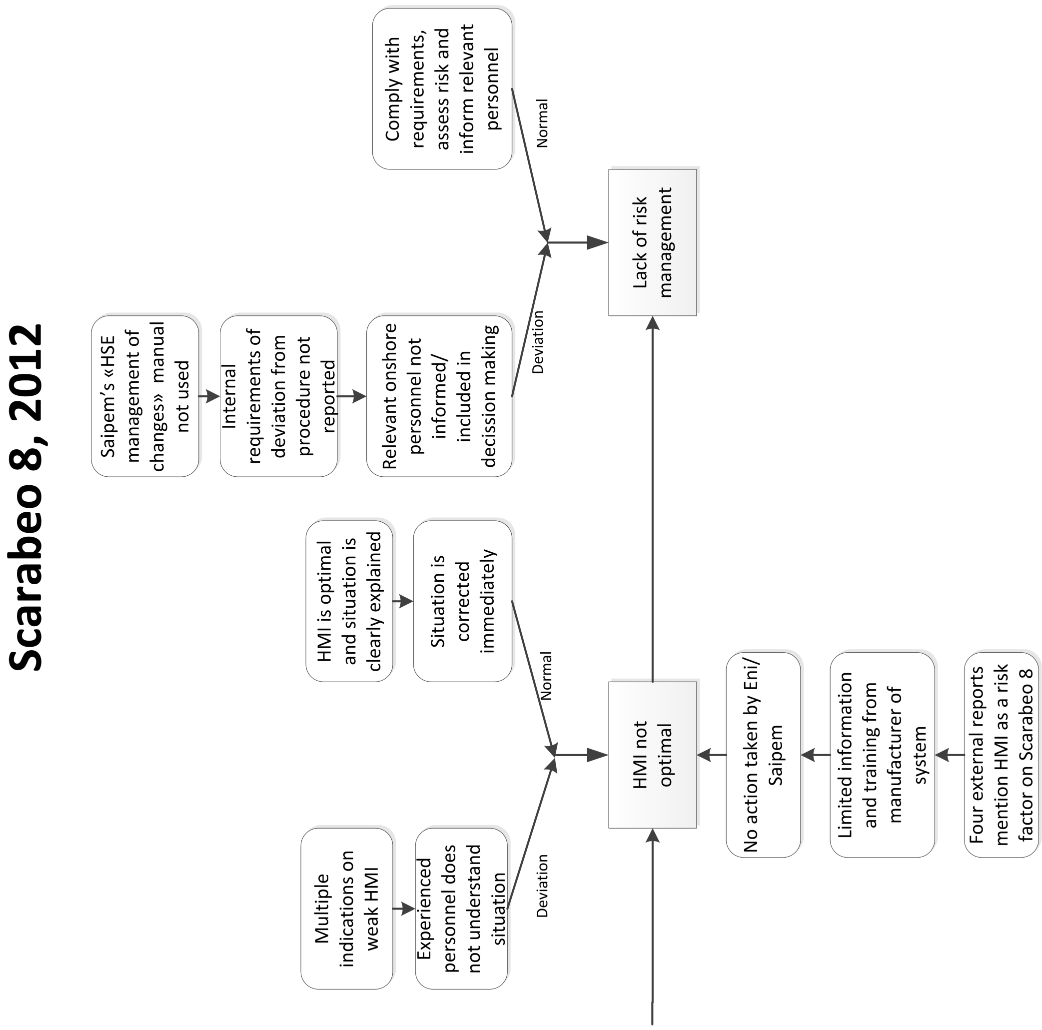


Figure B.7: MTO-diagram Scarabeo 8 (2/2)

(...), 2010

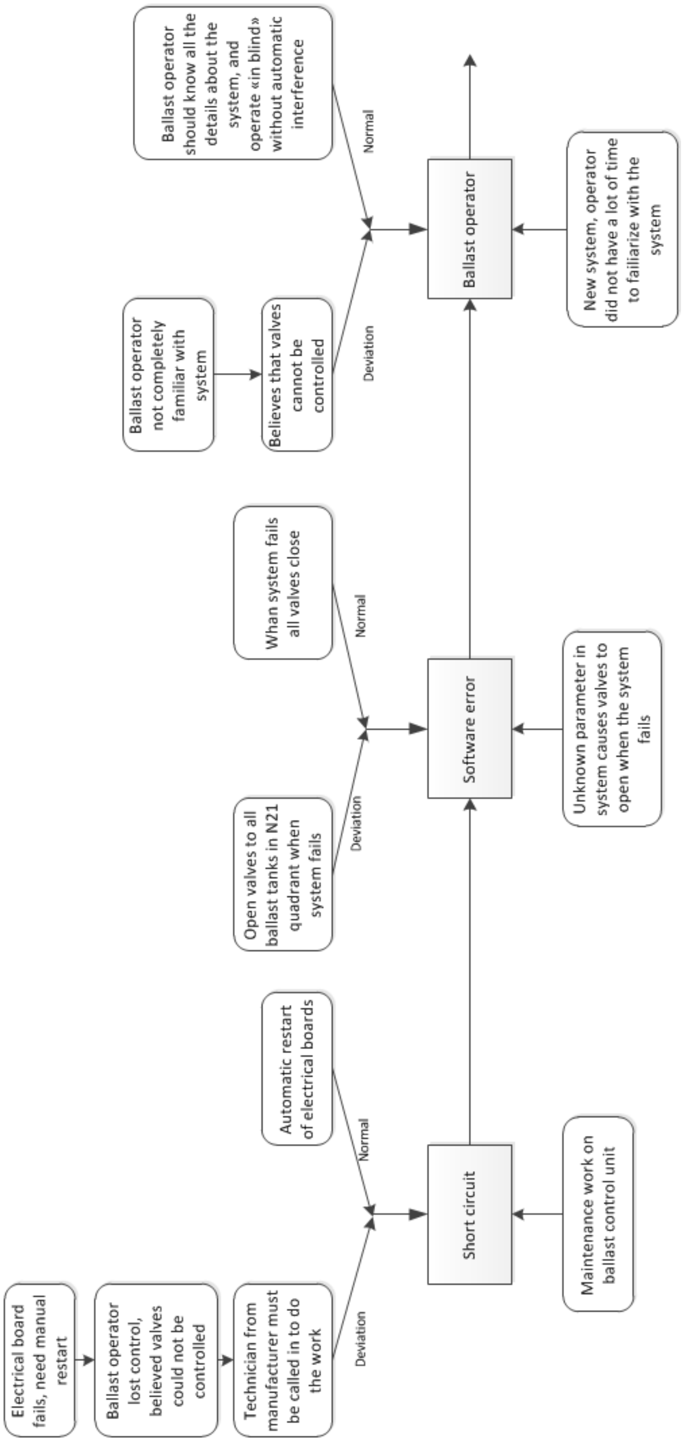


Figure B.8: MTO-diagram (...) (1/2)

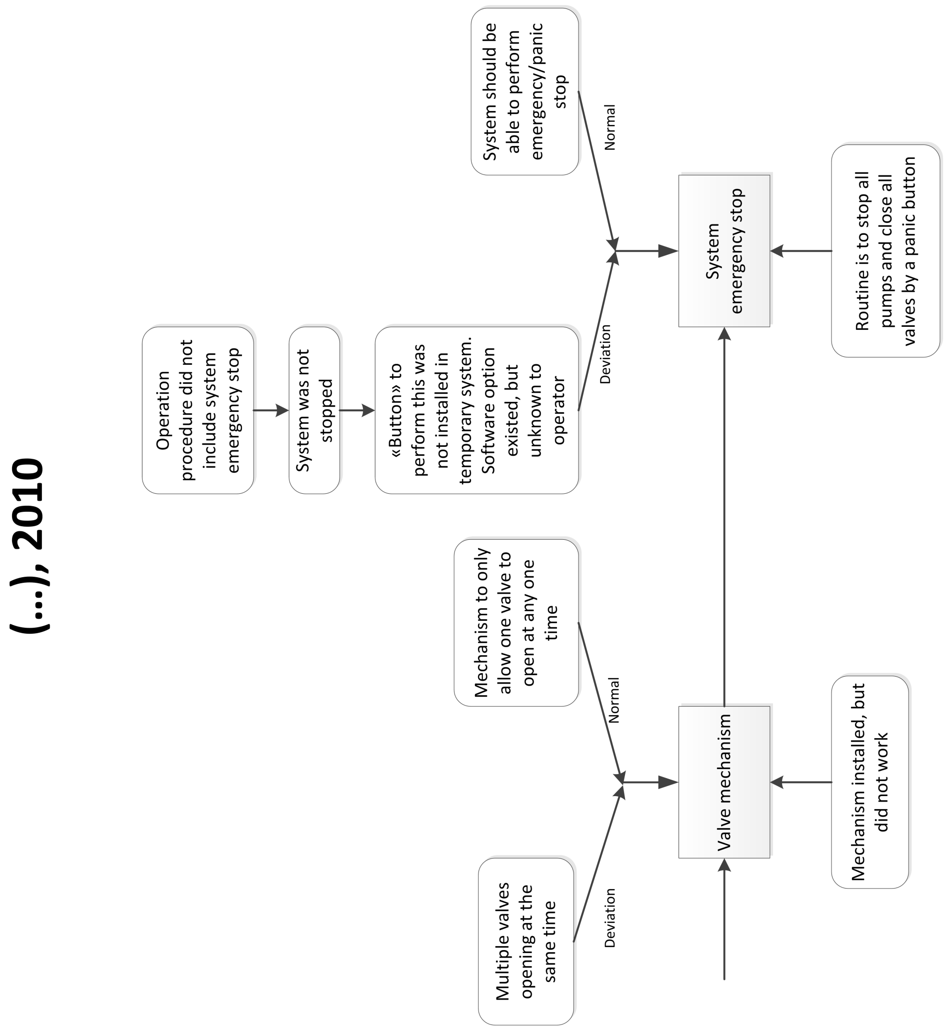


Figure B.9: MTO-diagram (...) (2/2)

Appendix C

Description of RIFs

RIF	Description
Training	Formal education and courses taken by employees. Does the level of education satisfy the internal requirements and external regulations. Both for operations and technical crew.
Experience and syst. knowledge	The level of understanding and familiarization with the particular system used on the semi-submersible in question. Both for operations and technical crew.
Operating procedures	Quality and availability of operating procedures. Including work tasks and responses that should be taken. Up to date instructions and drawings.
Fatigue	Does personnel get enough time to rest, overtime and extra work, night shifts
HMI	User friendliness of the system, labels on tools and equipment, feedback from system, alarms
Personnel selection	How well does the organization work when selecting personnel. Correct qualifications, enough experience, compliance to regulations
Stress	Are the personnel under stress when decision are made.
Weather	Describes weather conditions such as wind, waves, current and temperature.
Communication	Communication between personnel and different departments, eg. COOP, SSL and platform manager, or between control room and drilling or crane department.
Emergency drills	Describes the quality of and how often emergency drills are conducted.
Work practice	The normal practice of performing the work on the semi-submersible, compliance to guidelines and work procedures, checklists, use of short-cuts, focus on time before quality
Simultaneous activities	How does simultaneous activities affect performance of stability department, e.g. simultaneous drilling and crane operation

Table C.1: Description of RIFs (1/2)

RIF	Description
Supervision	Supervision on the semi-submersible, followup on activities, plans and deadlines
Equipment availability	Is the equipment ready for use when needed, easy to find, cleaned and tidy
Alarm management	How well does crew respond to alarms, practice drills, automatic alarm management procedure
Knowledge of the situation	is it possible to identify where the problem is form the central control room, level of indicators, CCTV, visual inspection possibilities, automatic identification systems
Operating procedures-[manitenance]	Quality of procedures, how well are the tasks described, how often should maintenance be done, what should be done
Spares and equipment	Are the necessary equipment and spare parts available when needed, time to get new shipment of spares and equipment.
3rd party insp.	How well and often are inspections performed on the maintenance work that have been done
Routine insp. and test	How often is equipment and safety systems tested, to what extent are these tests performed
Workload	How much work are the personnel expected to perform in a work shift, are there enough personnel to perform the tasks.
Cond. of valves	How well does the valves work, how often are they maintained and tested
Cond. of pumps	How well does the pumps work, how often are they maintained and tested
Cond. of logic and control	Does the unit work as intended, are test drills performed, programing errors detected
Cond. of structure	Quality of the structure, inspection programs for rust, corrosion, cracks, watertight integrity and other weaknesses.

Table C.2: Description of RIFs (2/2)

Appendix D

MATLAB Script for Generating a CPT

This MATLAB code will generate a CPT for a node having three states and two parents also with three states. The required input to this script are an array containing the weights that each parent has on the child, a R-value to determine the importance of the nodes and a “states” variable that tells how many states the node should have. The output is a $3x9$ matrix equivalent to the one in table 6.3.

```
%INPUT to the CPT code

R=1.5;
w=[0.4 0.6];
states=3;
```

```
%OUTPUT from the code

cpt =

  Columns 1 through 8

    0.7856    0.3772    0.2397    0.5246    0.1543    0.0867    0.4368    0.1136
    0.1753    0.5092    0.3236    0.3887    0.6914    0.3887    0.3236    0.5092
    0.0391    0.1136    0.4368    0.0867    0.1543    0.5246    0.2397    0.3772

  Column 9

    0.0391
    0.1753
    0.7856
```

```
function[cpt]=CPTgen(w, R, states)

parents = length(w);
Z=zeros(states,states^2);
s=zeros(states^2,1);
m=1;
cpt=zeros(states,states^2);

for i=1:states
    for k=1:states
        a(i,k)=abs(i-k);
    end

    for j=1:states^2

        if rem(j,states)==0

            Z(i,j)=a(i,m)*w(1)+abs(i-states)*w(2);
        else
            Z(i,j)=a(i,m)*w(1)+abs(i-rem(j,states))*w(2);
        end

        if rem(j,states)==0
            m=m+1;
        end
    end
    m=1;
end

for g=1:states^2
    for h=1:states

        s(g)=s(g)+exp(-R*Z(h,g));
    end
end

for l=1:states
    for n=1:states^2
        cpt(l,n)=exp(-R*Z(l,n))/s(n);
    end
end

end
```

Appendix E

BBN Analysis of Selected Accidents

This appendix includes screenshots from a risk analysis of the accidents studied in the MTO analyses in appendix B. The screenshots are taken from GeNIe and it illustrates the evidence given to the involved RIFs. The evidence is based on the investigation reports, and for the RIFs where the state is unknown, no evidence is inserted to the analysis.

Ocean Ranger

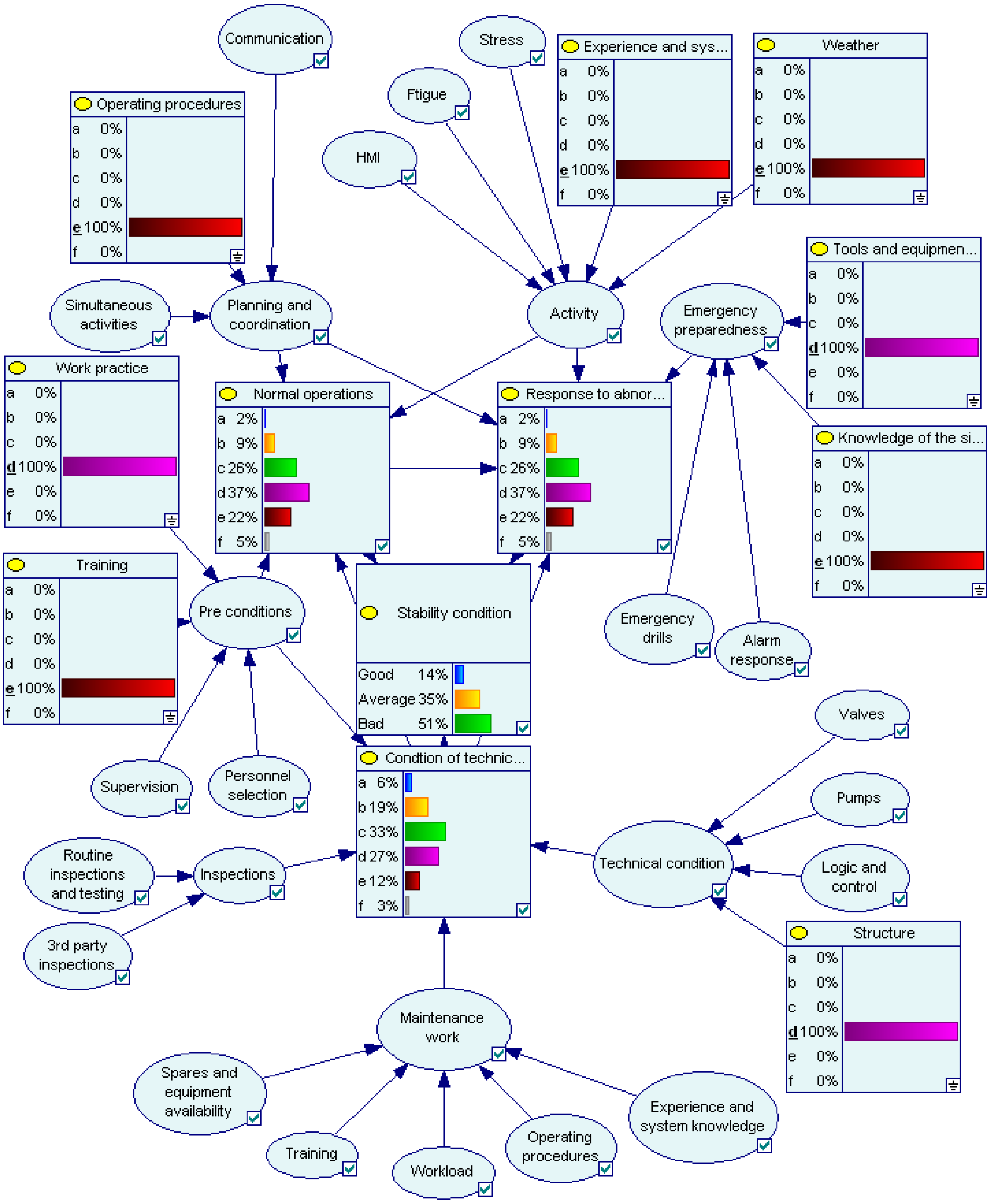


Figure E.1: Screenshot from BBN analysis of the Ocean Ranger accident

Thunder Horse

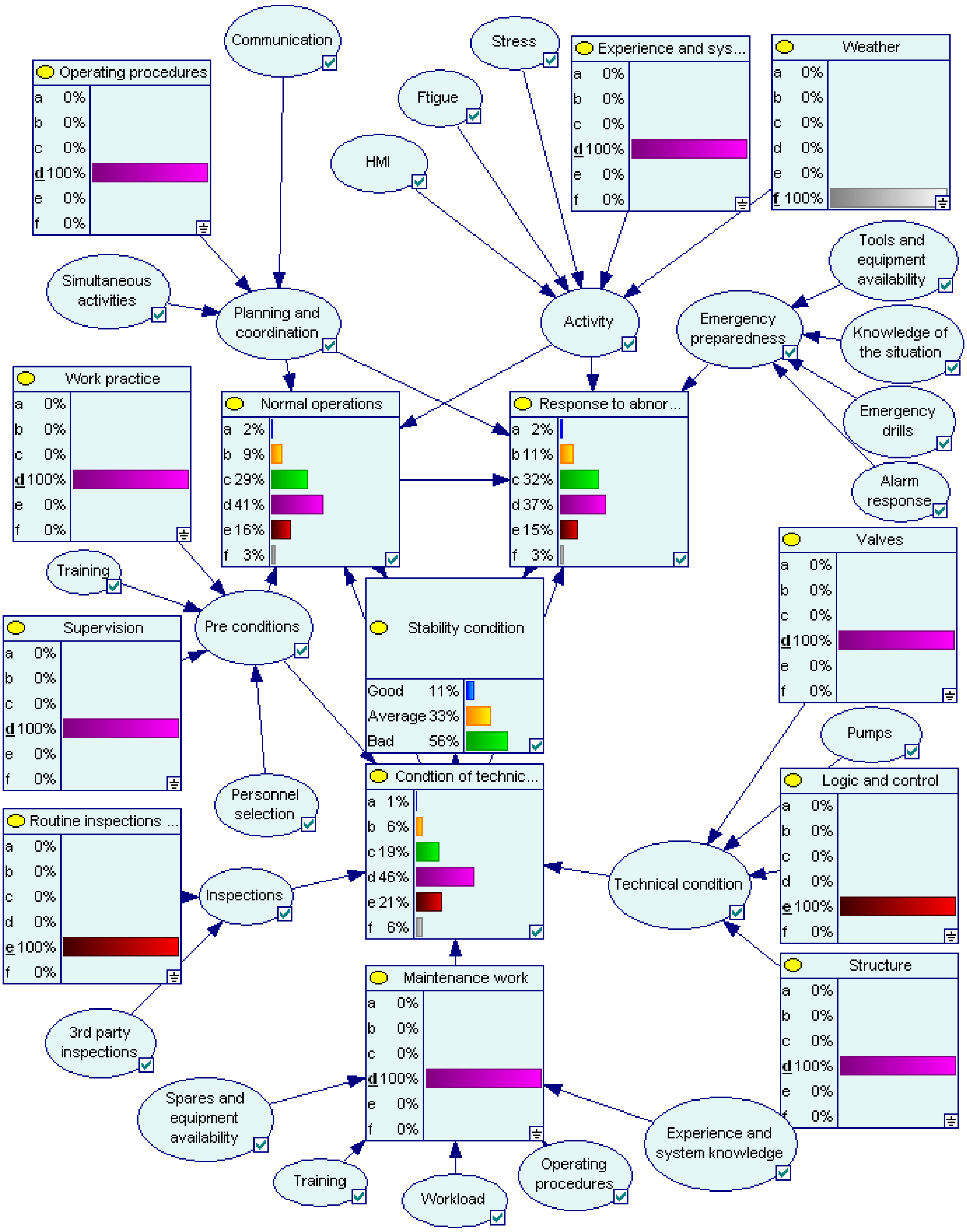


Figure E.2: Screenshot from BBN analysis of the Thunder Horse accident

Scarabeo 8

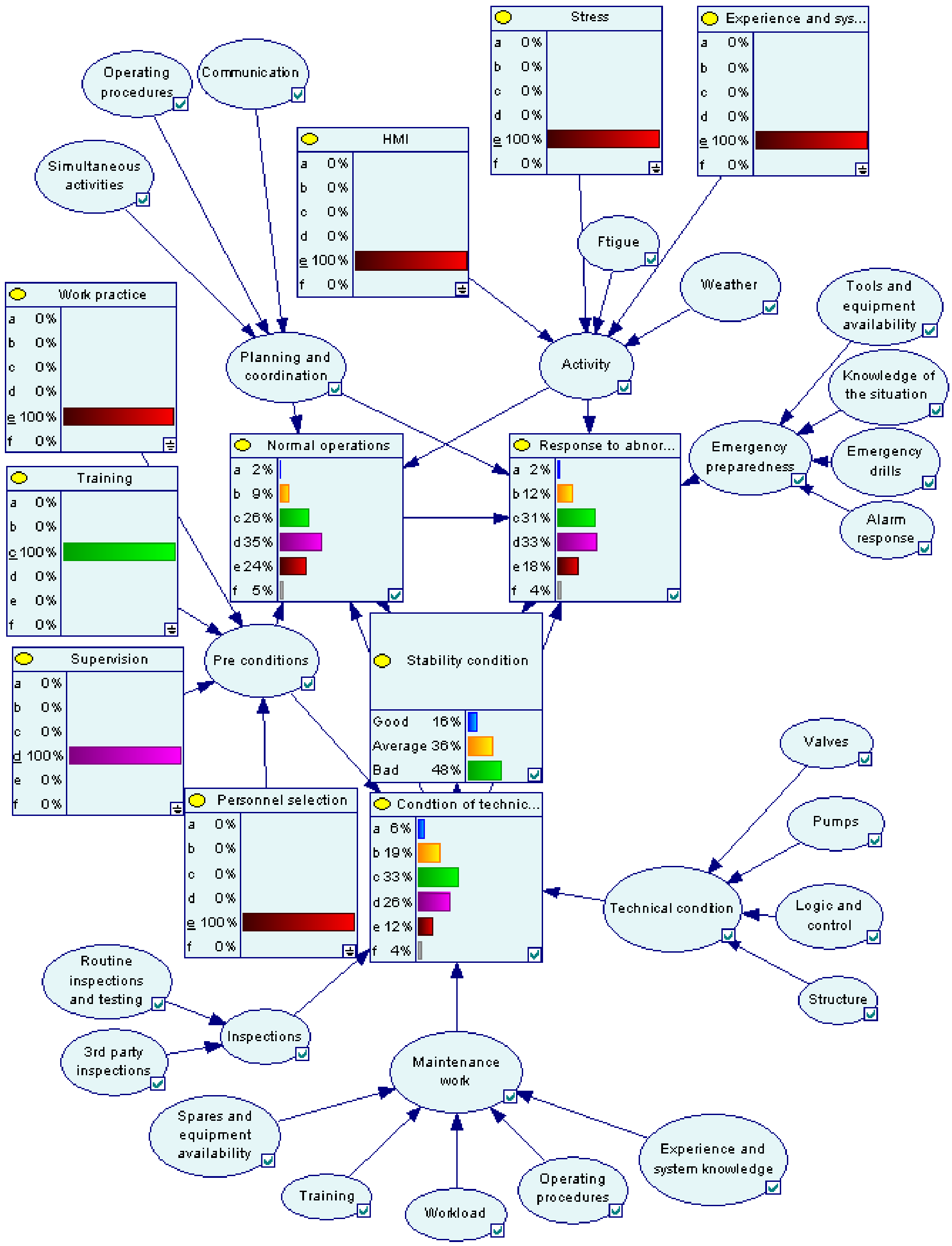


Figure E.3: Screenshot from BBN analysis of the Scarabeo 8 incident

(...), 2010

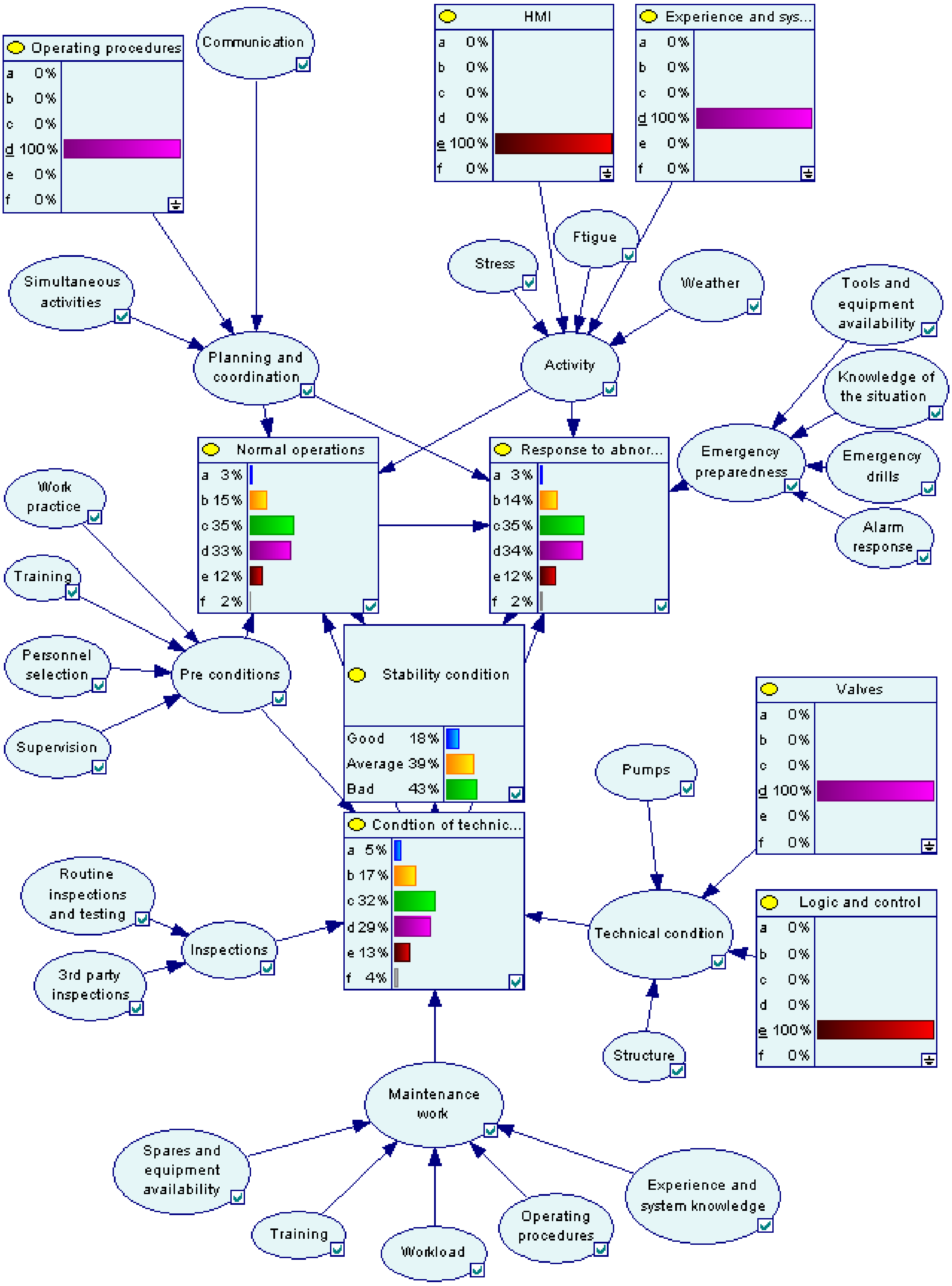


Figure E.4: Screenshot from BBN analysis of the (...),2010 incident

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