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Prediction of failure rates for subsea equipment

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Reliability, Availability, Maintainability and Safety (RAMS)
Submission date: July 2016
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Master Thesis

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Preface

This Master Thesis is written in culmination of the International Master Program in Reliability, Availability, Maintainability and Safety (MSc. RAMS) within the Production and Quality Engineering Department (IPK) at the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. This work has been performed during the spring of 2016. This report is prepared for proposing a new method of failure rate estimation. The intended reader for this report should have practical experience in areas related to reliability and safety. In addition, certain basic knowledge on Bayesian Belief Networks is required to understand the models discussed in this report.

Acknowledgement

There are several people I would like to thank for their comments, contributions and valuable assistance during the writing of this master thesis. Firstly, my supervisor, Professor Yiliu Liu and Nikola Patrinieri for his time, patience and invaluable guidance which was very vital in the execution of this work. A special thank you to Prof Mary Ann Lundteigen for his inputs on critical aspects of the master thesis. Special mention to the faculty of the RAMS study group at NTNU, without whom this master thesis would never be complete. Last but not the least, a heartfelt thank you to my family and friends especially Jeevith Hegde and Nathaniel J Edwin who supported me throughout the past years and especially during my study at NTNU

Abstract

Prediction of failure rate for new subsea equipment is a challenge in oil and gas industry mainly due to lack of relevant data and use of increasingly novel technologies. There is a lack of common guideline or framework for failure prediction process of novel technology and different companies and experts follow different procedures.

Many new technologies like Subsea processing with a subsea gas compression module installed at Åsgard field in Norway as recent as 2014 are emerging. The thesis proposes failure rate prediction method for new subsea equipment. The failure rate calculated is intended to be used as an important input for TQP during the early design phase.

A comprehensive literature review to study the reliability databases and other methods like BBN, ANN, Rahimi and Rausand's approach is done. The literature study was divided into two parts, reliability databases and other methods. Most of the generic methods do not consider the dynamic operational and environmental conditions during prediction process. It describes methods for failure rate prediction namely Regression models, Rahimi and Rausand's approach, Bayesian Networks and Artificial Neural Network.

A new approach is proposed using the available models. It mainly uses the weight parameters for RIFs and failure causes as inputs from Rahimi and Rausand (2013) and uses a BBN to calculate the failure rate for all failure modes of new subsea equipment. A BBN model is developed for quantifying the states of RIFs and its effect on failure cause and the failure rates of different failure modes of subsea equipment.

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1 Introduction

1.1 Background

The present global energy requirements are met with 34% from oil, 25% from coal, 21% from natural gas, 12% from renewable, and 8% from nuclear energy sources. The world energy consumption is expected to reach 20679 Mtoe in 2040, about 56% over the 2010 levels, with conventional fossil fuels continuing to supply around 80% of the world energy through 2040 (EIA, 2013). Figure 1.1 shows the contributing sectors where the demand for Natural Gas (NG) continues to be in the uptrend with the consumption in 2040 expected to reach 5.23 Trillion cubic meters (TCM), a 64% increase from the 2010 consumption level.

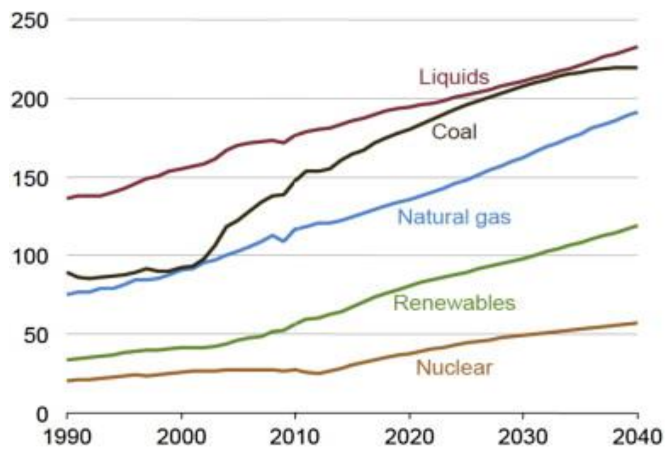

Figure 1.1 Global forecast on contribution of primary energy consumption Quadrillion BTU (EIA, 2013)

The petroleum industry is increasingly relying on subsea technology to produce oil and gas in deeper waters to meet the increasing demand. Subsea production systems are used to develop reservoirs at multiple proximate locations; or to access reserves that are too deep for fixed platforms, technically or economically (ISO13628-1, 2005). They maximize use of infrastructure and facilitate early startup (Mason, 2006). Although these systems are designed and tested to withstand the harsh subsea conditions, failures do occur for example five offshore subsea fields in Australia recently experienced more than 100 equipment failures over a six-year period. The cost of the intervention was around AUD150 million ($106 million) and therefore reducing failures is even more critical in the current low oil price environment(Offshore-Mag, 2016). Shell had shut in production at its Brutus platform in the US Gulf of Mexico following a 2100-barrel spill near the Glider field in May 2016. The cause of the spill was the release of oil from subsea infrastructure (Evans, 2016).

Subsea developments are often challenging both from a technical and operational point of view and the recent plunge in oil and gas prices poses new limitations. In many cases, prototype and novel technologies are developed to reduce operating costs and enhance the profitability and productivity for example all-electric XTs (Bouquier et al., 2007), subsea compression (Hedne, 2014) and many more. The operators are skeptic in using the novel technologies as they fear that the new system might fail and lead to production losses, hydrocarbon leakages and costly maintenance interventions (Rahimi and Rausand, 2013). Even though the novel technology typically goes through a formal qualification process, these technology qualification processes are limited with respect to providing a quantitative reliability prediction method (Brandt et al., 2009). Myhrvold et al. (2016) also points out the lack of confidence of industry in using new subsea technologies and emphasizes the need of efficient reliability quantification methods during re-qualification of systems which utilize qualified technologies under slightly different conditions or with slight modifications.

Quantitative reliability prediction[1] forms an important part of qualification process and one of its most vital steps is failure rate estimation. It is necessary to identify design flaws effecting reliability as early as possible because it has compounding negative effects on the later stages of the project. Figure 1.2 illustrates this effect with respect to cost of project.

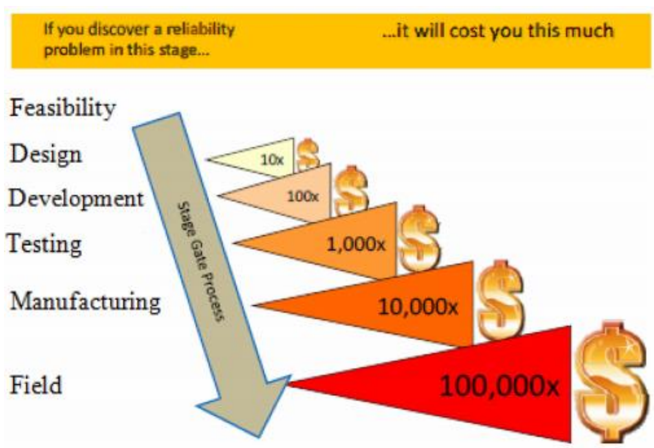

Figure 1.2 Compounding effects of design flaws in different stages of project

Reliability needs to be correctly estimated in the early stages of qualification because of the following reasons (Rahimi and Rausand, 2013):

[1] In this report, the terms reliability prediction and failure rate prediction are used interchangeably. Failure rate prediction is a part of Reliability prediction process.

- Identification of potential design weaknesses
- Failure rate estimation for quantification reliability and availability
- Comparison of different designs
- Early estimation of Lifecycle costs
- Establishing objectives and requirements of reliability testing
- High costs of re-designing in case of inaccurate estimation

The failure rate estimation of subsea equipment is difficult because the available failure rates for topside and subsea systems are based on generic databases (OREDA handbook (OREDA, 2009), Operator data etc.) and sparse failure data is available from subsea industry due to infrequent failures (Astrimar, 2015). Most of the failure rate prediction methods are based on field data analysis for estimation of parameters of life distribution which reflects deterioration characteristics (Toscano and Lyonnet, 2008)

OREDA (2009) provides data of constant failure rates, failure modes, failure mechanisms for many subsea and topside oil and gas systems. These are based on the assumption that the equipment is exposed to environmental conditions which are stable and the failure rate is constant at any given point of time during operation. This assumption has two major limitations. A) Over-estimation of the reliability of equipment/system in harsher conditions B) Limited impact of maintenance activities on failure rates. Rahimi and Rausand (2013) have proposed a new approach based on failure rate evaluation with influencing factors (Brissaud et al., 2010) to solve these limitations to a certain extent.

The subsea industry is moving towards the concept of standardization and modularization of components and systems respectively (Gjersvik et al., 2007, Mahler and Awo, 2014). It means that the basic components can be designed, qualified and combined according to specifications to be used in different environments. In such a scenario, there is a need of numerical and analytical method for reliability prediction against the costly physical testing approaches (Myhrvold et al., 2016).

As a consequence, there is a need of practical models which can use the operational data and incorporate the dynamic parameters like maintenance intervals, environmental conditions for reliability quantification. Integration of the dynamic parameters with an adaptive model can improve the accuracy of these models (Myhrvold et al., 2016).

1.2 Objectives

The main objectives of this thesis are, to study the present failure prediction methods used in subsea industry, identify the research gaps and propose a new model with illustrative example of subsea pump. The overall objective is achieved by accomplishing the following objectives.

1) Make a brief description of subsea production systems with the need and challenges of reliability prediction.
2) Give brief technical description for relevant new failure rate prediction methods.
3) Study the different Failure rate prediction methods: Bayesian Belief Networks, Artificial Neural Network, 3-Step Model with brief description of regression based models.
4) Identify the research gaps in the failure rate prediction methods when they are applied for subsea equipment.
5) Select a relevant subsea equipment with similar topside equipment (for which data are available) to identify design changes, difference in influencing factors and maintenance –
6) Develop a new approach to determination of failure rate functions for new equipment in subsea application.
7) Discuss the results, ideas for further work.

1.3 Limitations

The main focus of this master thesis is to provide a relatively new approach to estimate the reliability of new technologies such as subsea production systems. An illustrative example of subsea pump is used due the increasing significance of subsea pumps in the novel subsea processing technology and another reason of choosing this as an example is constraints on availability of data. As Bayesian belief network (BBN) incorporates all the influencing factors easily, it is chosen as the most relevant reliability analysis tool used in this report. Most attention is being paid to the sub-objectives 3, 4 and 6above, as these are the parts that are considered to be the most challenging of the sub-objectives. The thesis is carried out at NTNU, Trondheim. As a result there has been a limitation on the subsea equipment / system description and the reliability data. Only a selected failure rate prediction methods are discussed due to time and scope limitation of this thesis. As mentioned in the preface to the report, it is assumed that the reader has some prior knowledge of basic statistics and reliability studies. It saves the time and effort and lets the author to go straight to the problem. It is assumed that the reader is familiar with concepts like failure rates, failure modes, probabilistic failure rate distributions, and confidence intervals.

1.4 Approach

The master thesis begins with a brief description of subsea production systems (SPS) to let the readers gain basic knowledge of SPS and understand the unique nature of subsea environment. The literature review documented in Chapter 3, is an interpretative review of selected failure rate prediction methods within the subsea oil and gas industry. This provides the background knowledge built upon to address the research problem. A new model for failure rate prediction is proposed and subsea pump is chosen as an illustrative example to explain the method and quantify failure rate. An outline of this approach is illustrated in Figure 1.2.

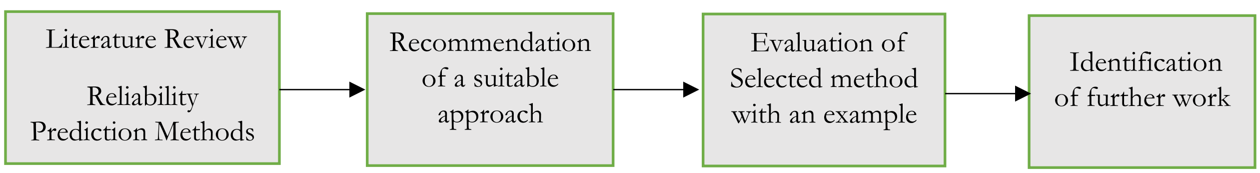

Figure 1.2 Research approach

1.5 Structure of the report

The rest of the chapters and their contents are as follows:

Chapter 2 gives an overview of the subsea production systems with brief explanation of all the sub-systems. It gives a basic idea of the different sub-systems and equipment of subsea production systems. The chapter also highlights the main challenges in design and operation of subsea production systems.

Chapter 3 briefly describes the terms failure rate and highlights the need of failure rate prediction for subsea systems. In addition, description of reliability handbooks/databases are presented.

Chapter 4 gives detailed literature review with discussion of failure rate prediction methods namely Cox model, Prediction of failure rate for new subsea equipment by (Rahimi and Rausand, 2013) Bayesian Networks, Artificial Neural Networks.

Chapter 5 presents the new model of prediction of failure rates based on the research gaps identified in literature review. The model is explained with an illustrative example of subsea pump.

Chapter 6 includes Summary, Conclusion and Recommendation of further work.

2 Subsea Production Systems – An introduction

This chapter briefly describes the sub-systems of a typical subsea production system and explains the need and challenges of the failure rate prediction process of a subsea equipment.

2.1 Overview of Subsea Production System

The continuous increase in the consumption of oil and gas combined with efforts in the industry to reduce operating costs is driving the research and development of new technologies in the industry. Accordingly, technologies and equipment for exploring and excavating the resources of deep sea areas that are buried underground under the sea have been gradually enhanced. Facilities that are used for the development of resources buried underground in coastal areas and the open sea are collectively prefixed with the term, subsea. The examples include subsea well, subsea field, subsea project, and subsea development (Woo et al., 2014).

A complete subsea production system comprises several subsystems necessary to produce hydrocarbons from one or more subsea wells and transfer them to a given processing facility located offshore (fixed, floating or subsea) or onshore, or to inject water/gas through subsea wells (ISO13628-1, 2005). Depending on the complexity of a system, subsea production systems can be classified into various types ranging from a system that consists of a single well that is connected to a fixed platform, FPSO, or an onshore platform through flowlines to a system in which a number of wells are connected to a manifold in a template or cluster form and transport oil to a fixed or floating platform or an onshore platform (ISO13628-1, 2005).

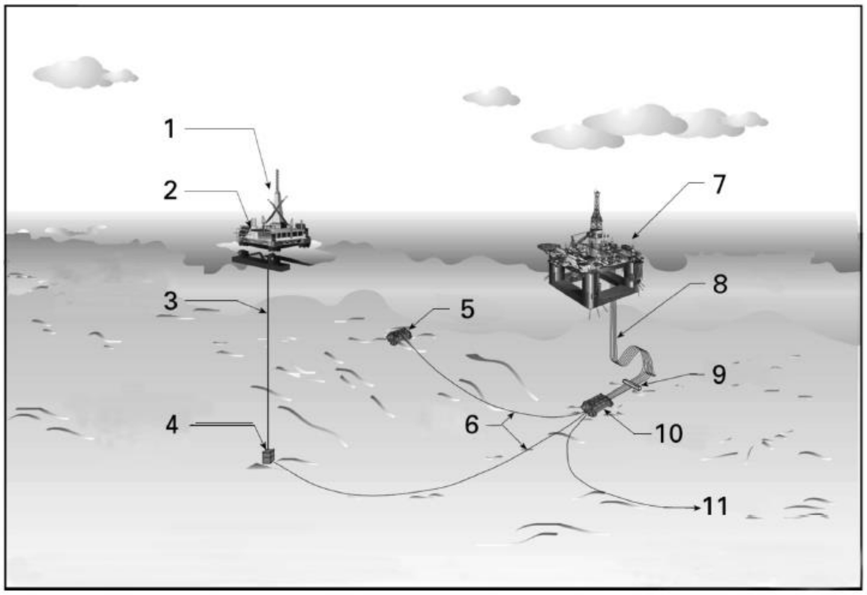

Fig 2.1 Typical Subsea Production System (ISO13628-1, 2005)

Key for reading figure 2.2

1. Running and retrieving tool
2. Installation and workover control
3. Completion/workover riser and workover controls umbilical
4. Satellite well
5. Template
6. Flowlines
7. Production controls
8. Production riser
9. Riser base/SSIV
10. Manifold
11. Export flowline

A subsea production or injection system shown in Figure 2.2 includes the following subsystems

- A wellhead and associated casing strings to provide basic foundation structure and pressure containment system for the well.

- A subsea Christmas tree incorporating flow and pressure-control valves. It controls the pressure and flow of the hydrocarbons coming out from the well and directs it to downstream equipment.
- A structural foundation/template for positioning and support of various equipment;
- A manifold system for controlled gathering/distributing of various fluid streams;
- A subsea processing equipment, including fluid separation devices and/or pumps/compressors and associated electrical power distribution equipment;
- A production control and monitoring system for remote monitoring and control of various subsea equipment.
- A chemical injection system;
- An umbilical with electrical power and signal cables, as well as conduits for hydraulic control fluid and
- Various chemicals to be injected subsea into the produced fluid streams;
- One or more flowlines to convey produced and/or injected fluids between the subsea completions and the seabed location of the host facility;
- One or more risers to convey produced and/or injected fluids to/from various sea floor to host processing facilities.

As the operation environment of subsea equipment corresponds to the deep sea or ultra-high deep sea, traditional equipment that has been previously used in offshore and onshore environments is not appropriate for this field development. Therefore, to collect oil and gas in the deep sea, safe and reliable equipment that is specialized for the deep sea needs to be developed pertaining to requirements of different fields (Woo et al., 2014).

The subsea oil and gas industry is moving more and more of the traditional topside fluid processing systems to the seabed. This strategy has the potential to give increased production from low-energy reservoirs and may also lead to significant cost saving (Mahler and Awo, 2014). In addition, the oil and gas industry is currently exploring new challenging areas, such as ultra-deep waters and the Arctic region. Statoil has announced the idea of "Subsea Factory" in which all the subsystems of subsea production system will be on sea bed (Statoil, 2014). Figure 2.2 illustrates the Statoil subsea factory with all the sub-systems onsea-bed.

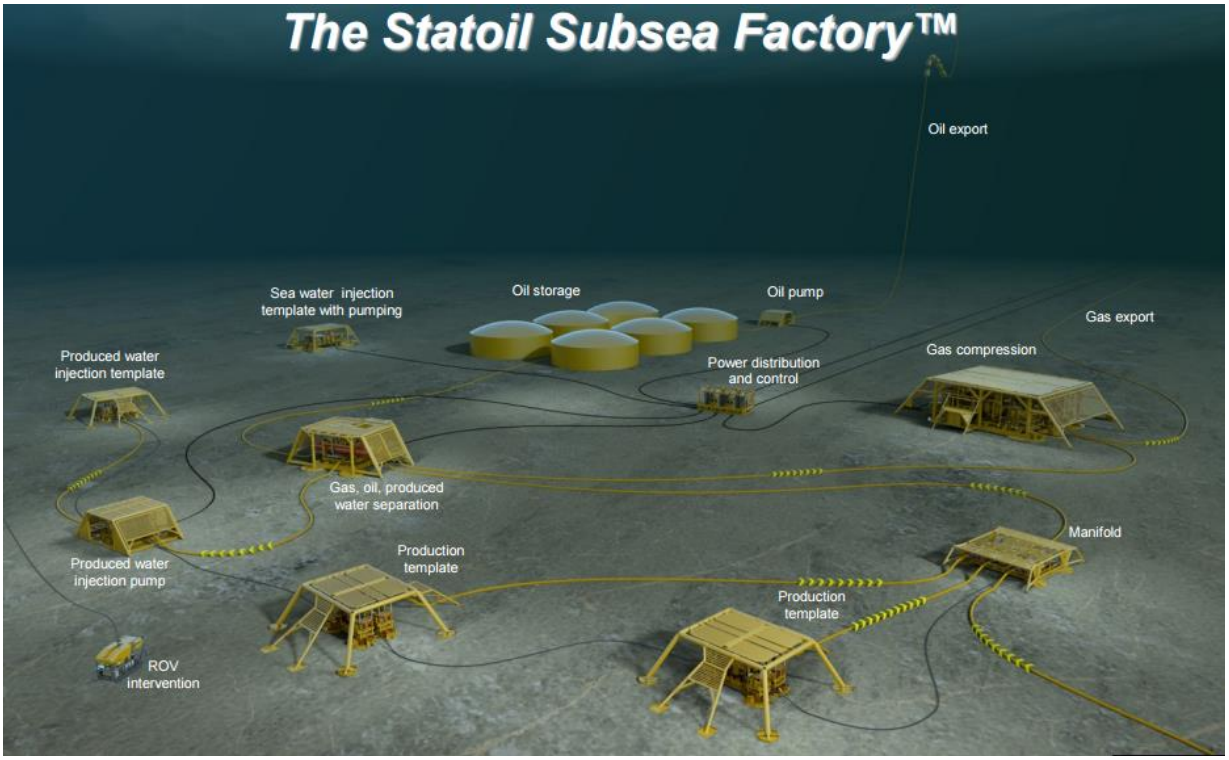

Figure 2.2 Statoil Subsea Factory (Statoil, 2014)

2.2 Challenges in Design and Operation of Subsea Production Systems

For the mechanical and electromechanical subsea equipment, there are some databases but no standard and accurate methods of failure rate prediction due to complex failure mechanisms. Moreover, when these equipment are used in subsea the challenges increase further. Some of those challenges are:

2.2.1 Flow Assurance challenges

The challenge of delivering multiphase reservoir fluids to the host with high availability is commonly known as flow assurance (Bai and Bai, 2012*).* The ultra-deep subsea environment is characterized by very low temperatures and high pressures and high hydrostatic pressure. These harsh conditions cause significant technical problems related to flow assurance like hydrates, corrosion, slugging and flow stability control. Longer tiebacks are required to connect the production wells to storage facilities. Increased hydrostatic pressure requires higher pressure to maintain production rates.

2.2.2 High cost of subsea interventions

To carry out maintenance of subsea equipment, it is required to use remotely operated vehicles (ROV). They are usually operated from a floating drilling rig of varying size and capacity depending on the nature of intervention. The intervention costs are driven by the duration of repair and for subsea equipment it's longer due to remote and deep installations. Figure 2.4 illustrates the average day rates for offshore rigs according to the internal data compiled by DNV in 2006.

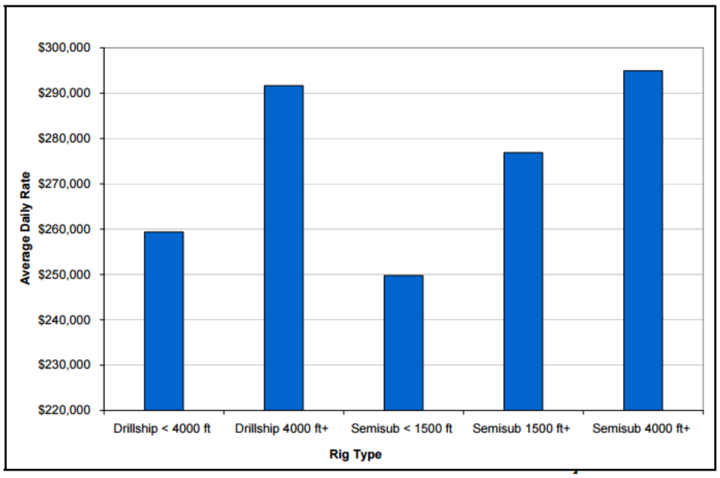

Fig 2.4 Average day rates of offshore rigs for intervention (Fanailoo and Andreassen, 2008)

2.2.3 Technical Challenges in assuring reliable operation

The reservoirs situated in high temperature and high pressure area require cooling of both drilling mud and electronics (Fanailoo and Andreassen, 2008).

2.2.4 Constant failure rate assumption

Data from OREDA presents constant failure rates which assumes that the routine maintenance keeps the equipment in "as good as new" condition. This assumption might not work for subsea equipment, for example when a valve has failed and it is replaced with a new valve of same type, it is wrongly believed that the equipment is as good as new, the environmental conditions in the well have changed to produce a more hostile environment (Rausand and Høyland, 2004). The high cost of subsea intervention drives the need of longer maintenance intervals for subsea installations. In addition, the harsh subsea environment, technical and flow assurance challenges increase the degradation rate of the equipment. As a result, constant failure rate model is not accurate and makes an increasing failure rate model is more suitable as shown in figure 2.5.

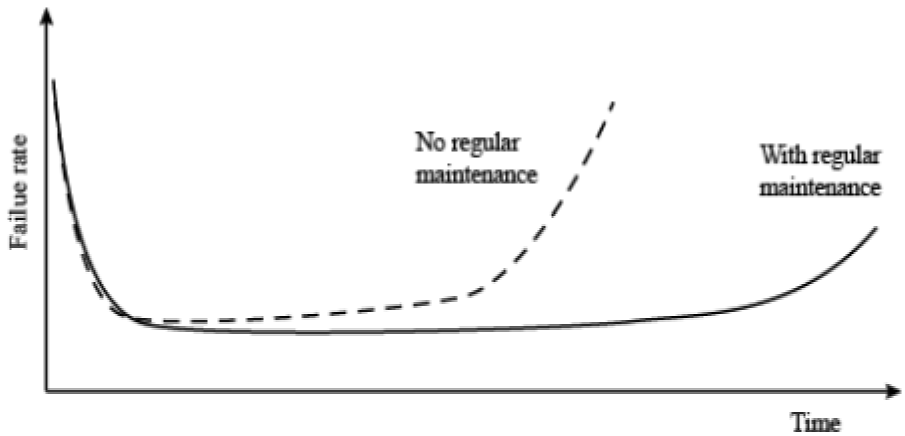

Figure 2.5 Failure rate of a maintained vs. non-maintained equipment (Rahimi and Rausand, 2012)

2.2.5 Increasing Novelty of subsea technologies

As the subsea systems are employed in deep and ultra-deep water depths, the industry is developing new and novel technologies for reliable, safe and highly productive operation. Some of the novel solutions include:

- Subsea separation and pumping(e.g. Åsgard
- All-electric actuators for valves
- Electric submersible pumps (ESP)

These new technologies were qualified by the many industry partners like Aker Solutions, Oceaneering and many others. During qualification ,the failure data for some of the components of these new subsea equipment were not available in OREDA but were derived from data of similar components with expert judgement (Brandt et al., 2009). These necessary crude adjustments lead to uncertainty in failure data and poses a challenge for using the failure rate data of these components in future subsea developments.

2.2.6 Adaptation from existing and proven technology and lack of data

For the failure rate data of a component in a novel subsea equipment, many subsea companies adapt the failure rate of components from existing and proven technology as far as possible. The application, operating environment, accessibility of maintenance are some of the factors which influence the failure characteristics of the component (Brissaud et al., 2010).

Qualitative means can be used to assess the level of adjustment by comparing the influencing factors between new and existing operating environment (Thies et al., 2009). For example, a hydraulic actuator moved from topside to subsea will be subjected to increased pressure, rate of corrosion, etc. As a result there will be an increase in failure rate. Quantitative measures can be used by quantifying the influencing factors such as lifetime loading, duty cycles, and pressure (Rahimi and Rausand, 2013).

Although these methods yield an idea about the new failure rate, they are not easily estimable because of no concrete methods in measuring the effect of influencing factors. This increases the uncertainty in overall reliability estimation during design.

2.2.7 Expensive Reliability Testing

Complex systems are being developed to overcome the increasing subsea challenges for example integration of power and control systems for subsea. As the complexity increases, the propagating failure modes, multiple failure modes and failure rates per component increases. This leads to the complexity in how a system might fail as makes it difficult to use the traditional reliability testing methods (Myhrvold et al., 2016). As a result, an extensive and cost incurring process is required to achieve the confidence of subsea industry partners.

3 Failure rate prediction databases

The previous chapter highlighted the challenges of failure rate prediction process in subsea industry. A literature review is done to study and describe the different methods and databases available for failure rate prediction. It is divided into 2 chapters. This chapter presents a literature survey on failure and reliability handbook which contain the databases of oil and gas industry and other industries for collection of failure data and analysis of operational and maintenance data.

3.1 Literature Survey

The literature has mainly been obtained through databases like Science direct, One petro, Scopus etc. The reference lists in the reviewed articles have also been explored in order to get further information.

The literature search began with using the terms "reliability assessment" and "reliability prediction". The following terms were also used in addition to narrow down the search results to get relevant results

- Failure rate prediction
- New technology
- Subsea
- Bayesian network

3.2 Failure rate – Definition and interpretation

NORSOK Z-016 (NORSOK, 2003) defines failure as "*termination of an ability an item have to perform a required function*". The failure rate function expresses the probability that an item that has survived up till time t, will fail during the next period of time. If the condition of the equipment is deteriorating, this probability of failure will increase with age *t*. The probability distribution of failure rate varies with time according to the condition of equipment. The selection of an appropriate failure distribution must be based on a thorough understanding of the deterioration mechanisms. Failure rates of products are usually affected by wear, fatigue, and other stress-related failure mechanisms, and these may result in equipment degradation and increasing failure rate with time.

The failure rate of mechanical products is often assumed to be bathtub-shaped as illustrated in Fig. 3.1, consisting of three distinct periods: (i) a burn-in period with a decreasing failure rate, (ii) a useful life period with a nearly constant failure rate, and (iii) a wear out period with an increasing failure rate (Rausand and Høyland, 2004).

The term failure rate has two different interpretations. It may be interpreted as the conditional probability as the product that is functioning at time "t" will fail in a following short interval (Rausand and Høyland, 2004). As such, the failure rate indicates how a single product improves or deteriorates over time. This failure rate is sometimes called the force of mortality (FOM). The other interpretation is related to the frequency of failures of products that are repaired. This concept is sometimes called as rate of occurrence of failures (ROCOF) and does not tell much about the deterioration of a single product (Rausand and Høyland, 2004).

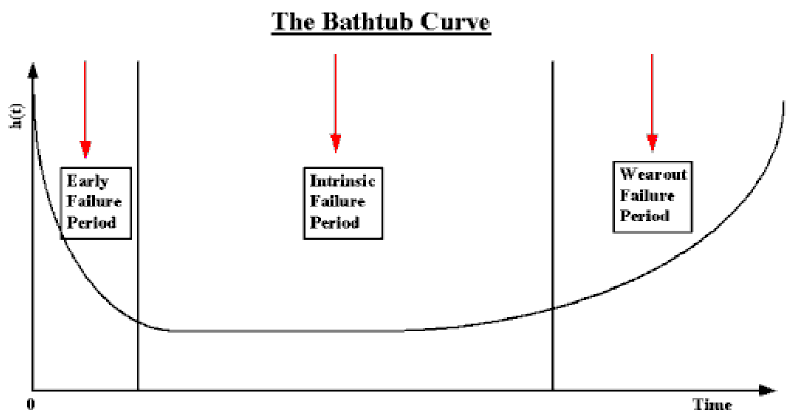

Fig 3.1 Bathtub curve

It is very common that reliability studies are based on field data (OREDA, 2009), but in case of subsea production systems the field data is incomplete and lacks sufficient detail (Brandt et al., 2009). Further sections in this chapter discuss the need of failure rate prediction in subsea systems and the research that has been done to formulate failure rate models and methods.

3.3 Need of failure rate prediction in Subsea Industry

Chapter 2 lists the high level of technology applied and qualified for subsea industry. Although subsea systems and equipment are designed and tested to withstand the harsh subsea conditions, failures do occur given that technology is relatively new and not much experience exists. And as the number of subsea installations increases, the likelihood of recording a failure increases (Uyiomendo and Tore, 2015). Reliability analysis quantifies the equipment/system reliability and acts as a decision support for the operator during development of a new equipment/system.

Reliability requirements should be based on 5 factors according to IEC 60300-3-4

1) The failure criteria
2) The application of the equipment/system
3) The environmental conditions
4) The operating conditions
5) The methods intended to be applied for determining the requirement

The requirement of system reliability can be expressed with failure rate, survivor probability, and the mean time to failure (MTTF). The probabilistic analysis of any given safety function design is one of the fundamental concepts in today's functional safety standard IEC 61508. The probabilistic analysis is possible only when the failure rate data for all the products that are installed or might be installed is available.

The need of failure rate prediction process for subsea equipment are listed below:

- Check the possibility of achieving reliability requirement
- Achieve a safe and reliable design which meets requirements of end-user(s)
- Provide input to safety analysis
- Establish maintenance/upgrade requirements

The deployment of subsea systems requires specialized equipment and processes and implies a very high cost. Any requirement to repair or intervene the subsea equipment is normally very expensive and this type of expense may result in economic failure of the subsea technology development. Figure 3.2 illustrates the different stages in a project cycle and significance of failure rate prediction.

Therefore, before an operator accepts to install a new subsea system, he must be convinced that the new system has a sufficiently high reliability and a prerequisite is that failures requiring subsea repair interventions must not occur. A subsea intervention requires an intervention vessel and often a long production down-time at a cost of several million US dollars. The time to the first planned intervention may be in five years, and even longer, and it is important that the installed system is able to survive at least this period without failure.

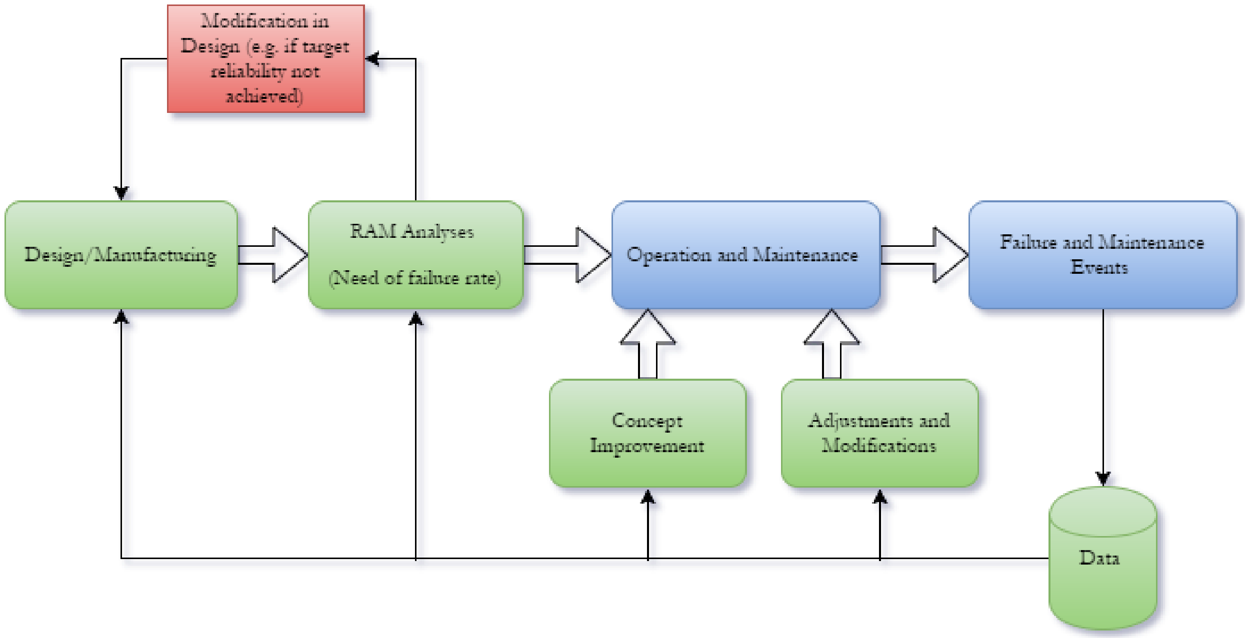

Figure 3.2 Failure rate prediction in feedback analysis from collected failure data (adapted from (Hameed et al., 2011))

The weaknesses and limitations of equipment and system design must be identified and improvements made in the early stages of product lifecycle. If flaws are revealed and corrected in the design phase, their consequences are not as significant as it will be during the later stages of product lifecycle. The issues like redesign and reengineering occurs due to failure in identification of the design flaws.

As most of the new subsea developments are gradually extended to the deep sea, relevant equipment and facilities require strict qualification for the functions and requirements of various systems. RAM (Reliability, Availability, and Maintenance) analysis using the predicted failure rate is an integral part of the qualification process (Fanailoo and Andreassen, 2008). It is a powerful tool to demonstrate the commercial performance and thus the economic impact of a proposed concept. In a RAM analysis probabilistic simulation models are established to provide a prediction of the future performance of a system or component. These models can then be used to simulate different development options and scenarios and could be a powerful tool for decision support when assessing different concepts and solutions. Failure rates of different subsystem and components are input RAM analyses.

Failure rate prediction processes include identification of critical failure modes which identifies the most significant contributors to failure. This enables the designer to make changes to provide a product with higher reliability. The results of the process can be used to plan technology qualification programs, and to arrive at a tradeoff between the system capital expenditure, operating expenditure, redundancy requirements, and subsea system modularity.

3.4 Reliability Handbooks

Several reliability databases are available as handbooks which list the failure data e.g. failure mode, failure cause, failure rates for electronic and general components and systems (OREDA, 2009, DoD, 2011). This section describes different methods used in the reliability handbooks.

These handbooks collect failure data for many types of components and assemblies, mainly of the electronics category and for different environments and analyze it using different models to provide failure modes and failure rates. Table 3.1 summarizes some of the most common reliability handbooks.

Table 3.1 Summary Table of Failure prediction methods

Application Area	Prediction handbooks/databases
Electronics	MIL-HDBK-217F (DoD, 2011) • Parts Count Technique • Parts Stress Technique
	Other Related Databases • Telcordia-SR332 (SR332, 2011) • PRISM
	FIDES (Guide, 2009)
Oil and Gas	OREDA (OREDA, 2009) FMEDA

3.4.1 Failure rate methods for handbooks of Electronic components

Foucher et al. (2002) proposed a broad classification of the reliability prediction methods for electronic devices into three categories:

(1) Bottom–up statistical methods

(2) Top–down similarity analysis methods based on an external failure database

(3) Bottom–up physics-of-failure methods

The first two categories are based on statistical analysis of failure data, while the last category is based on physics-of-failure models. The third category uses data from material properties, functional loads, design characteristics and usage environment to predict failure rate. Foucher et al. (2002) compare the methods based on eight specified criteria related to accuracy, ease of data exchange, amount of devoted resources, time to obtain reliability estimate, ease of customization, traceability, repeatability and ability for evolution. They conclude that the best reliability prediction will be achieved by a combination of different methods, depending on the phase of equipment's lifecycle and on the objectives and assumptions of the manufacturer or the customer.

3.4.1.1 Bottom-up statistical methods

Bottom-up statistical methods are based on prediction approaches using statistical curve fitting from component failure data, which is collected in the laboratory, in field or from manufacturers. It is assumed that failure of components are independent of each other. This section lists the bottom-up statistical methods mentioned in the literature.

MIL-HDBK-217F

Military handbook MIL-HDBK-217F is a database of the failure rate estimates for various types of parts used in electronic systems. The estimates are primarily based on laboratory testing under controlled environmental stresses. The United States department of defense (DoD) stopped updating after the latest version in 1995. Military handbook remains one of the important databases in the industry, alternative methods have been developed which are more accurate (Guide, 2009). The database employs two types of method for estimation

1) The parts count technique (prediction at reference condition)

2) The part stress technique (prediction at operating condition).

In "parts stress analysis" method, a detailed input of the parameters from stress analysis and environment, quality, applications, maximum ratings, complexity, temperature and other application-related factors are needed. IEC 61709 (Commission, 1996) presents stress models and values for electronic components as a basis for conversion of the failure rate data from reference (baseline) conditions to the actual operating conditions. The stated stress models are generic for the different component types and contain constants that are averages of typical component values taken from tests or specified by different manufacturers. In "parts count analysis", it is assumed that component operates under typical operating conditions.

3.4.1.2 Top-down similarity methods

Top-down similarity analysis methods are based on proprietary databases (TD) which use similarity analysis between previous sub-systems or systems with available reliability data and newly designed systems with less reliability data. It gives an insight into prediction of reliability for new technologies. All failure causes, not only component failure rates are considered and therefore, FMECA (IEC 60812, 2006) is most important. A typical TD approach is summarized for circuit card analysis by Foucher et al. (2002).

3.4.1.3 Bottom up physics of failure methods

PRISM

PRISM includes terms for failure rates from temperature cycling to solder joint but treats those contributions as constant failure rate without justification. Reliability Analysis Center (RAC) is an important source of reliability data which is managed by Rome Laboratory, New York.

RIAC 217Plus

The RIAC-Handbook-217Plus reliability prediction model published in 2006 is an official successor of the MIL-HDBK-217FN2 and the PRISM methodology.

FIDES Guide

FIDES Guide is created by FIDES Group in 2004. Fides group is a consortium of leading French companies: Airbus France, Eurocopter, GIAT industries, MBDA, THALES.

3.4.2 OREDA

The Offshore reliability data project (OREDA) started in 1981 in collaboration with the Norwegian Petroleum Directorate (now known as Petroleum Safety Authority, Norway). The initial objective of the project is to exchange and collect reliability data from wide range of equipment used in oil and gas exploration ranging from offshore topside to subsea equipment. The main purpose of OREDA project is to contribute to cost-effective and safe design and operation within the oil and gas industry; through a high quality database for reliability data. It is the most significant database available in this industry today.

The OREDA handbook lists the average failure and repair rates of equipment/sub-system. In OREDA, items are grouped into equipment classes on the basis of the main function of the item e.g.

pipelines, manifolds etc. Then, for each equipment class, boundaries are defined to identify the items that are part of it for example, for equipment class called valves, OREDA defined boundary includes a valve, an actuator, a solenoid/pilot valve and position monitoring equipment.

It is based on the assumption that the data comes from "useful life phase" of bath-tub curve where the failure rate is constant. So the failure rate function and mean time to failure (MTTF) is given as

$$z(t) = \lambda$$

$$MTTF = \frac{1}{\lambda}$$

The severity of failures and therefore the failure rates are classified into 4 classes: Critical failure, Degraded failure, incipient failure and unknown failure. The failure rates are estimated separately for each class depending on the no. and the nature of failures. The maximum likelihood estimator of λ when the failure data is from identical items that have been operating under same conditions i.e. homogenous sample is given by

$$\hat{\lambda} = \frac{Number\ of\ failures}{Total\ time\ in\ service} = \frac{n}{\tau}$$

where, n and τ denote the observed number of failures and aggregated time in service respectively. The uncertainty in $\hat{\lambda}$ is presented as 90% confidence interval (see Rausand and Høyland (2004).

The failure data for an item is collected from different installations with different operational and environmental conditions (multi-sample) is more practical with respect to homogenous sample. These samples may have different failure rates and different confidence intervals. Spjøtvoll (1985) proposed a rational estimation procedure for estimating failure rate from the merged samples. A detailed analysis by Vatn (1993) indicates that there may be a large variation between the data from different installations and therefore the multi-sample estimator should only be used.

4 Failure rate prediction methods for general components

There are various failure rate prediction methods developed for different systems and industries. This chapter explains some of the methods which are developed for subsea oil and gas industry. In addition, methods which are developed in other industries and can be applied in subsea industry are also studied. Table 4.1 lists the methods discussed in this chapter.

Table 4.1 Failure rate prediction methods discussed in this chapter

General Failure rate methods	Proportional Hazard (PH) Models Accelerated Failure Time (AFT) Models Brissaud's Approach BORA Project
	Rahimi's Approach
	Artificial Neural Networks
	Bayesian Belief Networks
	Reliability Prediction for intelligent transmitters

4.1 Regression type models

The most commonly used models for times between failures for repairable systems are renewal processes and homogeneous Poisson processes (HPPs). In a renewal process the times between failures are assumed to be independent and identically distributed. An HPP is a special type of a renewal process where it, in addition to assumptions for poison process, is assumed that the times between failures are exponentially distributed, i.e., with a constant failure rate. This means that repairable systems where the observed data indicate any form of trend due to deterioration or improvement of the system, these models are not appropriate. A model with time-dependent failure intensity, such as a nonhomogeneous Poisson process (NHPP) may be a better choice (Rausand and Høyland, 2004, RIGDON and BASU, 1990).

Several factors will influence the equipment reliability, and these are referred as reliability-influencing factors (RIFs). A RIF is a relatively stable condition, which by being changed will have a positive or negative effect on the reliability of the equipment. The RIFs should be identified and should, as far as possible, be quantified and monitored. A RIF may be constant (e.g., a design or material feature) or may vary (rather slowly) in time, such as temperature. Ascher and Feingold (1984) list 18 generic RIFs that influence the failure behavior of a repairable system, but they claim that those RIFs are usually ignored in reliability analysis.

Various types of regression models have been suggested and the RIFs are included in the models as explanatory variables or covariates. Some of the RIFs are qualitative and to include such a RIF into the regression model, it is necessary to define one or more measurable indicators that are correlated with the RIF. This indicator is called a covariate. A covariate may be a continuous variable, a discrete variable taking several values, or a binary variable. The binary variable takes the value 1 when a specific feature is present and the value 0 when the feature is not present.

The most commonly used regression-type models for reliability analysis fall into two main categories (Lawless, 1983).

1) **Accelerated failure time** (ALT) model assumes that the effect of a covariate is to multiply the time to failure by some constant. In this method, the covariates influence how fast the time is running. The accelerated failure time model can be used together with parametric life models such as the exponential (Feigl and Zelen, 1965, Lindqvist and Tjelmeland, 1989), Weibull, log-normal, and extreme value distributions (Lawless, 1983).
2) **Proportional Hazards** (PH) model is a method where the predicted failure rate λ(t) is assumed to be in the form of

$$\lambda\,(t) = \lambda_0(t)\,\pi(z)$$

Where, $\lambda_0(t)$ is the baseline failure rate determined in specific conditions and the factors π (z) models the covariates that are used to adjust the baseline failure rate to actual operating conditions. The covariates do not alter the shape of the failure rate function but they change its scale by a factor. Using this approach requires extensive data for determining the values of covariates and related parameters.

4.1.1 Cox Model

Cox proposed a new functional form for the representing covariates in PH model to estimate the effects of covariates on times to failures of a system (Cox, 1972).

$$\lambda\,(t) = \lambda_0(t)\,e^{\sum_{j=1}^{n}\alpha_j z_j} \tag{1}$$

where, α_1, α_2…. α_n are unknown parameters. A linear expression of the covariates can be obtained by taking the logarithm of the equation 1, such that the unknown parameters can be estimated using linear regression analysis. Cox developed a regression analysis based on partial likelihoods and this approach is Cox regression analysis. A detailed study by Cox (1972) explains the theory and applications of PH models. Figure 4.1 illustrates the steps involved in reliability prediction of an equipment using Cox model.

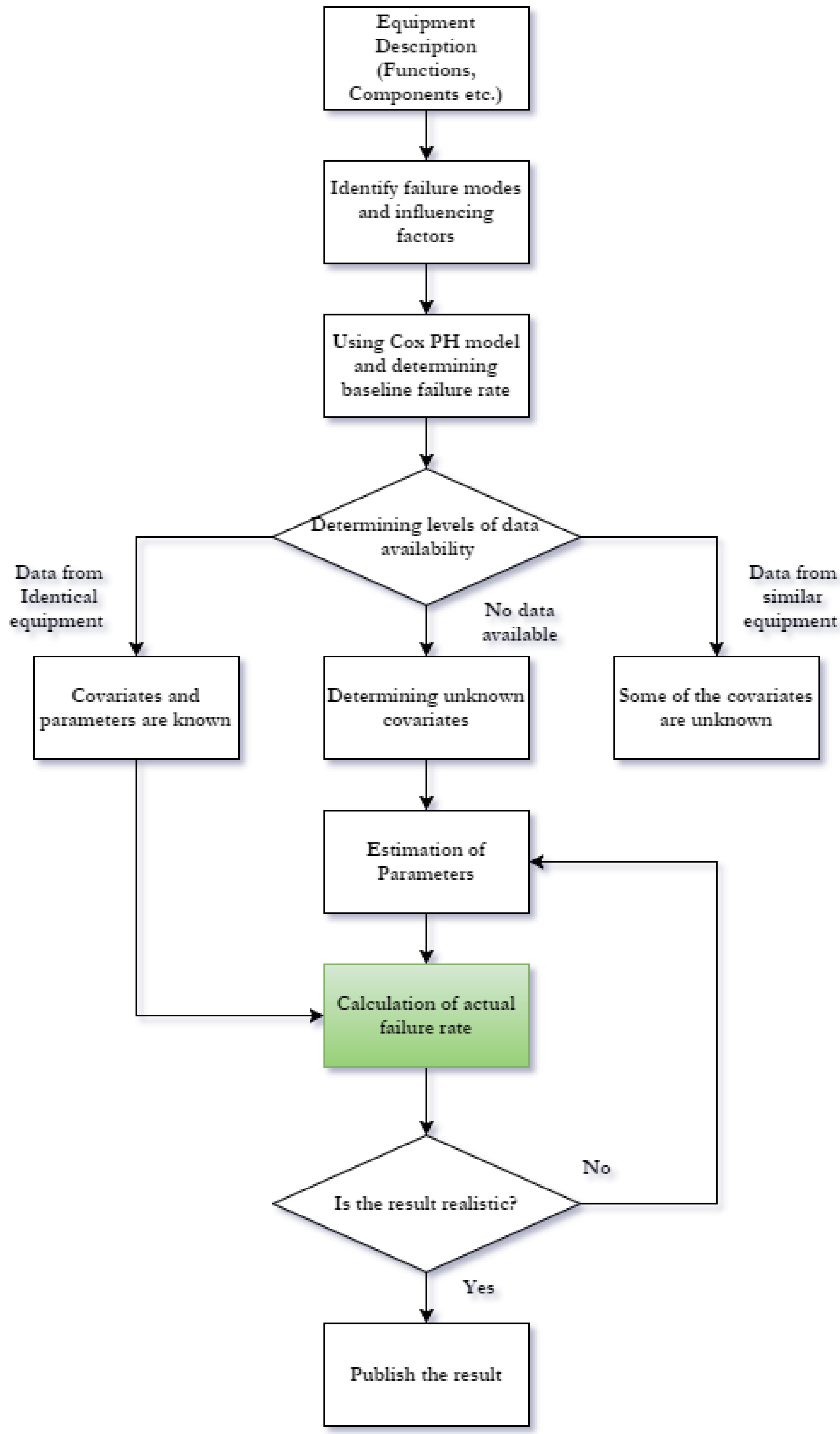

Figure 4.1 Reliability Prediction of equipment using Cox model (adapted from (Rahimi et al., 2011)

Other approaches based on PH model are summarized below.

4.1.2 BORA approach

The BORA project (Vinnem et al., 2009)discusses reliability assessment of safety barriers on offshore oil and gas installations. The approach is based on set of generic RIFs that are divided into five categories: human factors, task-related factors, administrative factors and organizational factors. The RIFs to be used for the particular assessment are selected using expert judgement and are delimited to six. An influence diagram is then set up linking the RIFs to a defined failure mode. The state of each RIF is classified into one out of six possible states and a scoring and weighing process is used to determine the effects of each RIF.

4.1.3 Brissaud et. al's approach

A similar approach based on PH model was suggested by Brissaud et al. (2010). This method uses RIFs that are divided into five categories: design, manufacture, installation, operation and maintenance. The estimation of the application specific failure rate is comparable to the approach in military handbook, but the calculation of multiplicative factors is done in another way by scoring and weighting procedure. The steps of this method are,

1) Divide system into several main component groups.
2) Represent the system failure rate as a sum of the main component groups' failure rates (i.e. as a serial system).
    a) If the system does not verify serial properties (e.g. redundant systems), the approach may be individually applied to each serial subsystem,
    b) The obtained failure rates are then combined into reliability functions according to the proper system architecture, through the system structure function.
3) Express the baseline failure rate of each component (i.e. main component group) as a percentage of the whole system baseline failure rate.

   The effects of the influencing factors are included by influencing coefficients. Each coefficient corresponds to one factor and vice-versa. If a component is susceptible to an influencing factor, its baseline failure rate is multiplied by the corresponding influencing coefficient. The coefficient values are defined according to the states of the influencing factors.

   Notice that having an a priori idea of the whole system failure rate is usually more realistic than getting accurate values for all of the components.

$$\lambda_s = \sum_{i=1}^{N} \lambda_i$$

$$\lambda_s = \sum_{i=1}^{N} [\lambda_{i,mean} \prod\nolimits_{j \in J_i} C_j^*]$$

$$\lambda_{i,mean} = w_i \, \lambda_{s,mean}$$

Where $\lambda_s$and λ_i are respectively the system's and the components' (i.e. main component groups) failure rates; $\lambda_{s,mean}$and $\lambda_{i,mean}$the system's and components' baseline failure rates; w_i the contribution (in percentage) of component *i* in the whole system's baseline failure rate *N* is the number of components which make up the system, $C_j^*$is the influencing coefficient corresponding to influencing factor j; and J_i is the set of indices of influencing factors which have an effect on component *i*.

4.2 Failure rate prediction method for new subsea equipment

Rahimi and Rausand (Rahimi and Rausand, 2013) developed this method to combine available topside failure data from available databases with the effects of RIFs on different failure causes for failure rate prediction of new subsea equipment. However, its applicability is not only in subsea technology and it can be applied to other new systems as well. As the failure rates for topside components is available from several databases, the failure rates for subsea environment are predicted using "marinization" of failure rates. The following steps summarize the approach:

Relevant data for the new subsea system is acquired from different databases depending on the availability and similarity between the new and existing equipment. For subsea equipment relevant topside data is used from OREDA (OREDA, 2009) and other databases. Several categories of data collected:

- *Technical data* is identified from similar equipment which is supplied by manufacturers and understanding the system models and functions
- *Environmental data* about the subsea and ocean operating conditions are necessary to identify the RIFs
- *Operational and maintenance data (field data)*
- *Expert judgement* is necessary in the process as the novel technology is applied and several decisions depend on expert knowledge during the process.

Brief Stepwise procedure:

Step 1: New system familiarization:

The application of new system is defined with its functions and sub-systems. DNV-RP-A203 (DNV, 2011) suggests list of critical items specifying key issues such as frequency of operation, materials, load and capacity etc.

Step 2: Identification of failure modes and failure causes:

FMECA (Rausand and Høyland, 2004) is carried out to identify the potential failure modes, failure causes and mechanisms. An influence diagram shows the different RIFs, failure causes (FC), failure modes (FM) and their inter-relationships. Figure 4.2 illustrates the RIFs, how they affect FCs and which FCs cause which failure modes and combination of failure modes for failure rate.

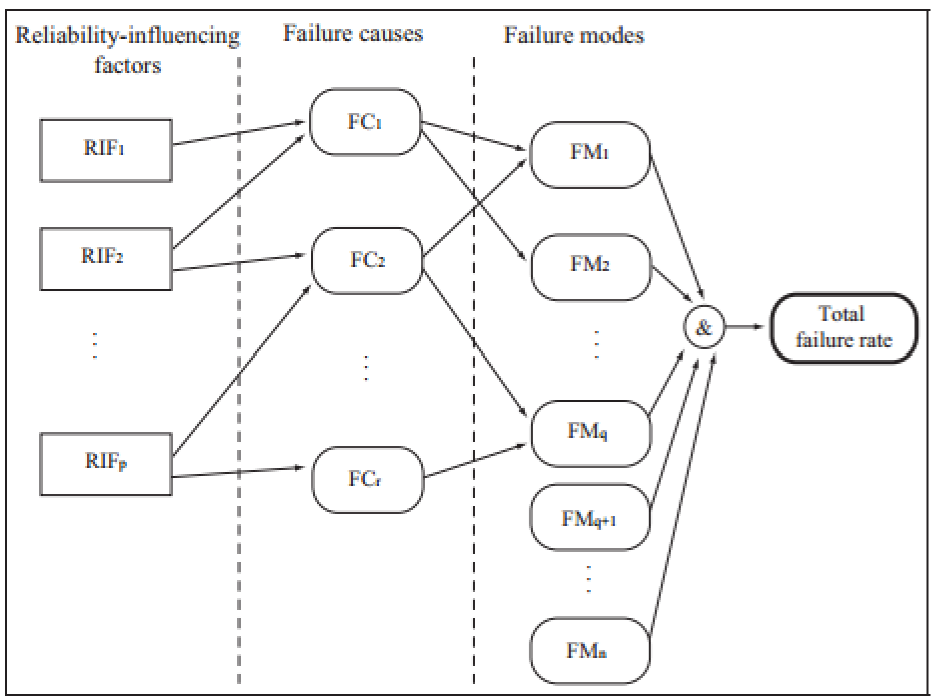

Figure 4.2 Factors contributing to total failure rate of subsea system (Rahimi and Rausand, 2013)

<u>Step 3:</u> Reliability information acquisition for similar known system; comparison of the new and the known system

OREDA and other databases e.g MechRel and RIAC are studied for collecting failure data of similar designed systems including failure mode, failure rate estimates including confidence interval, and failure mechanisms.

To start with, total failure rate $\lambda^{(T)}$ is expressed in terms of the failure rates due to different failure modes as

$$\lambda^{(T)} = \sum_{i=1}^{n} \lambda_i^{(T)}$$

where, $\lambda_i^{(T)}$is the failure rate for failure mode FM_i and it is assumed that all failure modes are disjoint such that

$$\lambda_i^{(T)} = \alpha_i \lambda^{(T)}$$

Where, α_i is probability of occurrence of failure mode FM_i given that system failure has occurred. New and existing systems are compared with regards to RIFs, failure causes, failure mechanisms and failure modes as shown in figure 4.3. The dashed outlined rectangles in figure 4.3 are parameters of topside system and the solid ones are for subsea system.

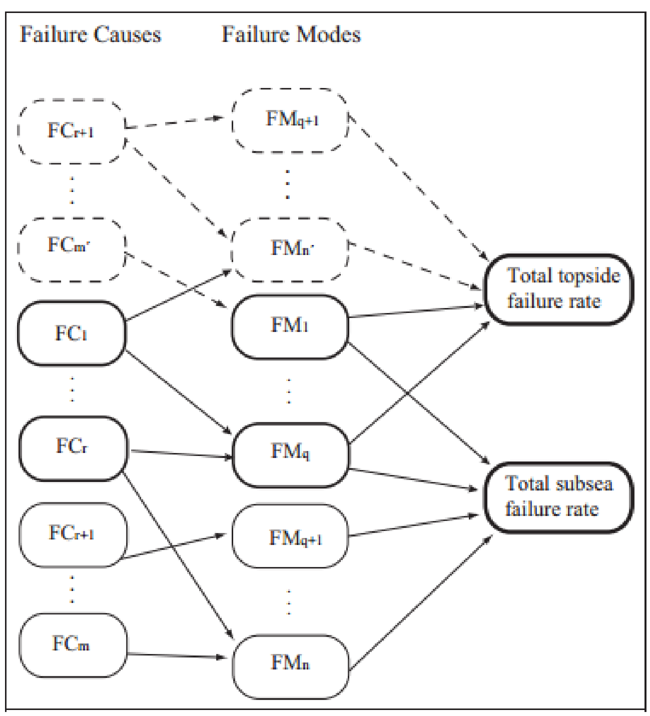

Fig 4.3 Comparison of topside and subsea systems

Step 4: Selection of relevant RIFs

RIFs influence the reliability of the system. The objective is to quantify the effect of RIFs on failure causes. Relevant RIFs are identified based on the insight gained in Step 3. Table 4.2 lists the generic RIFs (Ascher and Feingold, 1984, Brissaud et al., 2010).

Table 4.2 Generic RIFs (Ascher and Feingold, 1984, Brissaud et al., 2010)

Category		RIFs
Design and Manufacturing		System structure
		Materials
		Dimensions
		Loads and capacities
		Quality (manufacturing process, installation, etc)
Operational and Maintenance		Functional Requirements
		Time in Operation
		Mechanical Constraints
		Frequency of Maintenance
		Maintenance policy
		Accessibility for Maintenance
		Type and quality of maintenance
Environmental	External	Temperature
		Location of operation
		Pressure
		Corrosive environment
		Pollution
	Internal	Pressure
		Sand particles in the fluid
		Chemical content

Specific RIFs for new subsea system are selected by experts. They are then ranked according to their importance for each failure cause of new subsea system. This is done by first considering one failure cause at a time e.g. FC_j, and then comparing all the RIFs which influence FC_j pairwise i.e. comparing $RIF_{j,k1}$with $RIF_{j,k2}$for all pairs (k1,k2) for failure cause FC_j. The weight ε_{kj} denotes the weight of

RIF_k for FC_jThese weights represent the importance of relevant RIFs on a particular FC such that $\sum_{k=1}^{p} \varepsilon_{kj}$.

Step 5: Scoring the effects of RIFs

After the weights of each RIF for a particular FC is calculated, this step quantifies the effects of each RIF on a particular FC. Some RIFs can influence failure causes in both topside and subsea systems and some in only one of the systems. This is quantified by using indicators $\nu_{kj}^{(T)}$ for RIFs influencing topside FC and $\nu_{kj}^{(S)}$ for RIFs influencing subsea FC where topside indicator $\nu_{kj}^{(T)}$ is

$$\nu_{kj}^{(T)} = \begin{cases} 1, \quad if\ RIF_k\ has\ effect\ on\ (topside) failure\ cause\ FC_j \\ 0\ if\ RIF_k\ has\ no\ effect\ on\ (topside) failure\ cause\ FC_j \end{cases}$$

And subsea indicator $\nu_{kj}^{(S)}$

$$\nu_{kj}^{(S)} = \begin{cases} 1, \quad if\ RIF_k\ has\ effect\ on\ (subsea) failure\ cause\ FC_j \\ 0\ if\ RIF_k\ has\ no\ effect\ on\ (subsea) failure\ cause\ FC_j \end{cases}$$

For each $RIF_k$and failure cause FC_j an influence score η_{kj} is used to indicate how much higher/lower effect RIF_k has on FC_j for subsea system as compared to topside system. To score the effect of relevant RIFs on failure cause a seven point scale is used as shown in table 4.3.

Table 4.3 A seven point scale for scoring the RIFs (Rahimi and Rausand, 2013)

-3	-2	-1	0	1	2	3
Much lower effect	Significantly lower effect	Slightly lower effect	No difference	Slightly higher effect	Significantly higher effect	Much higher effect

In the table $\eta_{kj} = +3$ indicates that RIF_khas "much higher effect" on subsea FC_j compared to topside FC_j. $\eta_{kj} = 0$ implies that there is no difference in effect of RIF_k on FC_j of topside and subsea systems. $\eta_{kj} = -3$ implies that RIF_khas "much lower effect" on subsea FC_j compared to topside FC_j. All the seven points are applicable for scoring when $\nu_{kj}^{(T)}$=1, while only three points are applicable when $\nu_{kj}^{(T)}$=0 (only positive points are considered because $\nu_{kj}^{(T)}$=0 implies RIFs will atleast effect the subsea FC positively). The number of RIFs influencing the subsea FC_j is $\sum_{k=1}^{p} \nu_{kj}^{(S)}$

Step 6: Weighing the contribution of failure causes to failure modes.

It is assumed that the failure causes are as "disjoint" as possible which means that the effect of two or failure causes on a failure mode should not be dominated by the combined effect of failure causes. The failure causes for each failure mode might contribute with different weights compared to the topside system. $w_{ji}^{(T)}$represents the contribution of failure cause FC_j to failure mode FM_i from the topside system. Failure data from OREDA can be easily used to find $w_{ji}^{(T)}$. Expert judgement is used to find the corresponding weights for subsea denoted by $w_{ji}^{(S)}$. The weights are normalized in such a way that sum of the weights for a particular failure mode is

$$\sum_{j=1}^{r} w_{ji}^{(S)} = 1 \; for \; i = 1,2 \ldots q$$

Where, no. of failure modes is q and it is considered same for both topside and subsea systems.

Step 7: Determination of failure rate for similar failure modes

The final failure rate of the subsea system is expressed in terms of the topside failure rate and the quantified parameter calculated from the previous steps. This approach is similar to that of BORA approach(Vinnem et al., 2009). Assuming that failure rate for failure mode FM_i in the subsea environment can be expressed in terms of failure rate for failure mode FM_i in the topside environment,

$$\lambda_i^{(S)} = \lambda_i^{(T)} (1 + \kappa_i) \quad for \; i = 1,2,3 \ldots q$$

Where $\kappa_i > -1$ is a constant scaling factor that is calculated in further steps.

As $\lambda_i^{(S)}$ inderectly depends on the failure causes of the failure mode FM_i and their weights, the scaling factor κ_i must also depend on the weights $w_{ji}^{(S)}$ of the respective failure causes. The parameter $w_{ji}^{(S)}$ is interpreted as

$w_{ji}^{(S)}$= Pr(the failure is caused by $FC_{ji} | \, FM_i \; has \; occured$)

κ_i also depends on the various effects of failure causes on the failure modes as compared with the topside system. This is quantified as weighted average of scores of the RIFs that effect FC_j

$$\bar{\eta}_j = \sum_{k=1}^{p} \varepsilon_{kj} v_{kj}^{(S)} \frac{\eta_{kj}}{3} \quad for\ j = 1,2 \ldots r$$

The weighted average score is divided by 3 for normalization, as the 7-pont scale is from -3 to +3. Then scaling factor κ_i is calcualted as:

$$\kappa_i = c_i \,.\sum_{j=1}^{r} w_{ji}^{(S)}\ \bar{\eta}_j \quad for\ i = 1,2 \ldots\ldots q$$

Where, c_i represents the contant scaling factor calculated in further steps.

To calculate c_i, it is first assumed that the failure rate, $\lambda_i^{(S)}$can be delimited with respect to failure mode FM_i

$$\lambda_i^{(S)} = \left[\lambda_{Low,i}^{(S)}, \lambda_{High,i}^{(S)}\right]$$

Such that the boundary values are based on topside failure rate $\lambda_i^{(T)}$for failure mode FM_i. The boundary parameters are denoted by $\theta_{min,i}$ and $\theta_{max,i}$ for each failure mode as:

$$\theta_{min,i}\, \lambda_i^{(T)} \leq \lambda_i^{(S)} \leq \theta_{max,i}\, \lambda_i^{(T)}$$

The factors $\theta_{min,i}$ and $\theta_{max,i}$ are calculated using expert judgement. On combining equations, we get

$$\theta_{min,i}\, \lambda_i^{(T)} \leq 1 + c_i \,.\sum_{j=1}^{r} w_{ji}^{(S)}\ \bar{\eta}_j \leq \theta_{max,i}\, \lambda_i^{(T)} \qquad \textbf{(2)}$$

The values of $\bar{\eta}_j$ and $w_{ji}^{(S)}$are calculated earlier in this step and in step 6 respectively. As a result, c_i should be calculated as a function of $\theta_{max,i}$ and $\theta_{min,i}$.

To determine c_i, extreme cases of equation 2 are considered where all score for the RIFs, η_{kj} are given by extreme cases i.e the maximum case when all the scores η_{kj} are given as +3 and the minimum case when all the scores are given as -3. The value of $\bar{\eta}_j$ for failure cause FC_j would be given as +1 and -1 for maximum and minimum conditions respectively. This information, along with the fact that sum of all $w_{ji}^{(S)}$ is equal to 1, is used to infer that for minimim case, $c_i = 1 - \theta_{min,i}$ and for maximum case $c_i = \theta_{max,i} - 1$. The expression for c_i is then written as:

$$c_i = \begin{cases} 1-\theta_{min,i}, & when \sum_{j=1}^{r} w_{ji}^{(S)}\ \bar{\eta}_j < 0 \\ 0\ , & when \sum_{j=1}^{r} w_{ji}^{(S)}\ \bar{\eta}_j = 0 \quad \text{for } i=1,2\ldots\ldots q \\ \theta_{max,i}-1, & when \sum_{j=1}^{r} w_{ji}^{(S)}\ \bar{\eta}_j > 0 \end{cases} \tag{3}$$

The equation 3 becomes

$$\lambda_i^{(S)} = \lambda_i^{(T)} \left(1 + c_i \ . \sum_{j=1}^{r} w_{ji}^{(S)}\ \bar{\eta}_j\right) \ \ for\ i = 1,2 \ldots .q$$

Step 8: Determination of failure rate for new failure modes, calculation of new total failure rate

The limitation of this method is that the failure rates of failure modes which are only relevant to subsea system cannot be quantified and expert judgement and technical reports have to be used.

Finally total failure rate is calculated as sum of all the failure rates for the failure modes given as

$$\lambda_{Total}^{(S)} = \sum_{i=1}^{n} \lambda_i^{(S)}$$

The whole model is summarized in the flowchart shown in figure 4.4

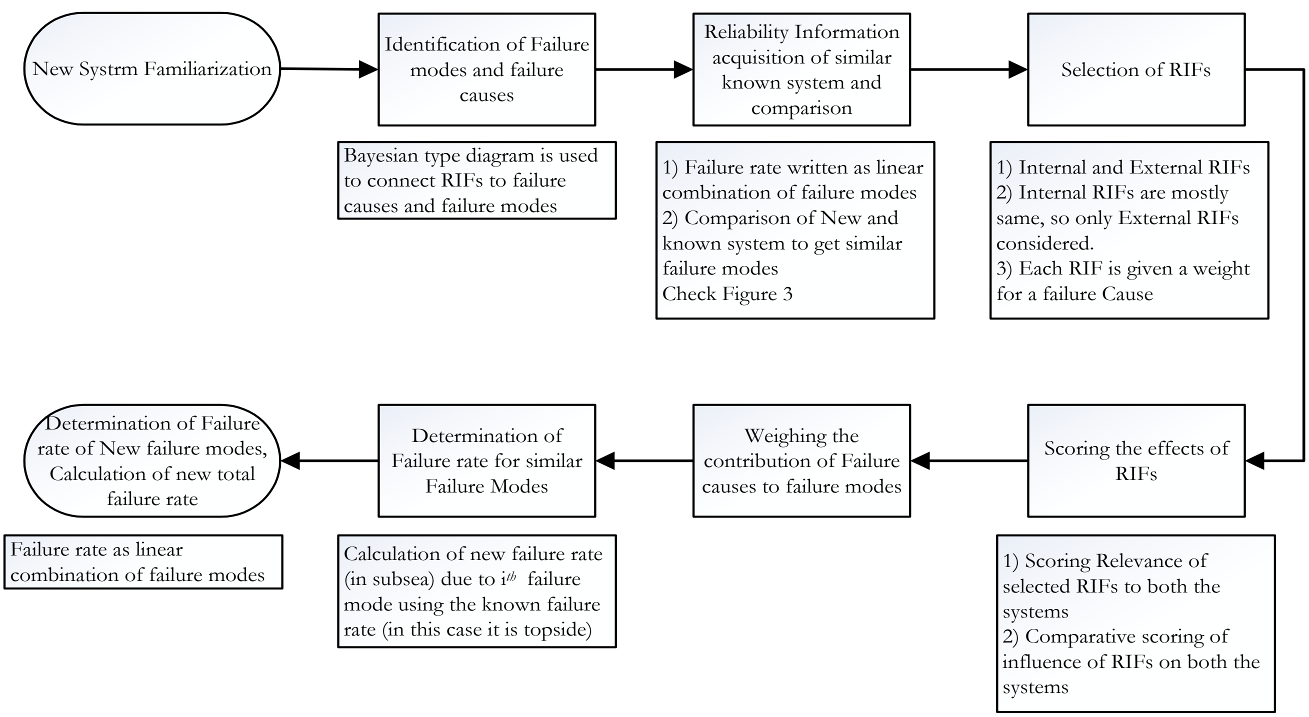

Figure 4.4 Flow chart showing steps of prediction of new failure rate based on Rahimi and Rausand (2013)

4.3 "3-Step" model (functions-material elements- faults and failures)

The development of microelectromechanical systems (MEMS) has led to evolution in sensor systems. New sensors are intelligent and can handle data acquisition, its processing, and transmission. As a result, these sensors can transmit the signals in an appropriate form. International Society of Automation (ISA) and IEC (Commission, 2006) refer to these sensors as "transmitters" in process industry. The advanced functionalities of these transmitters include: self-adjustment, self-diagnosis and validation, error measurement correction and online reconfiguration. This presents specific issues like interactions between material elements and functions on system level, undefined behavior in faulty conditions and little reliability data. Table 4.4 lists the advantages and disadvantages of these transmitters in terms of reliability and safety. To resolve these issues a reliability analysis as a "3-Step" model is proposed by Brissaud et al. (2011). Reliability analysis of intelligent transmitters are required to determine safety integrities for safety critical systems in addition to the advanced functions. The issues during reliability analysis are:

a) System complexity, many interactions between different material elements and functions
b) System behavior during failure/fault is usually difficult to predict and not well known (due to programmable units)
c) Various transmitted data may be wrong (e.g. diagnostic information and measurements) and are dependent on other data.
d) Lack of available reliability feedback (e.g. failure modes and reliability data) due to new technology.

These issues (b) and (d) make the qualitative analysis like FMECA extremely weak for identification of failure modes. Due to (a) and (c) handling fault and failure interactions is difficult. Binary reliability models like fault trees and reliability block diagrams are not applicable due to (b) and (c) and transition state approaches like Markov models have difficulty in defining state boundaries due to (a) and (b).

Brissaud et al. (2011) proposed a "3-step" model (functions-material elements- faults and failures) to handle functional and material aspects as well as various interactions during fault and failures for reliability quantification.

4.3.1 Modelling of complex systems

A new technology-based transmitter may present two levels of complexity:

a) At system level where intra and inter relationships between material elements and functions exist
b) At component level where behavior of specific units is difficult to define

As a result, the modelling of complex systems must be done with object-oriented and function-oriented approaches.

The system can be analyzed according to goals and functions using **function-oriented approaches**. They can be used in design phase to define functional requirements, or later phases of project to understand effective system operation (Lambert et al., 1999). Some examples of this approach are *structured analysis and design technique* (SADT) by Ross (1977)for intelligent transmitters; the *functional analysis system technique* (FAST) by Lambert et al. (1999). For reliability assessments an extended SADT has been developed that can be used in design phase when systems behavior can be defined in accordance with its components and functions.

In **Object-oriented approaches,** a more formal method is applied where the system is organized as a set of individual objects (Luttenbacher et al., 1995). The static or dynamic systems with respect to material elements and their interactions i.e. structural analysis may be modelled using object-oriented approach. Some examples of this approach include the UML class diagrams and fault trees. In practice, function-oriented and object-oriented approaches do not reflect opposing concepts and, in particular, they can be used as complementary techniques

.

Table 4.4 the advantages and disadvantages of these transmitters in terms of reliability and safety (Brissaud et al., 2011)

Criterion	Pros	Cons
Reliability	Self-adjustment may prevent drifts or other faults and failures which appear with aging.	The high amount of electronics, programmable units and software aspects implies new failure causes and modes which are usually not well known and difficult to predict.
	Faults and failures may be partly compensated using fault tolerant strategies (reconfiguration).	Each fault or failure may affect several functions and transmitted data (e.g. measurements, diagnoses).
	Digital communication is often assumed to be more reliable than analogue wires.	Digital communication reliability is questioned and may yield common cause failures.
Maintainability	Information on drifts, influencing factors, charge exceeding, previous faults and failures with corresponding circumstances etc. may be monitored over time and used for preventive maintenance. Digital communication and online reconfiguration can make corrective maintenance easier and more efficiency.	Specific expertise is required to maintain such complex systems.
Safety	Self-diagnoses allow better fault and failure coverage, and safe states can be defined in more detail	Transmitters are increasingly becoming "black box" systems.

4.3.2 Goal tree-Success tree and master logic diagrams

Goal tree-success tree approach (GTST) in combination with **master logic diagrams (MLD)** is used to develop the final model for reliability analysis of these transmitters (Brissaud et al., 2011). GTST has been used for various applications for risk assessment of nuclear plants. The idea is that the complex systems can be analyzed using hierarchal frameworks. Figure 4.5 illustrates how systems are analyzed according to goals and functions using goal tree (GT) and according to its objects using success tree (ST).

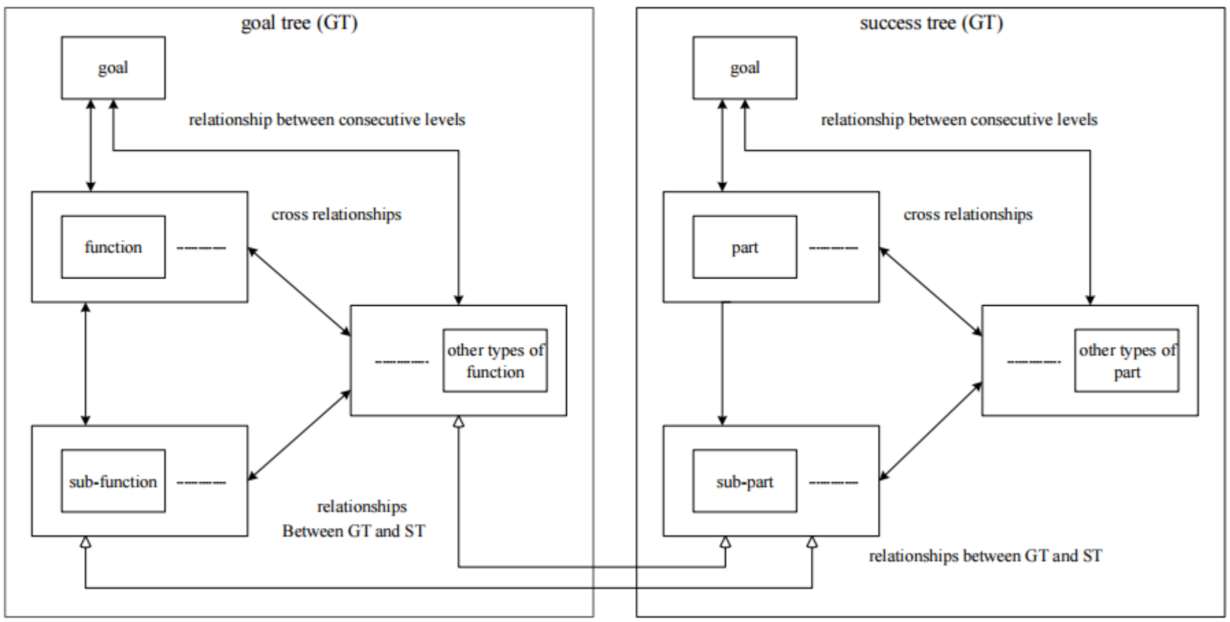

Figure 4.5 Conceptual goal tree-success tree with different types of relationships (Brissaud et al., 2011)

The system is analyzed using a top-down approach for both GT and ST. The topmost level of GT is defined as the system objective (or goal), and secondary level represents the necessary functions which have to be achieved to achieve the top function. Similarly the functions are analyzed until there is no possible of further development. The ST is analyzed as a system structure made of several system parts which are responsible for achieving sub-functions. The top most level of ST is the whole product/equipment and it is analyzed to its basic parts in different levels in a similar way to GT. Relationships exist between GT functions and ST objects as one ST object is may achieve one or many sub-functions of GT.

Master logic diagrams (MLD) are used to represent the relationships between GT functions and ST objects in a compact way. Figure x.x illustrates a typical MLD and the relationships between GT sub-fuctions and ST sub-parts.

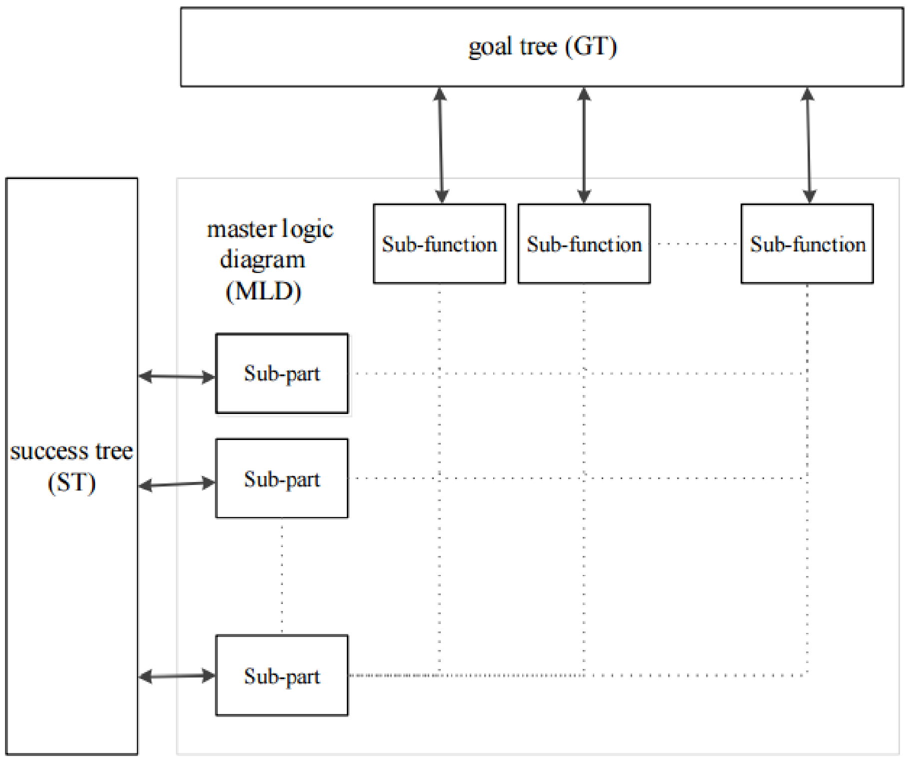

Fig 4.6 Conceptual GTST-MLD where MLD (Brissaud et al., 2011)

The combined diagram with both GTST –MLD provides a simple and efficient framework to understand and quantify causal relations for complex systems (Modarres and Cheon, 1999). This model acts as a supporting tool for 3-step proposed model with analysis of faults and failures introduced as an additional part.

4.3.3 "3-Step" Model

The basic description of this model with an example is described. For further details refer Brissaud et al. (2011)

Functional Tree

Goal-tree is referred to as functional-tree in this model as reliability of an equipment refers to the function of the equipment to perform its functions. The topmost function of the functional tree is called as the goal function. The goal function is described as a safety function which is used to prevent the occurrence of a hazardous event. The goal function is divided into sub-functions (global functions) such that the combination of sub-functions assure that the goal function is achieved. The analysis continues to until the last level of basic functions similar to the process of GT. Only "AND" gates are used to model the relationships. The functions are classified as goal function, global function and basic function (see figure 4.7). All relevant basic functions have to be achieved to fulfill global function and so on. In this approach, goal function is divided into main and supporting functions on the basis of importance of functions. The global and basic functions are main functions of the equipment and supporting functions are auxiliary function which are "optional". In figure 4.7 the goal, supporting, global and basic functions for intelligent transmitter.

Material Tree

Material tree provides the system structure with regards to material aspects of the system (interactions between the different system elements). Therefore success tree is referred to as material tree in this model. The materials or objects needed to achieve the functions given in the functional tree. It may include software elements, hardware elements and human factors. There are three level of analysis for material elements; system- where the whole system is analyzed, sub-systems refers to the materials or components which are functionally or physically grouped together and units are the basic elements. Similar to the functional tree the relationships between the elements and the parts are denoted by and gates. The material elements can also be distinguished as main material elements: which are required for the main system and supporting material elements which may be a part of other material elements. Fig 4.7 shows the system, sub-systems, units and supporting material elements of an intelligent transmitter.

Faults and failure

In order to proceed with the reliability analysis, faults and failures are studied to reveal dysfunctional aspects. Rausand and Øien (1996) describe the basic concepts of failure, failure mechanism, failure model and fault in detail. The model relates possible faults and to the particular material element given in the material tree. Then the effects of faults and failures are modelled by first the relationships between them and the material elements and then by relationships between functions and material elements. Both are represented in the relationship matrices. Fig 4.7 illustrates the faults and failures for an intelligent transmitter and ow they effect the materials and in turn the fuctions.

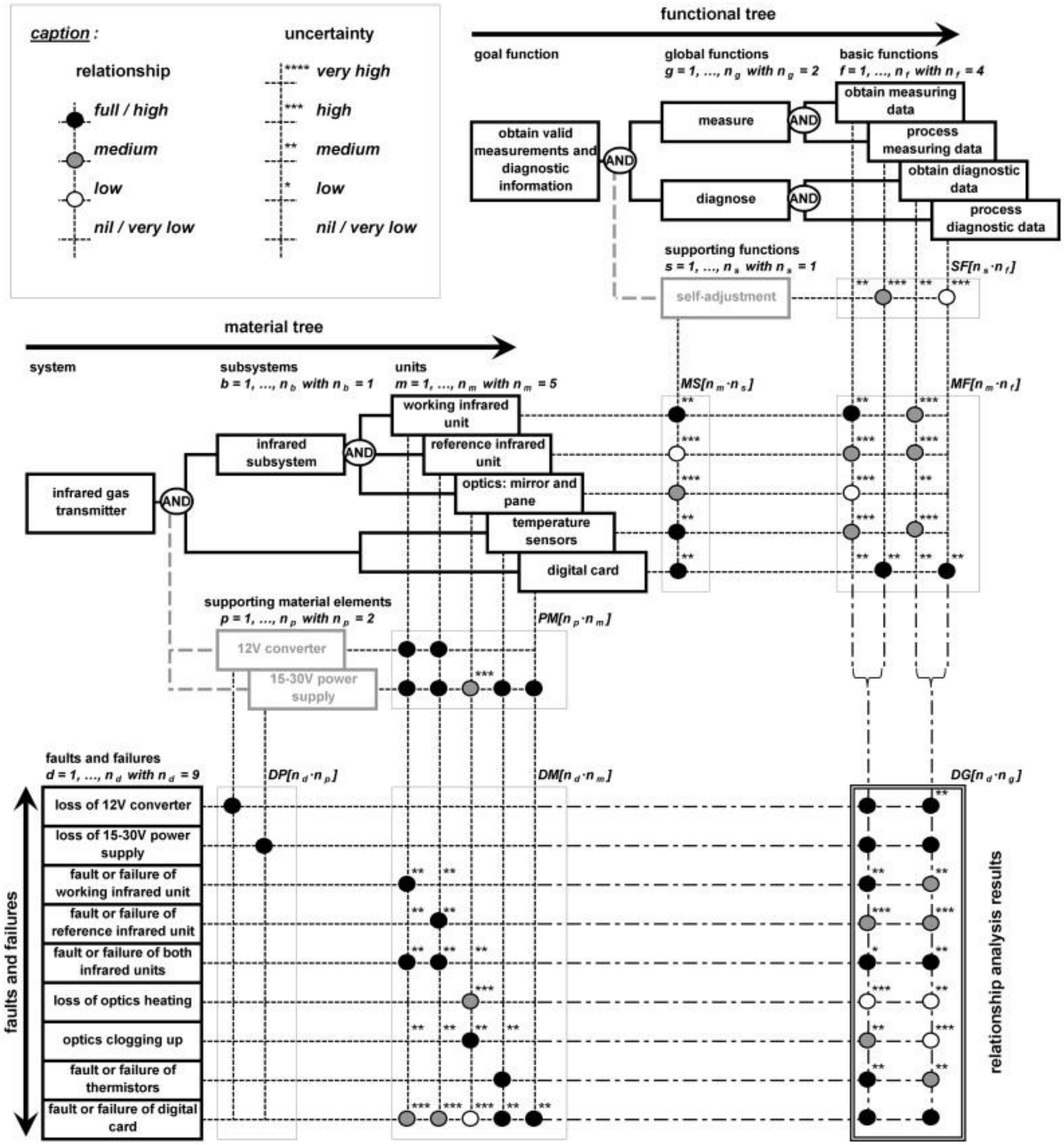

Fig 4.7 Illustration of 3-step model for an intelligent transmitter (Brissaud et al., 2011)

Relationship matrices

The relationship matrices or master logic diagrams (MLD) show the way of how a function is achieved by the material elements and supporting functions. The model uses a qualitative approach in this step with no numerical values. Stochastic relationships are used in further steps in the model. In the fig 4.7 the relationship of the components are represented using filled dots. The degree of relationship (e.g.

strong or weak) is shown using colour shades of the dots (a "semi-qualitative" model). A dark coloured dot means that the functions or the upstream element in the diagram always needs full operational condition of the material element or the respective downstream element as so on.

4.3.4 Reliability analysis based on the 3-step model

Relationship Analysis

To assess all the relationships between the elements (functions, faults and failures, material elements) considering both the direct and indirect relationship analysis is conducted. First, the terms are defined as

D_d	Fault or failure d occurs
P_p	Supporting material element *p* is in a failed state
M_m	Unit m is in a failed state
S_s	Supporting function s malfunctions
F_f	Basic function *f* malfuncitons
G_g	Global function *g* malfunctions

Then, the direct relationship event between as downstream element a and an upstream element b is represented in relationship matrix AB, in the row of index a and column of index b, and defined as follows:

$AB_{a,b}$	Event A_a directly implies event B_b
$DP_{d,p}$	An occurrence of fault or failure d directly implies a failed state of supporting material element p
$PM_{p,m}$	A failed state of supporting material p directly implies a failed state of unit m

Similarly other relationship events can be explained. The assumptions are

- All events are direct relationship events and are independent of each other and the probability of their occurrence is $P[AB_{a,b}]$
- The values of relationships are probabilities which depend on the dot colors in the relationship matrices

The equations mentioned in the relationship analysis of Brissaud et al. (2011) is used to calculate the probability of failure and assuming a constant failure rate approach, the final failure rate is calculated. Refer to Brissaud et al. (2011) for details.

Table 4.5 Translation of degree of relationship into probability and vice versa.

Relationship	Input value (probability)	Result translation for graphical representation
Full/high	1.000	0.833-1.000
Medium	0.667	0.500-0.833
Low	0.333	0.167-0.500
Nil/Very Low	0.000	0.000-0.167

4.4 Bayesian Method

In this approach, the probability of an event is a measure of our belief about the occurrence of the event and is referred to as the degree of belief. Bayes formula gives the probability of the parameter, given the observation in the data. This data is not limited to sample data only. It contains empirical and external data (prior) in addition. Bayes formula given below implies that the posterior distribution of a parameter is proportional to the product of likelihood and the prior distribution of the parameter.

$$Posterior = \frac{Prior \ \times Likelihood}{Normalizing \ constant}$$

Subjective prior belief is indicated by the prior distribution. The posterior distribution is the conditional probability of parameter given the observations. It is a powerful and coherent method to mathematically, combine the different types of information and to express the inherent uncertainties.

Bayesian belief network (BBN) is based on this theory. BBN is described ((Jensen, 1996)) as a directed acyclic graph (DAG) that defines the factorization of a joint probability distribution over the variables. The nodes of the DAG represent the variables. The directed links of the DAG give factorization. BBN provides an intuitive graphical model for reasoning under uncertainty. It provides a mechanism for representing the causal relationships between the entities of problem domain. Figure 4.8 illustrates a simple BBN. The nodes B and C are “parents” to the “child “node A. The probability distributions of B and C are specified across the possible outcomes/states that it can take. Node A is represented by conditional probabilities which are conditioned on the state of B and C.

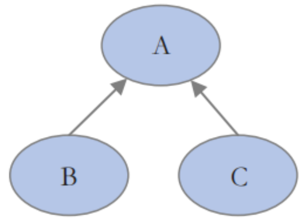

Fig 4.8 Generic BBN with one child and two parents.

4.4.1 BBN for reliability prediction

It is a popular method of modelling uncertain and complex systems in power/nuclear and aviation industries and the modelling has been done for diagnosis purpose. This kind of modelling is not yet can be used in reliability modelling as it is useful in modelling common cause failures and study uncertainties (Langseth and Portinale, 2007). Hybrid causal logic (HCL) (Røed et al., 2009) framework can also be used in reliability and is further discussed in last chapter. Papers by Bobbio et al. (2001) proposed a method to convert fault trees into Bayesian networks, Langseth (2008) Langseth and Portinale (2007) explain the importance of Bayesian Networks in the field of reliability engineering. BBN is extensively used in reliability modelling of subsea BOPs (Baoping et al., 2013, Cai et al., 2012) and it has alson been used for subsea X-mas Trees (Lyu et al., 2014). Therefore, it is worthwhile to evaluate the BBN as a choice of modelling tool for reliability prediction.

BBN modelling is carried out in two main steps. However, many detailed approaches can be found in the literature.

a) **Structural modelling of the network**: The structure of the model, which is a qualitative part, is modelled first. The variables, the relations among variables viz. the causal, functional, and informational relations are identified first as a part of qualitative modelling.
b) **Modelling of parameters**: Conditional probabilities and utilities, which are quantitative in nature, are modelled in step two. Determining the structure of a model is an iterative process and needs interaction with domain experts. Domain knowledge is thus captured in the structure while defining variables, conditional independence and identification of links and their directionality. This modelling approach is in line with the requirement of failure rate modelling approach where correlation and causal relations of failure mechanisms need to be identified in close communication with the domain experts. In case of subsea equipment, not all the causes and effects of failure are deterministic. Various kinds of uncertainties are related

with cause effect mechanisms, for example imperfect knowledge about the factors affecting failure mechanism, measurement errors, noisy sensor readings or discretization of the real valued observation. BBN can handle such uncertainties and hence it seems to be a proper tool for modelling failure rate.

4.4.2 Bayesian Method for determining device failure rates from zero-failure data

This method employs Bayesian data analysis techniques utilizing available field reliability data and accelerated life test (ALT) results. Bremerman (2013) proposes this method to calculate a component failure rate using field reliability data and ALT in a Bayesian analysis framework. It uses a special case of Bayesian method used by (Guo et al., 2010b), called Clopper-Pearson method or interval. It can be applied when no informative prior exists. Clopper-Pearson interval is a method for calculating binomial confidence intervals. A binomial proportion confidence interval is a confidence interval for a proportion in a statistical population. The interval gives conservative results which is useful in failure rate prediction methods.

The method uses a two-step procedure of finding out a Bayesian posterior estimate for failure rate.

1) Finding failure rate using Clopper-Pearson interval for binomial distribution when no informative prior is available and zero failures have occurred in the field.

2) Deriving Bayes posterior failure rate using the gamma informative prior distribution with results from ALT.

A detailed analysis of both the steps are:

Step 1: Finding failure rate using Clopper-Pearson interval for binomial distribution when no informative prior is available and zero failures have occurred in the field.

For an equipment, assuming that the probability of success is *p*, the simplest way to calculate the confidence interval for $\hat{p}$ is the normal distribution approximation (Guo et al., 2010b). It is given as:

$$\hat{p} \pm z_{1-\frac{\gamma}{2}}\sqrt{[\hat{p}(1-\hat{p}]/n} \qquad \textbf{(4)}$$

where $z_{1-\frac{\gamma}{2}}$ is the $1-\frac{\gamma}{2}$ percentile of the standard normal distribution, $\hat{p}$ is the maximum likelihood estimate of p and n is the sample size. The estimate $\hat{p}$ is calculated by simply dividing number of successes by the sample size. Basically, the confidence interval of the estimate $\hat{p}$ represents the likelihood of that this estimate is in the population sample which is selected at random in the sample space. Equation 4 has a limitation when $\hat{p}$ is either 0 or 1 as the value becomes 0 in both the cases. Clopper-Pearson (C-P) interval overcomes this limitation. Guo et al. (2010a) propose that it can be written as

$$p|P[Bin(n;p) \leq x] \geq \gamma/2\} \bigcap \{p|P[Bin(n;p) \geq x] \geq \gamma/2$$

Where Bin(n;p) is a binomial random variable with n trials and probability of success p and x is the number of successes. (Guo et al., 2010b) also propose to rewrite the above equation for C-P interval as:

$$\sum\nolimits_{k=x}^{n} \binom{n}{k} P_L^k (1-p_L)^{n-k} = \gamma$$
$$\sum\nolimits_{k=x}^{n} \binom{n}{k} P_U^k (1-p_U)^{n-k} = \gamma$$

Where p_U and p_L represent the upper and lower one-sided confidence bounds given the confidence level for p is $1-\gamma$.

For an equipment or system, the probability of success is equivalent to its reliability. As a result, the beta-binomial one sided lower bound for reliability can be calculated by:

$$\sum\nolimits_{k=0}^{y} \binom{n}{k} r_L^{n-k} (1-r_L)^k = 1 - CL = \gamma$$

Where $r_L$represents the lower bound for reliability, y – no. of failures experienced, CL – confidence level, and γ – significance level.

For a system to work without interruption, there should be no failures. With this assumption, and using the above equation, r_L can be calculated as:

$$1 - CL = \gamma = {r_L}^n$$

The above equation is solved for r_L and yields:

$$r_L = \gamma^{1/n}$$

This can be interpreted as, for n samples under test (in operation), the reliability is $\geq\ r_L$ with a confidence interval of (1-γ) %. With an assumption of constant failure rate with no infant mortality issues, it is correct to assume a HPP and the point failure rate estimate $\hat{\lambda}$ is calculated using the expression for reliability of exponentially distributed failure rate:

$$r_L = e^{-\hat{\lambda}t}$$

Using the last two equations, the failure rate estimate $\hat{\lambda}$ is given as

$$\hat{\lambda} = \frac{-\ln r_L}{t} = \frac{-\ln \gamma^{1/n}}{t} = \frac{-\ln \gamma}{nt}$$

$$\widehat{\lambda_{(1-\gamma)}} = \frac{-\ln \gamma}{nt}$$

This equation is used to find $\hat{\lambda}$ for a particular confidence provided zero failures have occurred in field on "n" samples in the field with total operating time of "t".

Step 2: Deriving Bayes posterior failure rate using the gamma informative prior distribution with results from ALT

Assuming that the failure rate is constant for the repairable systems, HPP model is applied. The next approach consists of three main tasks:

1. Define a prior distribution for the equipment failure rate.
2. Gather evidence, known as the likelihood function.
3. Construct the posterior distribution using Bayes' theorem

The most widely used prior distribution to define the uncertainty in failure rate is the gamma distribution [G(α,β)]. So, the process is assumed to be a HPP and G(α,β) is a natural conjugate prior distribution i.e. both prior and posterior distributions in Bayesian are from same family. It is also mentioned in the literature that gamma prior distribution is practical for many applications (Pandey et al., 2005, Scarf, 2007, Apostolakis and Mosleh, 1979, Martz and Waller, 1982). If the prior data is available, the failure rate is calculated using the gamma prior distribution with probability density function. Martz and Waller (1982): calculated it assuming that the frequency of the shocks to the system is constant and an HPP with a rate of λ, total no. of failures interpreted as the shape parameter α in total pseudo time units β. The probability density function is given as

$$g(\lambda; \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda};\ \lambda, \alpha, \beta > 0 \qquad \textbf{(5)}$$

The posterior distribution is given by equation (5) given the observed no. of failures "s" and total time "t" as (Martz and Waller, 1982):

$$g(\lambda|s) = \frac{e^{-\lambda t}\lambda^{s} g(\lambda)}{\int_0^\infty e^{-\lambda t}\lambda^{s} g(\lambda) d\lambda}; 0 < \lambda < \infty \tag{6}$$

By differentiating the above equation (6) with respect to λ and rearranging the terms in the form of bayes theorem, the posterior gamma function given "s" is given by:

$$g(\lambda|s;\alpha,\beta) = \frac{\lambda^{s+\alpha-1}e^{-(t+\beta)\lambda}}{\int_0^\infty \lambda^{s+\alpha-1}e^{-(t+\beta)\lambda} d\lambda}; \lambda > 0$$

Substituting y=λ(t+β) in the above equation, we find that

$$dy = (t+\beta)\, d\lambda$$

$$\frac{1}{(t+\beta)^{s+\alpha}}\int_0^\infty y^{s+\alpha-1}e^{-y}dy = \frac{\Gamma(s+\alpha)}{(t+\beta)^{s+\alpha}} \tag{7}$$

Using the above result in the equation (7) for posterior gamma distribution is reduced to:

$$g(\lambda;\alpha,\beta) = \frac{(t+\beta)^{s+\alpha}}{\Gamma(s+\alpha)}\lambda^{s+\alpha-1}e^{-(t+\beta)\lambda};\ \lambda > 0$$

which is a Gamma (s+α, t+β) distribution. The parameter (s+α) is referred to the combined number of failures, whereas (t+β) is the combined total test time. Now chi-distribution is used for the confidence interval and an estimate of failure rate is obtained (Refer to (Bremerman, 2013))

4.5 Artificial Neural Networks (ANN)

The classical approach consist of creating statistical-mathematical models that estimate the failure rate with respect of operative conditions of the equipment. Furthermore, the adoption of mathematical templates often results to be complex, unreliable and too much specific for each single equipment. A new approach based on artificial neural networks (ANNs) is proposed by Dohi et al. (2005). In particular, multilayer perceptions (MLPs) have been largely and often successfully adopted to categorize and to forecast, based on the postulation that if the training data sets are large enough, the network will be able to generalize a problem rather than simply memorize the proposed patterns.

There are several distinguishing characteristics of ANNs which make them a useful method for failure rate prediction

1) On the contrary to traditional model-based methods, ANNs are data-driven self-adaptive methods in that there are few a priori assumptions about the models for problems under study. They learn from past examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe.
2) ANNs can generalize. After learning the data presented to them, ANNs can only correctly infer the unseen part of a population even if the sample data contain noisy information.
3) ANNs are universal functional "approximators" and have more general and flexible functional forms than the traditional analytical and/or statistical methods can effectively deal with.
4) They are non-linear. Real word failure models are generally non-linear.

ANNs have been traditionally used for failure diagnosis and for lowering mean time to repair (MTTR) (Ogaji et al. (2002) Moon et al. (1998)). Kutyłowska (2015) uses neural networks for failure rate modelling of water-pipe networks.

Basic Information about ANN

The prototype of artificial neural networks is the brain and the entire nervous system in the human body. In artificial neural networks the method of information transferring is imitating the way of human nervous system performance. Natural neurons, the main elements of nervous system, are responsible for transferring information. ANN consists of neurons which are data processors. Each neuron is responsible for summarizing input signals.

Abstracting from the biological description, a neuron could be represented, in a mathematical form, with a threshold logic unit (TLU). Briefly, this consists of an object which accepts an array of weighted quantities (incoming from a set of synapses), sums them, and, whether the sum overcomes a certain bound (usually called threshold, u), outputs a value, generally known as the activation level. A transfer function takes this value and produces the output of the current artificial neuron (outgoing towards the neighboring neurons by means of an axon). In mathematical terms, said (X_n) the input array (W_n) the corresponding array of weights, the activation level is given by

$$a = \sum_{i=1}^{n} X_i W_i$$

Finally, the output value can be calculated as

$$y = f(a - \theta)$$

A MLP is usually composed of several layers of neurons. The first layer is conventionally defined as the input layer and is opportunely structured to receive the input array (the number of neurons being equal to the number of variables). The last layer represents the output stratum, where the solution is obtained. Any other level is invariably called hidden layer. Generally, each neuron (also known as node) in a layer, is fully connected to all nodes in the following level by means of unidirectional arcs, moving from the input nodes to the output ones. This justifies the feed-forward designation that identifies this kind of structure. Figure 4.9 illustrates a typical 3 layered ANN

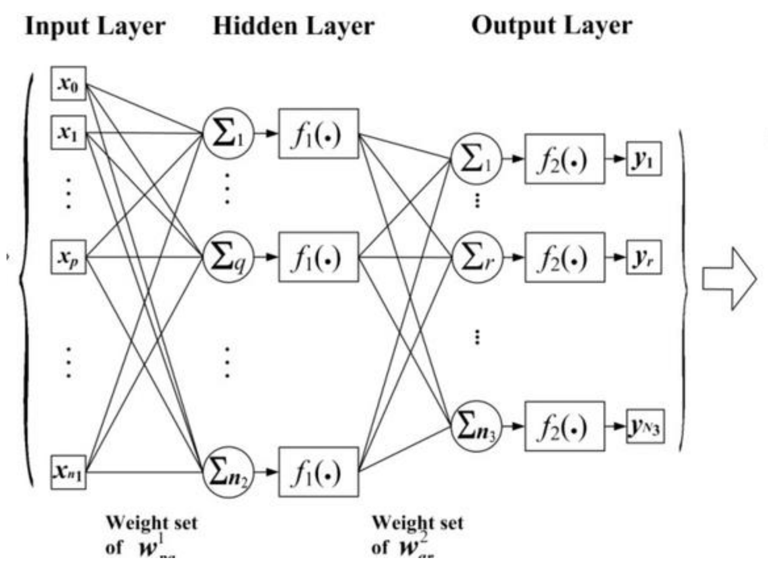

Figure 4.9 Illustration of a 3 layered network

The learning mechanism is modelled on the brain's adjustments of its neural connections. The most widely adopted method is by far the supervised learning rule. Briefly: a series of patterns (examples) is supplied to the net, along with the expected targets; and the net examines each pattern and adjusts the weights.

There are several different suitable methods for this purpose, but, generally, the delta rule (Widrow and Hoff, 1960) is preferred. It is based on the assumption that weights modification can be better estimated by some fraction of the difference between the target and the actual output. Substantially, the underlying mathematical concept is that of the gradient descent. In short, the error function describes a space surface having at least one minimum. The net should look for the weights distribution that minimizes the global error, moving along the surface to the minimum and, simultaneously, aiming to the shortest path to reach this target.

There are mainly 4 inputs for failure rate prediction using ANN:

a) **Choice of subsets**: It is important to divide the data between training and prediction. Training set contains the biggest chunk of data which is used to instruct the framework. The cross validation set is used to validate the current level of generalization reached by the network. The testing set for prediction is needed to test the network classification capabilities over restricted set of items.
b) **No of hidden layers**: 3 layers, an input layer, a hidden layer and an output layer is enough to solve any problem (Haykin, 1994).
c) **No. of nodes in the input and output layer depend on the matrix size of inputs and outputs. For no. of nodes in hidden layer the following steps can be conducted**
    1) The no. of hidden nodes should be set to 2
    2) The network should be trained and results recorded. The values of MSE indicate to stop the procedure if there is a growing trend
    3) The no. of hidden nodes is incremented by 1 and analyses is repeated.
d) **Activation functions in hidden and output layer**: A sigmoid function is the most adopted activation function in MLP applications. However, hyperbolic tangent function can be used to compare the results.

4.6 Discussion

A discussion on the literature review is carried out to compare different methods with regard to different parameters of reliability prediction. Table x.x lists the parameters which are used to discuss the methods on the basis of the challenges of reliability prediction for subsea equipment.

4.6.1 Regression models ALM and PHM

Both ALMs and PHMs propose a baseline probability model which describes the evolution of operating process in normal operating conditions e.g. in laboratory testing conditions and then, introduces covariates on the degradation process to account for conditioning aspects of the component life, environment, loading, etc. As a result, both the methods require large amounts of data for prediction process. The difference between ALMs and PHMs lies in the modelling of the dependence of the aging process on the covariates. While in PHMs, the effects of covariates are modelled as multiplicative factors in the failure rates, ALMs model explicitly the operating environment impacts on TTFs (Kumar and Klefsjö, 1994, Ansell and Philipps, 1997).

4.6.2 Rahimi and Rausand's Method for new subsea equipment

This method gives a decision support by failure rate prediction in the early design process of a new subsea equipment. The suggested failure rate is an essential input to the technology qualification process (TQP). It compares subsea and topside subsea system and uses the generic data from topside system to form a linear relationship between the respective failure rates. Influencing factors like pressure, temperature, maintenance policy are quantified in the modelling process. It does not use knowledge available from subsea elements already used in other subsea systems(Rahimi and Rausand, 2013). The calculated failure rate cannot be updated during the project cycle when more information is available.

4.6.3 3 Step Model

As the industry is moving towards predictive maintenance, there are high possibilities of intelligent sensor applications in safety instrumented system (SIS) in the future. The method uses GTST-MLD for defining the basic material elements, the sub-functions which depend on them and the degree of relationship between them (Brissaud et al., 2011). It proposes an appropriate model for reliability analysis of new technology-based transmitters even if the reliability data available is low. There is no way of finding to what extent does the redundancy in the system effects reliability. Only "AND" relationships are considered while analyzing the system both in case of system functions and system materials. As a result, other kind of relationships are ignored. The "semi-qualitative" approach with quantification might be too simple for explaining the complex relationships of system during fault and failures. All the direct relationships are considered as independent which might not be a valid assumption for complex systems.

4.6.4 Bayesian method with zero failure data available

Subsea dnv white paper emphasizes on use of mathematical models, modularization and simulation for reliability testing as it forms on of the most expensive parts of the qualification process. As a result, this method which is currently proposed in space industry can be used in subsea industry.

Disadvantages or Limitations?

Industry might not accept testing equipment using just mathematical models. But it might be helpful to test them using the models in the initial design phase of the project and get a good estimate of the failure rate and reliability of the component or sub-system.

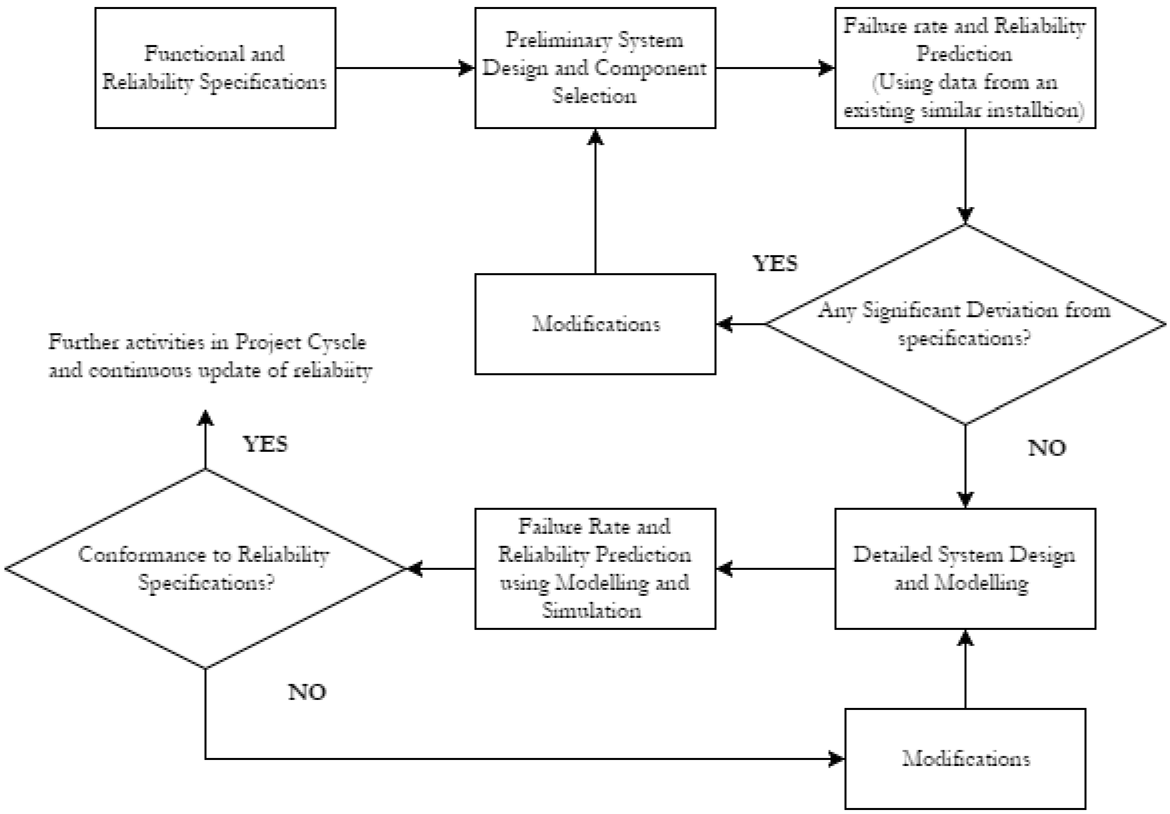

Figure 4.10 Basic Steps in reliability Prediction methodology (adapted from Zafiropoulos and Dialynas (2005)

4.6.5 Neural Networks

Huge operational and condition data might be required for using neural networks. Condition data includes the raw condition data and the associated covariates that are extracted from original data, such as pressure, temperature etc. Event data means the records of the installation, maintenance and failure calendar time. With a data-driven model, there is no need to know the failure initiation mechanism exactly. However a large amount of data is necessary to ensure an accurate model.

Subsea installations not only demand addressing peculiar technical issues in design and construction, but also greatly challenge maintenance engineering, as the harsh environment renders it difficult to perform required actions, with consequent large downtimes and business interruptions. For these reasons, it is fundamental that failure rate assessment of subsea equipment takes due account to the influence of the environmental and operational parameters (e.g., fluid properties for engines, turbines, compressors, etc.) on the Time to Failure (TTF).

Table 4.6 Comparison of all the methods

Method of Reliability prediction	Developer	Basic Principle	Inputs (type of data)	Amount of system input data required	Applicability in design phase of product
ALT	Many developers	Physics of Failure Regression	Failure mode, Testing procedures	Average	Maybe
PHM	Cox (1972)(Most popular)	Regression RIFs	Influencing factors, Baseline failure rate, Probability distribution of covariates	Average	Maybe
Prediction of failure rate for new subsea equipment	Rahimi and Rausand (2013)	Regression, RIFs	Top-side failure rate data, RIFs Data related to RIFs	Less/No data	Yes
3-Step model	Brissaud et al. (2011)	GTST-MLD Relationship Analysis	Structural details of equipment Function details	Less/No data	Yes
Bayesian with zero failure data	Bremerman (2013)	Bayesian inference, Confidence intervals, Probability distribution Physics of failure	Operating data Reliability testing results	Average	Yes
ANN	Dohi et al. (2005)	ANN, MLP	Operating data with all the parameters	Large	No

5 Proposed Model with an illustrative example

The objective of this chapter is to present a new model for the prediction of failure rates for subsea equipment. This chapter uses the concepts from existing models in literature of failure rate prediction process to develop a suitable method to quantify failure rate in pre-design qualification process for new subsea equipment.

The proposed model takes advantage of the potentiality of different reliability prediction approaches. It combines the use of FMECA, reliability influence diagrams and hierarchical RIF model in Rahimi and Rausand (2013) to predict failure rates using the available data from similar topside equipment.

5.1.1 Scope of model

The model intends to provide a tool to calculate the failure rate with scope of handling uncertainties in the input data. It helps in the decision making during the design process of new equipment. However, it has some limitations. Failure modes which are not common between subsea and topside are not considered in the model. Knowledge of existing systems can be utilized but a specific approach is not covered in this model.

5.1.2 Choice of Model

The model proposed by Rahimi and Rausand utilizes the relevant existing data available for subsea equipment but does not introduce uncertainties in the model. It proposes a good way of calculating the effects of RIFs on failure causes, effects of failure cause on failure mode and contribution of failure modes on total failure rate of subsea equipment. With Bayesian approach, it is possible to determine the prior probability distribution with confidence interval, update it with the evidence available and get the posterior distribution. In addition, when more information is available during later stages of the project, evidence can be added in the Bayesian network for a more certain failure rate prediction. Therefore, the new model combines both the methods for predicting failure rate of new subsea equipment.

5.1.3 Model Structure

The model comprises of 3 main steps:

a) Execution of Rahimi and Rausand (2013)'s method step-wise to obtain the weights and the range of subsea failure rate.
b) Creating a BBN with RIFs, failure causes, failure modes and the total failure rate.
c) Use the weights calculated in Rahimi's method and apply it in the BBN and use the total failure rate to obtain the intervals of failure rates for different states of total failure rate in BBN.

5.2 Model description

The model is based on Bayesian Belief Networks (BBN), the basic principle of which has been briefly described in Section 4.4.1 and Rahimi's approach described in detail in Section 4.2. One of the most important assumptions in BBNs is the dependence of probability distribution of a node on the parent nodes (Jensen, 1996). BBNs are extensively used in dependability, risk analysis and maintenance applications now e.g. the Risk OMT method (Vinnem et al., 2012). Details of mathematical background of BBNs is not mentioned in this section as it has been mentioned briefly in previous sections of this report. Refer to Jensen (1996) for basics of BBN.

Further, the model is explained with the help of an illustrative example of a new subsea pump.

5.2.1 Illustrative example using a Subsea Pump

Subsea pump is considered because of its significance and novelty of subsea gas compression technology. Due to the decrease in reservoir pressure of existing wells and increase in tie-back of subsea installations, there is a need of boosting the flowrate and pressure of the fluid coming out from the well. High flow rate and pressure helps in increasing the production and distribution of oil and gas. The subsea gas compression technology is developed recently to solve this problem. It first subsea gas compression module is installed at Åsgard (Hedne, 2014) and is developed and tested for Ormen Lange (Henri et al., 2010). Figure x.x illustrates a generic set up of Subsea gas compression module (Bjerkreim et al., 2009). The pump is used to increase the pressure and flow of the oil coming from the separator.

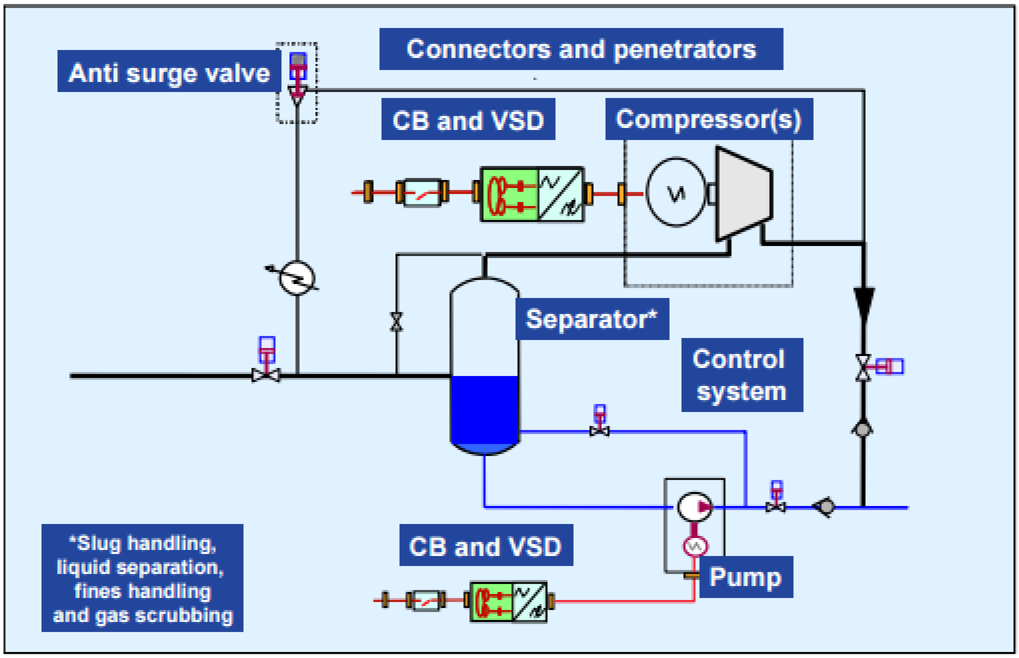

Figure 5.1 Generic Setup of Subsea Gas compression module (Bjerkreim et al., 2009)

Subsea pump is usually made of components used in topside but the materials and the design is improved to minimize the interconnections and improving the reliability. Due to lack of available data from the industry, and a method based on open source data is used in this study. The objective of this example is to illustrate the approach and not present an extensive and realistic case study.

5.3 Modelling details with an example

This section describes the model in main steps mentioned in section 5.1.3.

5.3.1 Step 1: Using Rahimi and Rausand (2013)'s method for calculating weights to be used in BBN

This section illustrates how this method can be applied for a new subsea pump to move the fluids as a part of subsea processing. The main objective of this step is to calculate the relative weights of RIFs and failure causes of subsea pump. The pump is made of components which are similar to that of topside pumps with improved design. Information of RIFs, failure causes and failure modes are taken from (Rahimi and Rausand, 2013) as this data is not available in such detail for a subsea pump. The steps in this procedure are as below:

Step1: New system familiarization

The pump is a multiphase pump and must have a high reliability. The maintenance procedure is also not similar to topside application. The pumped fluid's properties change overtime.

Step 2: Identification of failure modes and failure causes

Table 5.1 illustrates the failure modes and failure causes listed after a FMECA (Rahimi and Rausand, 2013)

Category	Description
Failure modes	Fail to start on demand (FTS) Low output (LOO) Spurious stop (UST)
Failure Causes	Mechanical failure-general (MFG) Blockage/plugged (BLK) Instrument failure-general (IFG) Control failure (CF)

Step 3: Reliability information acquisition for similar known system; comparison of new and known system.

The physical boundary of the topside pump is mentioned in OREDA (OREDA, 2009). The assumption is all failure modes in subsea pump is similar to that of topside pump, failure causes are also similar with different effects. The subsea pump and topside pump are compared using

Step 4 Selection of RIFs

The procedure of selection of RIFs is extensive and hence not a part of this study. The selected RIFs are taken from the similar example in (Rahimi and Rausand, 2013). Figure 5.2 illustrates the effect of these RIFs on failure causes.

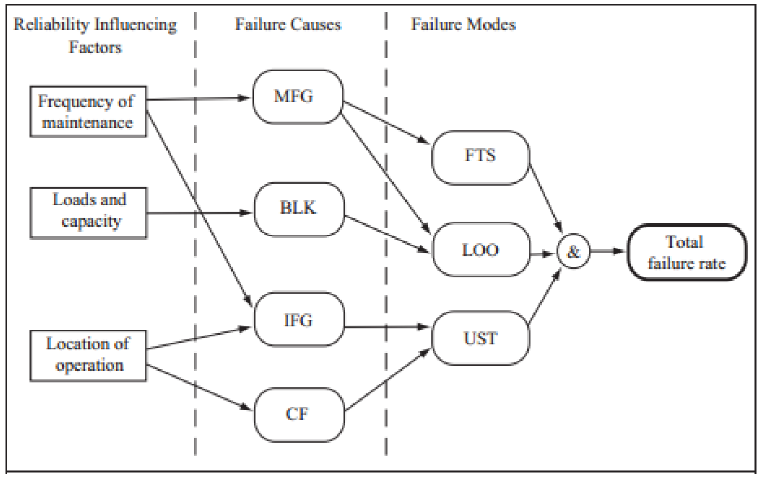

Figure 5.2 Reliability influencing diagram for a subsea pump (Rahimi and Rausand, 2013)

The selected RIFs are;

Location of operation; Frequency of Maintenance; Loads and capacity.

Step 5: Scoring the effects of RIFs

RIFs are scored on a scale of -3 to +3 if they are relevant for subsea or topside. For example, "Location of operation" effects the failure cause "IFG" for both subsea and topside pump and therefore "Relevance" is 1. Also, the effect of "location of operation" on IFG for subsea pump is significantly lower than topside pump because of the location of pump in a capsule. Therefore it gives a value of "-2". Table 5.2 illustrates the assessment of RIFs for topside and subsea pump on the basis of discussion in the Section 4.2.5.

Table 5.2 Scoring of RIFs for subsea pump by comparison with topside pump (adapted from (Rahimi and Rausand, 2013)

				Failure Causes			
RIFs	Category	Interpretation		MFG	BLK	IFG	CF
Frequency of Maintenance	TS	Every year	Relevance	1	0	1	0
	SS	Every 5 year	Relevance	1	0	1	0
			Score	1	0	0	0
Loads and Capacity	TS	Normal	Relevance	0	1	0	0
	SS	Up to 2 times more	Relevance	0	1	0	0
			Score	0	0	0	0
Location of operation	TS	Offshore	Relevance	0	0	1	1
	SS	Seabed	Relevance	0	0	1	1
			Score	0	0	-2	1

Step 6: Weighing the contribution of the failure causes to failure modes

The failure data in OREDA (2009) for topside pump is used to find the contributing weight of each failure cause to each failure mode. Table 5.3 lists the weights of failure causes for failure modes. For calculating relative weights (ε_{kj}) of RIFs with respect to failure causes, the equation 7 is used. The values of $\nu_{kj}^{(S)}$, η_{kj} are given in table 5.2 and values of $\bar{\eta}_j$ in table 5.3a. The value of ε_{kj} is calculated using

$$\bar{\eta}_j = \sum_{k=1}^{p} \varepsilon_{kj} \nu_{kj}^{(S)} \frac{\eta_{kj}}{3} \quad for\ j = 1,2 \dots r \tag{7}$$

However, as all the other values are assuming the 7 states of for ease of understanding the model, we continue the calculation with the On calculation, it is found that the weight of "Location of operation" and "Frequency of Maintenance" for failure cause IFG are 0.33 and 0.67 respectively. Refer to Section 4.2.8 for further understanding.

Step 7: Adjustment of old failure rate for each failure mode, calculation of total failure rate.

The minimum and maximum parameters delimiting the subsea failure rate for the relevant failure modes are $\theta_{min,i} = 0.3$ and $\theta_{max,i} = 1.1$. The topside failure rates for failure modes FTS, LOO, UST are 40.73, 81.46 and 101.82 respectively.

Table 5.3a Values of $\bar{\eta}_j$ for each failure cause (adapted from (Rahimi and Rausand, 2013))

Failure causes	MFG	BLK	IFG	CF
$\bar{\eta}_j$	0.33	0	-0.33	0.33

Table 5.3b Contributing weights for failure causes to failure modes (adapted from (Rahimi and Rausand, 2013))

	MFG	BLK	IFG	CF
Failure modes				
FTS	1	-	-	-
LOO	0.75	0.25	-	-
UST	-	-	0.4	0.6

5.3.2 Step 2: BBN Approach

After getting the information about the relative weights of RIFs and failure causes, Bayesian belief network (BBN) is used to calculate failure rate, study uncertainties and sensitivities. The steps mentioned in (b) and (c) of section 5.1.3 are combined in this section for better explanation. A Bayesian belief network (BBN) can be used as an alternative to fault trees and cause and effect diagrams to illustrate the relationships between a system failure or an accident and its causes and contributing factors (Rausand and Høyland, 2004). In operational risk analysis, BBNs are used to model the effects of organizational and operational risk influencing factors on major accident risks. Two recent methods RiskOMT (Vinnem et al., 2012) and hybrid causal logic (Røed et al., 2009) demonstrate the impact of BBN on basic events used in FTA. The procedures described in Risk OMT and hybrid causal logic method are combined to demonstrate RIFs and a modified tool based on the original tool in excel (Edwin, 2015) is used for using the Bayesian Network tool called GeNie[2].

Note that in the BBN, only 5 states are considered for each node and RIFs due to computational limitations of MS Excel. Ideally, 7 states should be used in BBN because Rahimi and Rausand's approach uses 7 states for scoring the RIFs. However, we will use the weights calculated in section 5.3.1 for ease of computation. The model gives a better understanding and confidence to the parameter failure rate.

Step 1: Construct Influence diagram/BBN using RIFs, failure causes and failure modes.

RIFs are represented as outermost parent nodes. Different combinations of RIFs influence different failure causes which are child nodes. Failure causes affect different failure modes. For subsea pump, the influence diagram illustrated in figure 5.2 is translated into a BBN with top child nodes as the failure modes of subsea pump.

Step 2: Determine the importance of RIFs with respect to each other and the weights of failure causes for each failure mode.

The importance of RIFs on each failure cause and failure cause on each failure mode are expressed as weight $\mathbf{w_i}$, where 'i' is the parent node so that,

$\sum \mathbf{w_i} = 1$.

Weights ε_{kj} and $w_{ji}^{(S)}$ which are calculated in the results of section 5.3.1 are used to ease the weight assignment process. For example, for the failure cause IFG, weights found from the previous step for RIFs frequency of maintenance and Location of operation are 0.33 and 0.67,

[2] http://www.bayesfusion.com/#!genie-modeler/lf73d

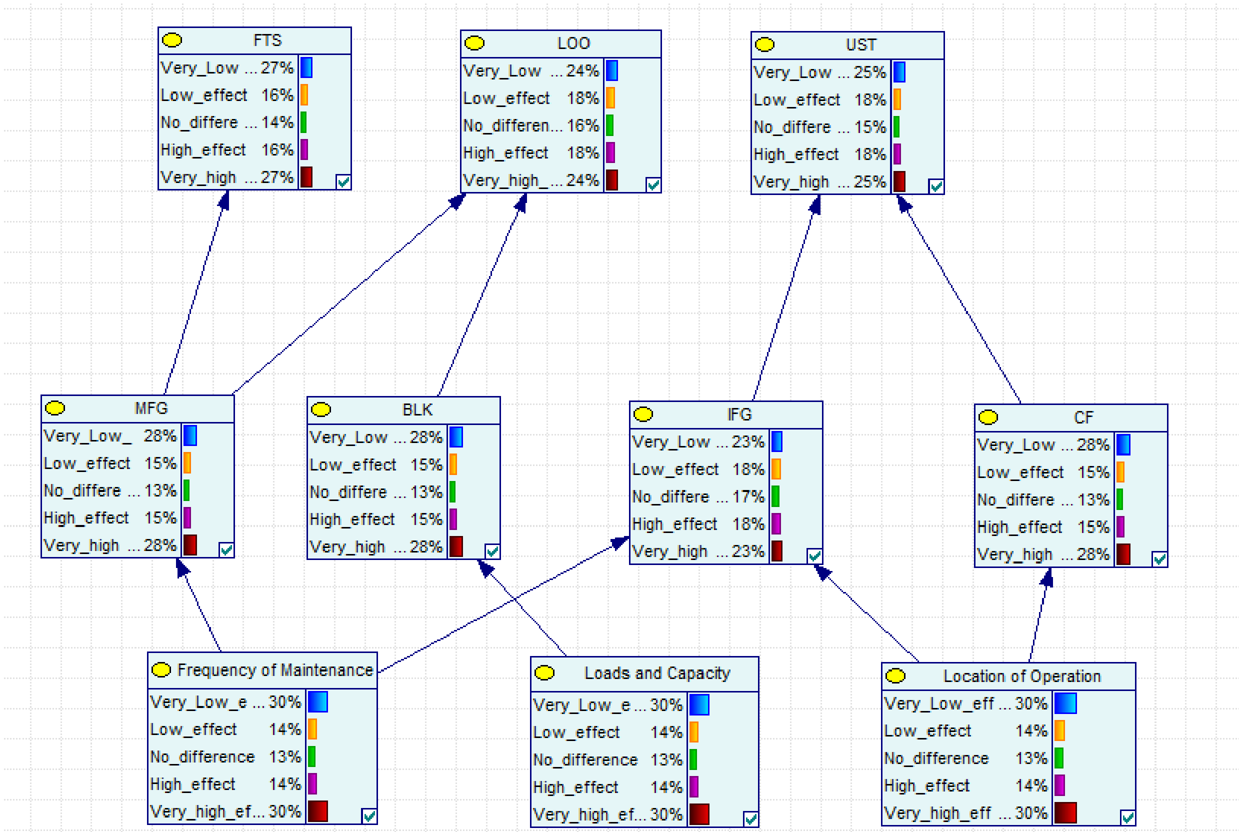

Figure 5.3 Initialization of BBN using prior probability mass

Step 3: Assign R-value

Assume all nodes take 5 states representing the severity of each RIF such that '5' indicates that RIF has very high effect on the subsea failure rate and '1' denotes that RIF has very low effect on subsea failure rate (which means it will decrease the failure rate with respect to topside). Assign the R-value which represents the distribution of probability mass across the possible outcomes of child node. This is a subjective entry made by experts based on their belief of how close the child RIF distribution must be in relation to its parents' state (Røed et al., 2009). Figure 5.4 illustrates the assignment guide for deciding a suitable R-value. In the calculations done in the example in this report, an R-value of 2.5 is assumed.

Step 4: Assign the conditional probability table (CPT) for the child nodes (failure causes and failure Modes).

Using the weights obtained for the child nodes (failure modes) and R-value, CPTs are calculated. For the given example, this is implemented in MS Excel by Edwin (2015) with modification done by the author for reducing states to 5 and adding the case of RIF=1. For the parent nodes, unconditional node probabilities are assigned. The method of their assignment is discussed in further steps.

Step 5: Assign unconditional probabilities to parent nodes (RIFs) and express uncertainty in RIFs.

The RIF may be treated as a stochastic quantity to reflect the uncertainty in the measurement of its true value. A mathematically appropriate probability distribution for random quantities on a scale of 0 to 1 is the beta distribution (Vatn, 2013). The prior probability distribution of a RIF is beta distributed with parameters (α_0, β_0). Jeffery's prior (α_0=0.5, β_0=0.5) is the best choice to reflect ignorance in a particular parameter in Bayesian statistics.

Table 5.4 Assignment guide for deciding a suitable R-value

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

Vatn (2013) proves that an approximate posterior distribution is also beta distributed with parameters$\left(\alpha_0 + \frac{s^2(1-s)}{V_s}, \beta_0 + \frac{s^2(1-s)^2}{V_s}\right)$. Where V_s is the variance which reflects the expert's belief on how accurate the observed score reflects the true score of the RIF. The BBN is initialized with prior probabilities calculated in MS Excel. This is illustrated in Appendix A.

Step 6: Initialize the BBN and Provide evidence and update node probabilities.

The weights obtained from Section 5.3.1 for child nodes (failure modes), R=2.5 and respective CPTs for each child node is used. The prior probabilities are used to initiate the parent nodes (RIFs) with a variance V_s=0.0025. BBN is then initialized with the unconditional probabilities of RIFs and CPTs for child nodes. Figure 5.3 illustrates the initialized BBN.

The next step is to give evidence to RIFs with the same states which are used during the procedure of scoring the RIFs in Section 5.3.1. Using the beta distribution explained by Vatn (2013), the parent nodes' (RIFs) distributions are updated based on the observed RIF score (S) and the posterior probabilities are observed in BBN.

Step 7: Observe the states of failure modes and translate it into failure rate

The failure rates of relevant failure modes are of interest. The final probability distribution of states is mapped to failure rate intervals obtained by dividing the delimiting range of final failure rate obtained from result of section 5.3.1. Changes in probability mass distribution in this node are observed when evidence is provided.

It is illustrated with the example below.

For the failure mode FTS: Topside Failure rate is 40.73 (per 10^6 hours) as mentioned in OREDA. The maximum and minimum ranges obtained for the failure rate of FTS mode are

$$\theta_{min,i} * 40.73 = 0.3 * 40.73 = 12.219\ (per\ 10^6\ hours)$$

$$\theta_{max,i} * 40.73 = 1.1 * 40.73 = 44.803\ (per\ 10^6\ hours)$$

Similarly for LOO and UST the maximum and minimum ranges obtained for the subsea failure rate are,

$$LOO\ (\text{max}) = 89.606\ (per\ 10^6\ hours), \qquad LOO\ (\text{min}) = 24.438\ (per\ 10^6\ hours),$$

$$UST\ (\text{max}) = 112.002\ (per\ 10^6\ hours), \qquad UST\ (\text{min}) = 30.546\ (per\ 10^6\ hours),$$

By dividing these ranges into 5 states, it is possible to match each range of failure rate to a state of failure mode in BBN. This is illustrated for failure mode FTS in the table 5.5. It can be done similarly for other nodes.

Table 5.5 Mapping of state of failure mode FTS in BBN to Failure rate of that failure mode (failure rates are in ($per\ 10^6\ hours$)

States	FTS
State 1	12.219 – 18.73
State 2	18.74-25.26
State 3	25.27 -31.76
State 4	31.77-38.28
State 5	38.29-44.803

Figure 5.4 illustrates the BBN when Location of operation has significantly low effect on CF and IFG and frequency of maintenance has high effect on MFG and IFG and loads and capacity has no difference in effects in subsea and topside..

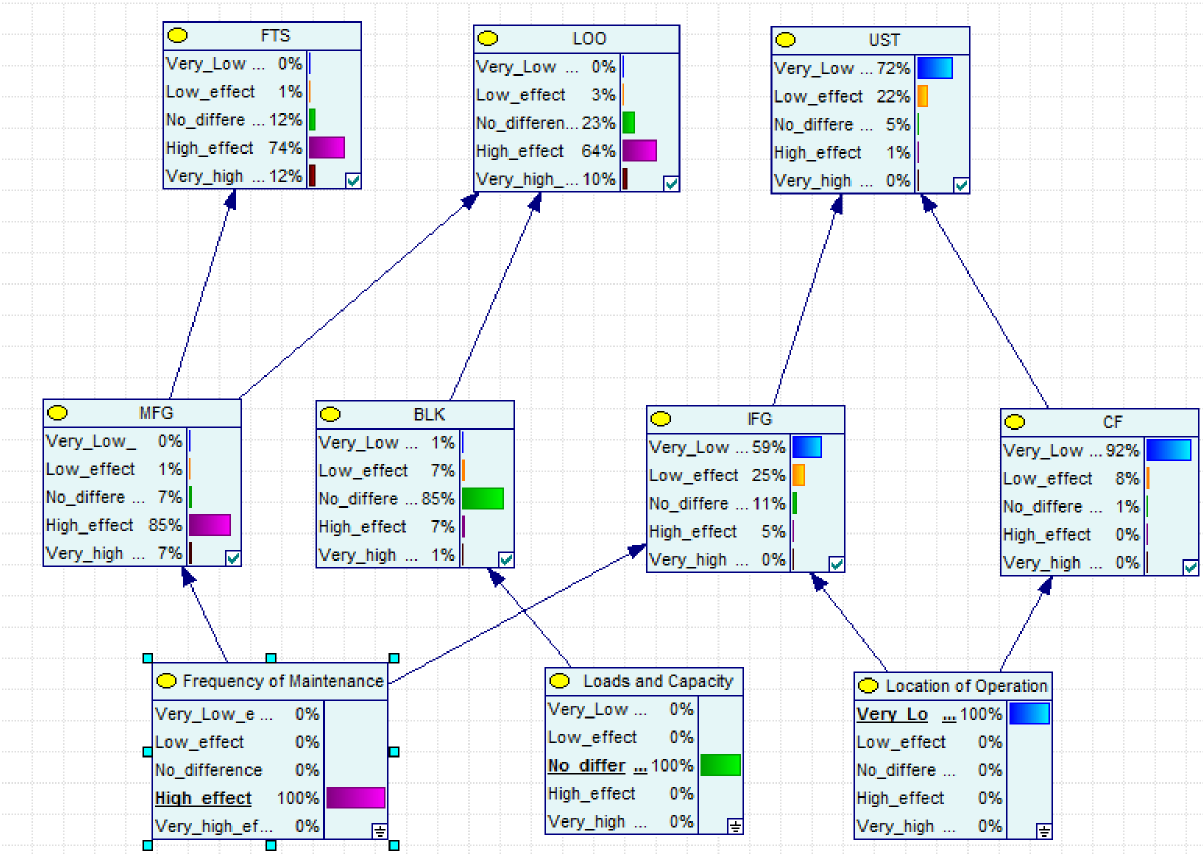

Figure 5.4 Results of BBN model by forcing the RIFs in the state for a subsea pump

It is observed that FTS and LOO has a high effect of RIFs with respect to topside and hence it will have a slightly higher failure rate. To quantify this effect we use the maximum and minimum values of failure rate for each failure mode. The failure rate ranges for each failure mode is calculated and ahown in the table

5.3.3 Sensitivity Analysis performed using GeNie

A sensitivity analysis performed using GeNie by setting the different failure modes as target nodes reveals that the failure cause FTS and LOO are most sensitive to MFG and UST is most sensitive to CF. Figure 5.5 illustrates all the sensitivity diagrams from GeNie

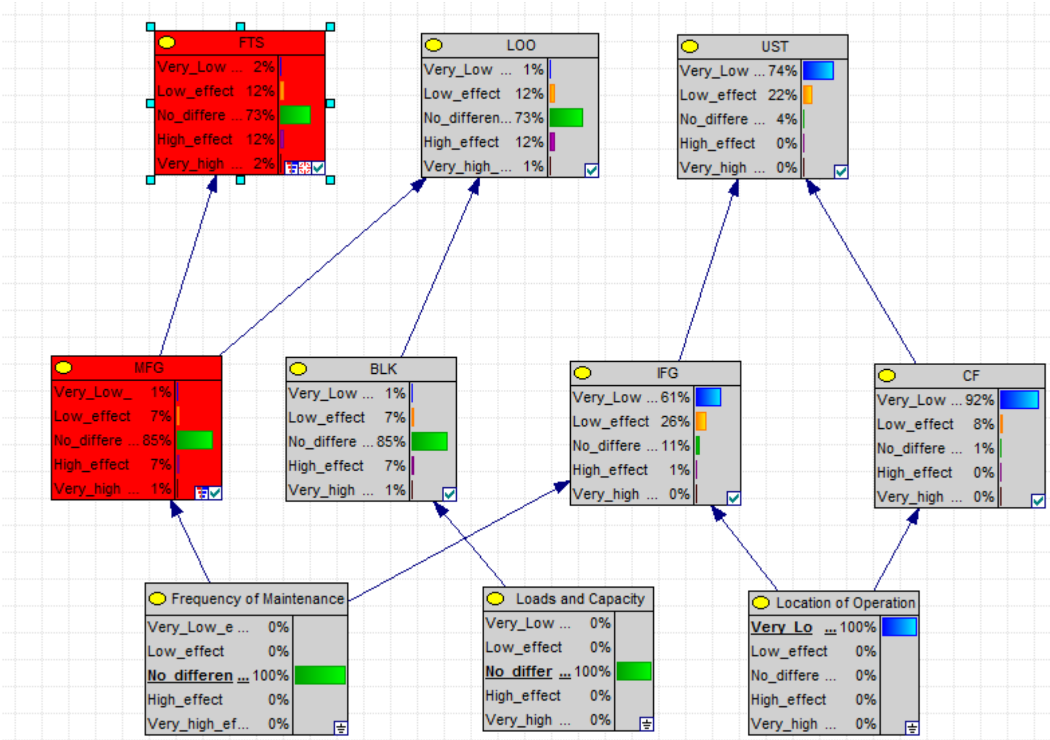

Figure 5.5a Sensitivity analysis of FTS

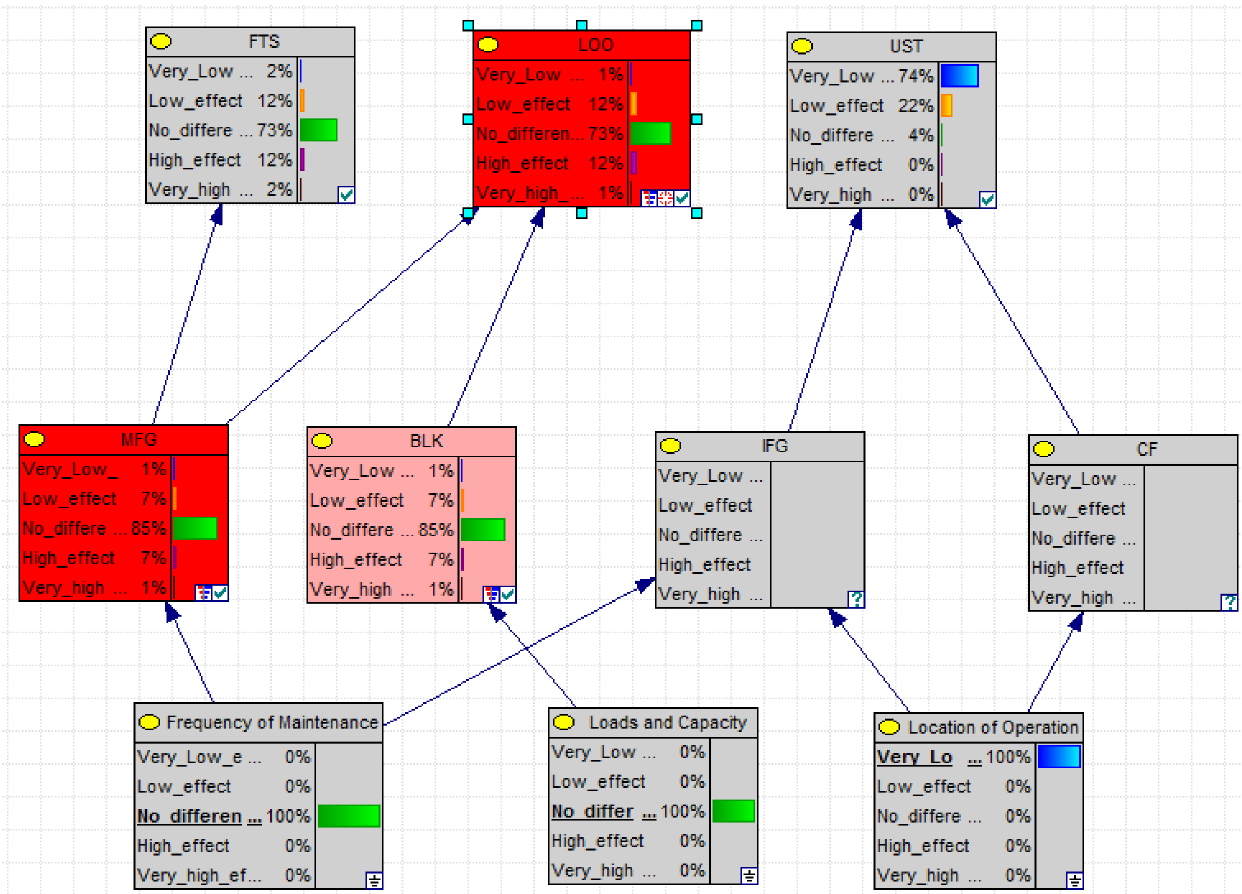

Figure 5.5b Sensitivity analysis of LOO

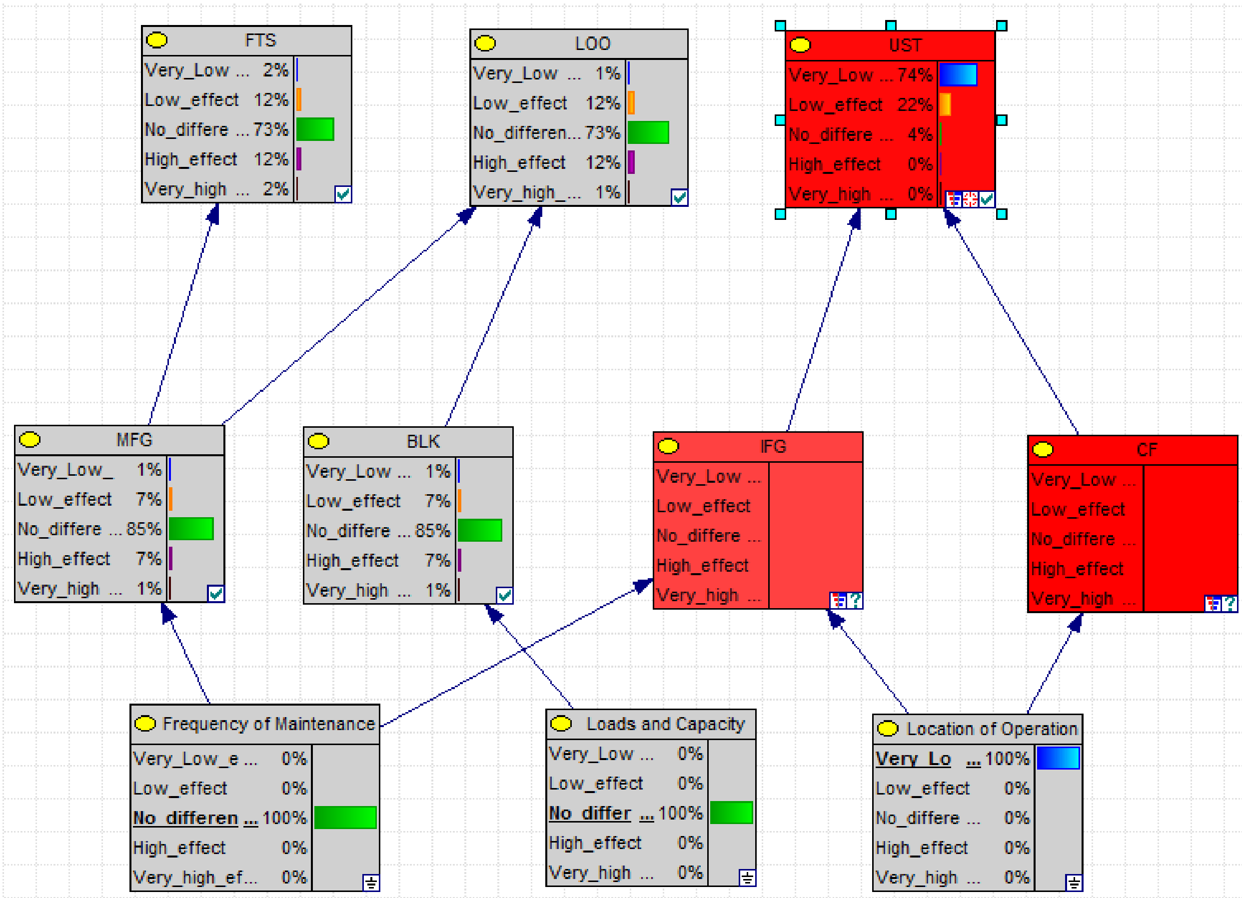

Figure 5.5c Sensitivity Analysis of UST

6 Summary and Recommendation of further work

This chapter summarizes the work performed in the thesis and the results obtained. The results and findings are discussed and recommendation for further work is given in following sections.

6.1 Summary and Conclusion

Prediction of failure rate for new subsea equipment is a challenge in oil and gas industry mainly due to lack of relevant data and use of increasingly novel technologies. There is a lack of common guideline or framework for failure prediction process of novel technology and different companies and experts follow different procedures.

The main objective of the thesis was to propose a new method for prediction of failure rate for new subsea equipment and explain it with an illustrative example. The example chosen is of a subsea pump which forms a part of subsea processing system. Subsea processing is a novel technology with a subsea gas compression module installed at Åsgard field in Norway as recent as 2014. There is a lack of relevant data from similar equipment and even if the data is available, there is an uncertainty in the selection and usage of the method for using the available data as an input for new model. The failure rate calculated is intended to be used as an important input for TQP during the early design phase.

Another important objective of the thesis was to study the existing failure rate prediction methods and reliability databases (e.g. OREDA, FIDES etc.) and identify the research gaps in literature. A comprehensive literature review to study the reliability databases and other methods like BBN, ANN, Rahimi and Rausand's approach is done. The literature study was divided into two chapters, Chapter 3 and 4. Chapter 3 lists the important reliability databases and methods used in them. In most of the databases namely OREDA, MIL-HDBK 217F and many more, bottom-up statistical methods are used for calculating failure rates, identify failure causes and failure modes. FIDES uses a Physics of failure (PoF) approach in which the material factors, operational factors, and functional stress factors are used for predicting the failure rate. Most of the generic methods do not consider the dynamic operational and environmental conditions during prediction process. Chapter 4 describes methods for failure rate prediction namely Regression models, Rahimi and Rausand's approach, Bayesian Networks and Artificial Neural Network. It is found that there is a lack of methods which can be used during the early design phase of TQP for a novel subsea equipment. Most of them require large amount of input data for the failure rate prediction process. However, the approach by Rahimi and Rausand (2013) only uses topside data, FMECA and comparison methods between topside and subsea (by quantifying reliability influencing factors like frequency of maintenance, pressure etc.) for predicting the subsea failure rate for different failure modes. But it uses a linear relation and lacks the ability of handling uncertainty. As there is a lot of uncertainty in the choice and usage of input data during the reliability prediction process, Bayesian Belief Networks (BBN) are the best to model these factors.

The new approach is described stepwise in chapter 5. It mainly uses the weight parameters for RIFs and failure causes as inputs from Rahimi and Rausand (2013) and uses a BBN to calculate the failure rate for all failure modes of new subsea equipment. A BBN model is developed for quantifying the states of RIFs and its effect on failure cause and the failure rates of different failure modes of subsea equipment. The method to easily generate conditional probability tables for BBN is based on the Hybrid Causal Logic (HCL) approach. The new model gives the possibility of inserting uncertainties into Rahimi and Rausand (2013)'s model. A sensitivity analysis is performed for the new subsea pump and is found that failure mode "Fail to start on demand (FTS)" is most sensitive to "Mechanical Failures".

6.2 Limitations of the work

The model is currently designed for RIFs that can be in five states. Ideally 7 states of RIFs (as used in Rausand and Rahimi's Model) and other nodes should be considered during modelling but it was not possible due to computational constraints of MS Excel. It is also assumed that if one RIF is effecting more than one failure causes at the same time it cannot influence each of them differently with respect to the state of the RIF. It means that for example the RIF, "Frequency of maintenance" effects failure causes FC1 and FC2 then it is not possible to set the state of RIF as "1" for FC1 and "2" for FC2 at the same time in the model. This is an inherent limitation of BBN. But in Rahimi and Rausand's method "Frequency of maintenance" can be say "2" while effecting FC1 and "1" while effecting FC2.

The new failure rate estimate for subsea equipment relies on the maximum and minimum limits calculated in Rahimi and Rausand's approach. To select realistic estimates of these limits, extensive knowledge is required.

The failure rate estimate model is just a proposal and cannot be verified by the author. It can only be verified by using the approach to estimate the failure rate of a subsea system for which enough experience is available. The suggested approach is made for new subsea systems but it can be used in other industries.

6.3 Recommendations of further work

The new failure rate estimate model only uses the weights for RIFs and failure cause obtained from Rahimi and Rausand (2013)'s model, a better way of calculating weights for the BBN network is a possibility of further study. In addition, one of the major future scope of this model is updating the model for 7 states of RIFs and testing it on a simulated system in the industry for obtaining the estimates and verifying the results.

As uncertainty is handled in this model and gives the experts the liberty to change the states of RIFs in an intuitive way, another scope of study is using another prior probability distribution in BBN and validating the results.

Appendix A

Additional information about the reliability databases for electronic devices.

Additional information about the reliability databases for electronic devices discussed in Chapter 3 is presented in this Appendix. Table A.1 illustrates the comparison criteria of BS, TD and BP methods as management of objectives.

Table A.1 Comparison criteria of BS, TD and BP methods as management of objectives. (Foucher et al., 2002)

Objectives	BS	TD	BP
Determine if a reliability requirement is achievable	Low[b]	Yes	Yes
Help to achieve a reliable design	No	No	Yes
- By tracking down overstressed parts	No	No	Yes
- By performing a failure root-cause analysis	No	Yes	Yes
- By comparing design trade-off studies	Yes	Yes	Yes
Help to achieve a reliable manufacturing process	No	No	Yes
- Assess potential warranty risks	Low[b]	Yes	No
- Provide inputs to safety analysis	Low[b]	Yes	No
- Establish baseline for logistic support requirements	Low[b]	Yes	No

[b] Use of external databases makes the reliability figure relative and therefore brings little confidence to subsequent steps of the process.

IEEE 1413 (IEEE, 2009)gives the criteria for a guide which reviews the engineering information assessment that is critical for developing an IEEE 1413-compliant reliability prediction and describes the reliability prediction methods such as handbooks based on historic data (MIL-HDBK-217, RAC's PRISM, SAE's reliability prediction method, Telcordia SR-332 (SR-332, 2001), the CNET reliability prediction model), predictions using field data and test data, and the stress and damage model approach. Examples of use are provided for each method. Table A.2 lists the assessment criteria of reliability prediction methodologies.

Table A.2 Assessment Criteria of Reliability Prediction Methodologies (IEEE, 2009)

	IEEE 1413 Assessment Criteria
1	Does the methodology identify the sources used to develop the prediction methodology and describe the extent to which the source is known?
2	Are assumptions used to conduct the prediction according to the methodology identified, including those used for the unknown data?
3	Are sources of uncertainty in the prediction results identified?
4	Are limitations of the prediction results identified?
5	Are failure modes identified?
6	Are failure mechanisms identified?
7	Are confidence levels for prediction results identified?
8	Does the methodology account for life cycle environmental conditions, including those encountered during a) product usage (including power and voltage conditions), b)packaging, c)handling, d) storage, e) transportation, and f) maintenance conditions?
9	Does the Methodology account for material, geometry, and architectures that comprise the parts?
10	Does the methodology account for part quality?
11	Does methodology allow incorporation of reliability data and experience?

Applendix B

VBA Code and MS Excel Interface

Basic knowledge in VBA coding and use of pivot tables in MS Excel is required to understand code syntax and formulation. The Excel based tool made by Edwin (2015) is modified for using 1 RIF and the number of states of each node in BBN is reduced to 5. This is done to make the number of states used in the new model with number of states used for quantification of RIFs in Rahimi and Rausand (2013)'s method.

B.1 Create all possible parent-child combinations

```
Sheets("CreateCPT").Range("A12:ZZ46666").ClearContents
Sheets("CreateCPT").Range("A11:G46666").ClearContents
Sheets("CreateCPT").Range("A9:F9").ClearContents
Application.ScreenUpdating = False
Count = 11 'Index row number to start creating combinations

If Range("NoRIFs") = 1 Then
  i = 1
  'CreateCPT.Cells(9, i) = 1
  For RIF1 = 1 To 5
  For Child = 1 To 5
  CreateCPT.Cells(Count, 1) = RIF1
  CreateCPT.Cells(Count, 7) = Child
  Count = Count + 1
  Next Child
  Next RIF1

ElseIf Range("NoRIFs") = 2 Then
  For i = 1 To 2
```

```
    CreateCPT.Cells(9, i) = 1 / 2
    Next i
    For RIF1 = 1 To 5
    For RIF2 = 1 To 5
    For Child = 1 To 5
    CreateCPT.Cells(Count, 1) = RIF1
    CreateCPT.Cells(Count, 2) = RIF2
    CreateCPT.Cells(Count, 7) = Child
    Count = Count + 1
    Next Child
    Next RIF2
    Next RIF1

ElseIf Range("NoRIFs") = 3 Then
    For i = 1 To 3
    CreateCPT.Cells(9, i) = 1 / 3
    Next i
    For RIF1 = 1 To 5
    For RIF2 = 1 To 5
    For RIF3 = 1 To 5
    For Child = 1 To 5
    CreateCPT.Cells(Count, 1) = RIF1
    CreateCPT.Cells(Count, 2) = RIF2
    CreateCPT.Cells(Count, 3) = RIF3
    CreateCPT.Cells(Count, 7) = Child
    Count = Count + 1
    Next Child
    Next RIF3
    Next RIF2
```

```
    Next RIF1

ElseIf Range("NoRIFs") = ….Continue similarly for all RIFs …
Else
End If
 Range("H11:W11").Select
    Selection.AutoFill Destination:=Range("H11:W279946")
    Range("H11:W279946").Select
 MsgBox ("Configure interaction effects if any")
End Sub
```

B.2 Code to Create Conditional Probability Tables

```
Sub CreateCPT()
   Application.ScreenUpdating = False
   'Delete already existing table
   Sheets("CPT").Select
   ActiveSheet.PivotTables("PivotTable2").PivotSelect "", xlDataAndLabel, True
   Selection.ClearContents

  'Selecting DataRange
  Worksheets("CreateCPT").Activate
   Sheets("CreateCPT").Range("A10").Select
   Range(Selection, Selection.End(xlToRight)).Select
   Range(Selection, Selection.End(xlDown)).Select
   'Create PivotTable
   ActiveWorkbook.PivotCaches.Create(SourceType:=xlDatabase, SourceData:= _
       "CreateCPT!R10C1:R46666C23", Version:=xlPivotTableVersion15).CreatePivotTable _
       TableDestination:="CPT!R1C1", TableName:="PivotTable2", DefaultVersion:= _
       xlPivotTableVersion15
   Sheets("CPT").Select
   Cells(1, 1).Select
```

```
 With ActiveSheet.PivotTables("PivotTable2").PivotFields("CHILD")
    .Orientation = xlRowField
    .Position = 1
End With

'For 1 Parent
If Sheets("CreateCPT").Range("NoRIFs") = 1 Then
With ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF1")
    .Orientation = xlColumnField
    .Position = 1
End With
 ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF1").Subtotals = Array( _
    False, False, False, False, False, False, False, False, False, False, False, False)

'For 2 Parents
ElseIf Sheets("CreateCPT").Range("NoRIFs") = 2 Then
With ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF1")
    .Orientation = xlColumnField
    .Position = 1
End With
With ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF2")
    .Orientation = xlColumnField
    .Position = 2
End With
 ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF1").Subtotals = Array( _
    False, False, False, False, False, False, False, False, False, False, False, False)
 ActiveSheet.PivotTables("PivotTable2").PivotFields("RIF2").Subtotals = Array( _
    False, False, False, False, False, False, False, False, False, False, False, False)

Else
End If
```

```
   'include the Conditional probabilities
ActiveSheet.PivotTables("PivotTable2").AddDataField ActiveSheet.PivotTables( _
       "PivotTable2").PivotFields("Pj"), "Sum of Pj", xlSum
End Sub
```

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