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Reliability study of Subsea Control Module with focus on statistical methods

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Reliability, Availability, Maintainability and Safety (RAMS)
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PROJECT THESIS

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Preface

This master thesis was written during the spring semester 2015 as a fulfilment of one of the prerequisites for the award of master's degree, at the Norwegian University of Science and Technology. The topic "Reliability study of Subsea Control Module with focus on statistical methods" was chosen and the thesis is written with the guidance of my supervisor professor Anne Barros at the department of reliability, availability, maintainability and safety (RAMS), faculty of Production and Quality Engineering. The report is written for readers with some background of statistical theory and reliability engineering. I would like to thank my supervisor Anne Barros for her help and guidance with this project.

Trondheim, 2015-07-10

Askar Bitanov

Acknowledgment

My special thanks goes to my supervisor, Professor Anne Barros for the support and mentoring during this project. Her patience, encouragement and coaching has made it possible for the realization of this project. I would also like to thank my parents, my family and friends for their moral and psychological support during this project period.

A.B.

Summary and Conclusions

The importance of data in carrying out reliability analysis cannot be over emphasized. Failure rate is the basic input for reliability assessment. Therefore, identifying a realistic estimate helps to achieve accurate results. This master thesis looks at some practical aspects and elements of statistical methods in reliability analysis using the case study. We estimated the failure rate of Subsea Control Module based on the company's database reliability record (e.g. failure times).

This thesis applies available methods and models of reliability and lifetime analysis by performing functional analysis, failure analysis, and reliability assessment of the SCM. Different literature was used to understand reliability concepts and its application in various forms of required analysis. We reviewed the development cycle of statistical methods starting with pure mathematical parametric models which evolved into reliability tools (non-parametric and semi-parametric models). Some of the identified statistical data analysis methods were further used to derive the failure rate of an SCM for equipment performance assessment.

We performed a failure distribution analysis for the case study using the failure and censoring times from the database record and this shows a high hazard/failure rate at the initial phase of operation. The covariate analysis revealed that there is no environmental impact on the reliability performance of the SCM but the manufacturer (brand) of the equipment has a significant impact.

This work further presented the utilization of failure rates for in-dept reliability assessment of systems. Qualitative assessments like the functional failure analysis using FMECA is considered the usual method for simple systems. Failure rate is the basic data input for performing quantitative reliability assessments. We showed how it can be used to calculate the availability and frequency of system failures using the Markov approach and simplified formula.

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Chapter 1

Introduction

The effectiveness of any production company's performance can be measured by indicators. The most important indicators are reliability, availability and safety. To meet requirements of successful performance under stated conditions, the technical properties of components and systems should be evaluated. A reliability analysis gains more importance in respect of functional performance assurance, acceptable risk and safety level.

1.1 Background

Nowadays systems comprise of complex equipment to deliver varieties of functions. The modern society has become more vulnerable in case of systems fault. The consequences can be dramatic. It can result in serious economic losses, human safety and environment pollution. All equipment degrade with time and operation. They fail when they are no longer capable of delivering the required functions. The occurrence of failures can be controlled or predicted by studying the system's behaviour. High-risk issues associated with equipment failures can be reduced by robust design and implementing recommendations of the analysis from existing facilities to make the operations safer and more reliable.

The reliability of systems also has an effect on profits obtained by the company since it impacts on planning of maintenance activities. Reliability analysis forms the basis for the proved and effective method of facilities management such as reliability centered maintenance (RCM). The obtained results of reliability analysis can be utilized to build cost-effective and lifetimeoptimized operation of the system.

Demand in reliability engineering was increased in the 1950's due to rockets failures in United States as well as the plane crashes of the first commercial jet aircraft "the British de Havilland comet". Standard mathematical techniques were used at that time for such engineering reliability problems. Reliability theory started developing as a separate discipline from publication of "Multi-Component Systems and Structures and Their Reliability" Birnbaum et al. (1961). An undeniable influence on the development of reliability theory had the Boeing Scientific Research Laboratories with their programs headed by Z.W. Birnbaum(1903–2000), which had a strong mathematical background. (Barlow, 2002)

The military during the Cold War were concerned with robustness of arming equipment and maximizing reliability under required cost, weight and other parameters. Proschan (1965) presented "Mathematical Theory of Reliability". His focus of research was optimal redundancy, spare parts allocation and he derived algorithm for it. He investigated the log concavity of the survival distribution which is inherent to increased failure rate of the system. At the same time Gnedenko et al. (1965) published "Mathematical methods of reliability theory" in russian with emphasis on maintenance and replacement problems.

1.2 Problem Formulation

Reliability is of paramount importance in product performance indicators. This should be quantified and evaluated in order to meet specified requirements or initiate improvement to achieve success. Reliability analysis allows to reveal problems of a system or a product in different phases of life cycle. Even certified and robust products can have shortcomings during the operational phase due to wrong installation, unanticipated loading, operator errors or inappropriate maintenance. Reliability analysis is a part of qualification procedure for new technologies to ensure performance of required functions. The failure of a safety instrumented system could lead to loss of lives, environmental disaster and damage of assets. Reliability assessments help to verify that the system is performing as required and specified in the safety requirement specification. Reliability study in past was concerned only with failure events which was believed to be the only factor influencing the reliability characteristics of a system. Parametric approach gained success by modeling the lifetime distribution in the field of failure data analysis. Further it was realised that many factors have influence on system survival. Hence non-parametric approaches were introduced which do not require any distributional assumptions and considering censoring for analysis. Proportional hazard model considers even more factors, known as covariates, to investigate influence on system reliability.

Reliability analysis requires reliability data as an input. This data may have big variation or collected from different sources for databases. The reason for variation is a number of factors which may differ under which the reliability data was collected. This leads to a challenge for estimation of a single failure rate with a realistic confidence interval. However, not all reliability study requires statistical methods. The objective of a study to be performed influences the choice of reliability analysis approach to utilize for achieving the required result.

1.3 Objectives

The main objective of the master thesis is to identify, document and clarify the methods, models and approaches for reliability analysis study. For this purpose the following objectives shall be achieved:

1. To clarify key concepts of reliability analysis for possible different applications.
2. Present and explain the importance of the strategies of reliability studies.
3. Identify and describe different approaches for reliability study, using a literature survey as basis.
4. Describe the use of elements of statistical data analysis in the field of reliability using a case study as a basis.
5. Discuss the results in light of areas of future research and recommendations identified based on the case study.
6. Describe the use of qualitative and quantitative approaches in reliability analysis.

1.4 Limitations

The subject of the thesis is reliability study with the main focus on reliability data analysis. The thesis applies available methods and models of reliability and lifetime analysis studied during MSc RAMS program at NTNU and concepts from different literature. The books "System Reliability Theory: Models, Statistical Methods, and Applications by Rausand and Høyland (2004)", "Practical methods for reliability data analysis by Ansell & Phillips (1994)" and IEC 14224 are the base sources used in this report. Other information sources for this work are search engines like Scopus, Google scholar and Sciencedirect. Another limitation is commercial confidentiality and limitation of information access to the company database for the case study. Reliability study involves broad range of methods and approaches respectively to different assigned objectives for analysis. The analysis performed in the thesis covers limited number of statistical techniques and models due to limitation in the company's information.

1.5 Approach

The concepts of reliability analysis, methods and approaches are studied in the thesis based on literature review. It is also very important to demonstrate the techniques through case studies and show their application. The identified objective for the case study is to estimate the failure rate of a component which can be a basis for further analysis and decision making. The feasible approach for this objective is application of statistical methods. The procedure is implemented and demonstrated in Minitab, a statistics software. Other results in addition to the failure rates were achieved by utilizing the theory in practice. Statistical approach requires careful examination of the data before choosing a technique. In the case study, a main feature is presence of censoring times and different ways for treating the censoring times are used. Furthermore, the following steps of statistical approach are considered: validation of the data, simple statistics, trend and dependency investigation, plots of failure time distributions and more specific modelling techniques.

1.6 Structure of the Report

Chapter one gives an introduction to the general subject matter, discussing the need for reliability analysis. In chapter two, an explanation of reliability studies and associated concepts is given. In chapter three, we review the development cycle of statistical methods starting with pure mathematical parametric models which evolved into reliability tools (non-parametric and semi-parametric models). The study case in chapter four analyzes failure time data and problems encountered in the analysis with the presence of censoring. Stochastic process is used to model the behaviour of the component. Finally the failure rate of the component is estimated and the assessment of component reliability performed. In chapter five, qualitative assessments like the functional failure analysis using FMECA is considered the usual method for simple systems. Failure rate is the basic data input for performing quantitative reliability assessments, performed in chapter six. Markov approach and simplified formula used to calculate the availability and frequency of system failures. Chapter seven contains the observations and conclusion summary.

Chapter 2

Introduction to reliability analysis

2.1 Basic concepts

Theory distinguishes three types of reliability analysis applications(Crowder et al., 1994; Rausand and Høyland, 2004). First is *hardware reliability*, the reliability of technical components and systems. Second is *software reliability*, measure of software operation without failure for a specified requirements. This mainly reflects a design perfection, because software does not age. Third is *human reliability*, when study applied to human being and evaluate personal ability to perform certain tasks according to a specified standard.

In the past reliability was purely qualitative term. Nowadays systems comprise of complex equipment to deliver varieties of functions and it requires methods of measuring reliability and it became a quantitative concept. The reasons for this could be several. Firstly, it is economical, since reliability improvement costs money or a failure of critical component leads to loss of production. Another not less important is safety, in order to evaluate a risk reduction measures or maintaining human health well being. For these purposes statistical methods are used to measure reliability for different study objectives. It may be measured in different ways: in a more routine application as mean time to failure (MTTF), number of failures per unit time (failure rate), survival probability for a time period.

Hardware reliability

High level of automation is involved in extreme conditions or hazardous industry in form of safety measures and to reduce human interaction. Therefore the concern of this dissertation is hardware reliability which is crucial to a complex system functionality. There are two approaches for this study: the physical approach and the actuarial approach.

The physical approach is used in structural design. Traditional approach for structural design is based on deterministic analysis. Mechanical properties of materials and loads are determined with safety factors during design phase. In the real world, structural loads and material properties have statistical nature and dependent on stochastic factors during manufacturing or operation. Statistical methods were developed to deal with these effects. This approach has advantage of comparison reliability of different structures with different structural shapes. It allows also assessing of complex structures that have redundancy and consequently perform sensitivity analysis to identify critical load or design parameters (Madsen et al., 2006).

The actuarial approach uses the probability distribution function $F(t)$ of the time to failure T, which models interaction of operating loads and strength of a component. Component or system reliability analysis does not consider explicit modeling of these two variables. Reliability measures are derived from the probability distribution function $F(t)$(Rausand and Høyland, 2004).

2.2 Reliability definition

☞ **Reliability**: The ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time(ISO8402:1994).

Item denotes system or component, which the *reliability* is defined as the probability that the item perform specified required function(s) for a stated period of time. Usually the period of time is initial interval of length t, which is denoted by $[0, t)$.Reliability function is time dependent of time t and can be defined as:

$$R(t) = P\big(System\ operates\ during\ [0, t)\big),$$

where P denotes the probability of an event of interest.

The practical interest of reliability study is also in some associated concepts like quality, availability, safety, security, and dependability. All of these concepts are more or less interconnected.

2.3 Application

Reliability study is widely used in industries for different areas. Rausand and Høyland (2004) presents examples of some applications of reliability analysis:

1. *Risk analysis* is conducted in three main steps. Some of the methods applied during the study are related to quantitative risk analysis (QRA) (Rausand, 2013). The first step is identification and description of potential accidental events with follow applicable methods:

    - Checklists
    - Preliminary hazard analysis (PHA)
    - FMECA
    - HAZOP
    - Event data sources

    The second step is causal analysis. The potential causes of each accidental event with possible estimation of probability of occurring may be identified by the following methods:

    - Fault tree analysis
    - Reliability block diagrams
    - Influence diagrams
    - FMECA
    - Reliability data sources

    The third step is consequence analysis. Assessment of adequate activation of barriers and analysis of event consequences to the assets by the following methods:

- Event tree analysis
- Consequence models
- Reliability assessment
- Evacuation models
- Simulation

2. *Environmental protection.* Improving reliability of the technical treatment systems have direct effect on environment by reducing the industrial pollution. Analyses shows that major environmental pollution is caused by industry due to production process upsets. Optimization of resources and reliability improvement have important role in environmental protection. Environmental risk analysis interconnected with reliability analysis and is carried out in same procedure as a standard risk analysis.

3. *Quality.* Quality is associated with reliability which can be one of the most important characteristics of products. Requirements for quality management are regulated by IS09000 series of standards.

4. *Optimization of maintenance and operation.* The modern society has become more vulnerable in case of systems fault. The consequences can be dramatic. It can result in serious economic losses, human safety and environmental pollution. All equipment degrade with time and operation. It fails when it is no longer capable of delivering the required functions. The occurrence of failures can be controlled through maintenance actions, including preventive maintenance, inspection and condition monitoring. High-risk issues associated with equipment failures can be reduced by robust design and effective preventive maintenance actions to make the operations safer and more reliable. Maintenance function gain more importance in respect of required risk and safety level. This serves as a basis for the implementation of reliability centered maintenance (RCM) approach. RCM is an approach to cost-effective maintenance planning. This is achieved by comparing different maintenance policies and choosing the best option.

5. *Engineering design.* Reliability is the most important characteristic of equipment in critical systems. For this robust design is the key factor in reliable operation. Integrating relia-

bility program in earlier design phase allows to reduce operational expenses and improve safety of systems in such critical industries as nuclear power, aviation and aerospace.

6. *Verification of quality/reliability.* Authority regulations require manufacturers' products to comply with codes and standards' requirements. It is the usual requirements for safety and environmental protection. Also some users of equipment can request manufacturer to meet internal specifications. To verify and demonstrate equipment reliability quantitative study is required. This verification documentation can be used and utilized during operational phase of the products for maintenance scheduling and reliability and safety level assurance.

2.4 Objectives and strategies for reliability studies

The prime objective of a reliability analysis is to provide the information for decision making. The first step of the study is to define the objectives and there are a number of factors influencing this. For example, there are: areas of application, initiator of a study, the life cycle phase of the system, etc. Some of the possible objectives for stated applications above can be:

- evaluation of system performance
- estimation of improvement cost for achieving required level of system performance
- optimization of resources for achieving required level of system performance
- assessment of the likelihood of events

There are two approaches to meet the objectives of study: qualitative and quantitative or combination of both. Quantitative study have three areas of interest: assessment, identification and prediction. The objective of assessment study is quantification of reliability or system lifetime distribution. Criticality analysis or covariates estimation, which have significant effect to lifetime, is the interest of identification process. Prediction is the process of future system's characteristics extrapolation based on historical data. Ansell et al. (1994) emphasizes the importance of study objectives during the statistical analysis to establish approach which will be 'problem-led' rather than 'technique-led'. This helps to focus on relatively simple techniques to achieve the desired objective.

Cox and Snell (1968) describe a strategy of the analysis as a process of checking different hypotheses describing the model of the system or the distribution involved. Techniques used during analysis and applied to data allows to choose the model thought to be most appropriate. This process of application is described in four steps:

1. Selecting the technique
2. Application of the technique
3. Diagnostic tests associated with technique
4. Interpretation of the results

The technique for analysis should be selected according to objective of the study. For instance, typical objectives are the prediction of system performance, detecting a trend in failure occurrence, comparing systems or components, which can be achieved by fairly simple technique. As a consequence after selecting the technique, we can determine what required data, information and approach for the analysis are needed.

2.5 Databases and data collection

All facilities need a system to collect, store and utilize operational data for their plants. The information are sometimes spread on several types of recording systems (CMMS, reports, etc.), thereby not easily accessible for systemic and comprehensive reliability analysis. Reliability recording faces various practical and managerial constraints. This should be considered in design phase for better integration into operational system and to have compromise between the desirable and the feasible. The factors influencing the application will mainly depend on the amount of input data and extent of data acquisition. Therefore the limitation in type and extent of reliability data processing which can not be treated in isolation, must be looked upon within an integrated approach for the complete reliability information system.

The potential benefits from the data analysis will evidently increase with the extent and quality of input data. However, this will require increasing resources which is one of the constraints. The input data can be classified as

- Inventory data
- Operating conditions
- Event data

Table 2.1 shows 4 levels of **event data** with relation to application areas. **Level 1** of input data is the lowest conceivable level of reliability recording to provide any meaningful information and typically, it is relevant for simple non-repairable items. Analysis on this level has to assume an exponential failure distribution (constant failure rate). **Level 2** is slightly more comprehensive and used for simple repairable items. Trend analysis and ensuing optimization analysis may be performed on this level. The first two levels consider all failures as an event of termination of function without analyzing the consequence, while **Level 3** records Failure modes. The consequence of failure modes is classified by functional effect and by criticality. **Level 4** does not provide additional data more the lower levels. Its advantage is that it provides better background for understanding failure mechanisms and more comprehensive feedback to a maintenance department. However, it is often the case that human factor failures may be covered up by operators and some atypical failure mechanism be unrecognized.

Inventory data and **operating condition** information helps to increase the confidence level and understand failure mechanisms, also to identify "stressors" effecting reliability. The extent of data and format of registering the information are stated in details in ISO-14224 (2006).

Table 2.2 shows three major application areas/phases:

- Operating phase
- Planning and Engineering phase
- Company reliability database

Different assessment methods of the input data is considered in the following chapters.

Table 2.1: Relation between input data and application. (Lydersen et al., 1987)

Level	Event data input	Applications	Applicable equipment
1	1.No of events 2.Accumulated operating time	-Safety and Reliability analysis of critical items -Location of equipment -Maintainability -Spare parts -Replacement cost	Simple units Significant quantities Non-repairable Considering only failures Low criticality
2	1.Failure event 2.Failure time 3.Time since new/last repair 4.Shutdown and repair time	Additionally to level 1: -RAM analysis -Trend analysis -Maintenance optimization -CBM feasibility -LCC	Low complexity Repairable Few failure modes Medium criticality
3	1.Failure event 2.Failure time 3.Time since new/last repair 4.Shutdown and repair time 5.Failure mode/effect	Additionally to level 2: -FMECA -Elucidate failure mechanisms	Medium complexity units Repairable Critical failure modes Medium criticality
4	1.Failure event 2.Failure time 3.Time since new/last repair 4.Operating mode 5.Failure detection method 6.Failure mode/effect 7.Failure consequence 8.Failure cause 9.Remedial action 10.Shutdown and repair time 11.Additional information	Additionally to level 3 in-depth: -Elucidate "stressors" -Effectiveness of failure detection methods -Common cause failures -Downtime analysis "bottle-necks"	Medium to high complexity Repairable Critical failure modes Medium/high criticality

Table 2.2: Applications of reliability data. (Lydersen et al., 1987)

Phase	Main application	Comments
Operation	Operation performance	Various statistical overviews for a chosen time interval such as no. of events, outage time. Mandatory operational/reliability data.
	Maintenance intervals	Adjusting maintenance intervals according to recorded failure rates.
	Test intervals	Optimizing test intervals according to recorded failure rates.
	Failure probability distribution	Assessment of any lifetime dependency. Applicability of trend analysis and/or condition monitoring
	Spare parts	Optimization of spare part store and logistic.
	Operating procedures	Effect on reliability of alternative operating procedures or modes.
	Maintenance scheduling	Job priority scheduling.
Engineering	Safety analysis	Input to various types of analysis at various stages of concept and engineering phase.
	RAM studies	Calculation of availability of safety equipment and regularity of production.
	Equipment location	Input for deciding best location versus effect of major damages, and required maintainability.
	Selection of make	Selection of equipment with best reliability experience.
	Planning maintenance	Input to choice of maintenance strategy, interval for periodic maintenance, applicable CM, and required reporting.
	QA-level/testing	Deciding general QA-level and QC-routines such as qualification testing.
Company data	Pooling of data	Pooling reliability data for similar equipment, thereby increasing statistical confidence.
	General reliability analysis	Depending on no.of data, and data quality, a significant no. of analysis are possible (reliability in relation to operating, environmental conditions, location)
	Inter company consulted services/analysis	Expert judgment and specific analysis for project organizations and operating units
	Cost/reliability	Cost/reliability relation evaluation (e.g. use of high alloy material)
	General "in house" reliability engineering	Testing and improving reliability analysis. Training and reliability programs.

Chapter 3

Statistical methods

In order to understand the behavior of the system, reliability data and other related information are the subject for analysis. Statistical methods are involved in process of collection, processing, analyzing, and interpretation a variable numerical data. In contrast with deterministic methods, which can be experimentally repeated with obtaining a same result, statistical methods are used for stochastic processes and random phenomenas. Statistical methods are widely used in areas where uncertainty is presented to obtain an expected value with variation and where deterministic approach is difficult to apply. This allows to quantify reliability by lifetime distribution of the time to failure T. The time T is considered as a stochastic variable. As an example it can be a unit of time, such as the number of hours a component is used, or a unit of distance, such as how far a car is driven. There are a few different functions describing the probability of times to failure: **Cumulative Density Function** $F(t)$ describes the probability that a specific component fails before the time t:

$$F(t) = P(T \leq t)$$

Survival Function / Reliability Function $R(t)$ describes the probability that a specific component is working at time t:

$$R(t) = P(T > t), t \geq 0$$

The Hazard Function $z(t)$ describes the failure rate at time t, given it is still working at that time:

$$z(t) = \lim_{\triangle x \to 0} \frac{P(t < T \leq t + \triangle t \mid T > t)}{t} = \frac{f(t)}{R(t)}, t \geq 0$$

Table 3.1: Relationship between the Functions $F(t)$, $f(t)$, $R(t)$, and $z(t)$. (Rausand and Høyland, 2004)

Expressed by	$F(t)$	$f(t)$	$R(t)$	$z(t)$
$F(t) =$	-	$\int_0^t f(u)du$	$1 - R(t)$	$1 - exp\left(-\int_0^t z(u)du\right)$
$f(t) =$	$\frac{d}{dt}F(t)$	-	$-\frac{d}{dt}R(t)$	$z(t) * exp\left(-\int_0^t z(u)du\right)$
$R(t) =$	$1 - F(t)$	$\int_t^\infty f(u)du$	-	$exp\left(-\int_0^t z(u)du\right)$
$z(t) =$	$\frac{dF(t)/dt}{1-F(t)}$	$\frac{f(t)}{\int_t^\infty f(u)du}$	$-\frac{d}{dt}\ln R(t)$	-

where $f(t) = F'(t)$

The Availability $A(t)$ describes the probability that a specific component is functioning as demanded at time t. For component that are not repaired or replaced, $A(t) = R(t)$.

Once one of these function is known, any other function can be derived. The relationships between the functions $F(t)$, $f(t)$, $R(t)$, and $z(t)$ are presented in Table 3.1.

3.1 Parametric models

Lifetime distribution models the behavior of the system. Different families of distribution functions are used for this, and they are functions of a variables inherent to different distributions, known as *parameters*. Values of parameters have to be specified in order to define the failure time distribution by particular function.

Some distributions have more than one parameter, say r parameters, and can be denoted by the vector $\beta = (\beta_1, \beta_2, ..., \beta_r)^T$. The reliability function can be written respectively as $R_T(t;\beta)$.

Parametric analysis also allows to model dependency of the failure time distribution of T on the variation of k other variables represented by the vector $z = (z_1, z_2, z_3, ..., z_k)^T$. These Z information along with the component's failure time t represent other information about the component or its environment. Typically it is represented by information on the design of the component, the level of degradation of the component or the condition in which it functions. These Z variables are called *covariates*. The joint distribution of the failure time T and the covariates Z should be denoted in order to perform analysis. These extra information provide more basis for better understanding of system performance. The reliability function can be written respectively as $R_{T,Z}(t,z;\beta)$.

Then, it is possible to obtain the covariates value z of a model and "fix" the values. The interest after, would be to derive the failure time distribution, which is become the conditional distribution of T given z:

$$f_{T|Z}(t \mid z;\beta) = \frac{f_{T,Z}(t,z;\beta)}{f_Z(z;\beta)},$$

where

$$f_Z(z;\beta) = \int_0^{\infty} f_{T,Z}(t,z;\beta)\,dt.$$

Another objective for the reliability study can be for example, to study system behaviour through temperature variation. Such variables vary with time and called *time-dependent covariates*. The *covariate history* at time t is presented by covariate z and denoted by $z(t)$.

One can face challenges with *estimation* of the parameters β, or some function of β for choosing the best fitted model based on observed data and afterwards checking how good the estimates are (*hypothesis testing*). For solving these problems there are three main accepted statistical methods (Rausand and Høyland, 2004; Leemis, 1995; Ansell et al., 1994): *classical, likelihood*, and *Bayesian*.

3.2 Non-parametric models

Non-parametric method allows to model failure time distribution without specifying the reliability or probability density function. It is mainly used and developed for lifetime distribution with right censored data cases. Non-parametric estimators can be derived for the reliability (survivor) function and the cumulative hazard function of the failure time distribution.

The Kaplan-Meier (KM) estimator $\hat{R}_T(t)$ of the reliability function, $R_T(t)$, which was proposed by Kaplan and Meier (1958), is a step function, see the figure 4.6 and represented by

$$\hat{R}_T(t) = \prod_{i:t_{[i]}\leq t} \left\{1 - \frac{m_i}{r_i}\right\}, \tag{3.1}$$

where, m_i is a number of failures at the failure time $t_{[i]}$, and r_i is a number of components under observation (*risk set*) at time $t_{[i]}$. The KM estimator is a single value for reliability function at any time t. Variance of the KM estimator for different samples is provided by $log(\hat{R}_T(t))$ of **Greenwood's formula**:

$$\widehat{Var}(log(\hat{R}_T(t))) = \sum_{i:t_{[i]}\leq t} \left\{ \frac{m_i}{r_i(r_i - m_i)} \right\} \tag{3.2}$$

Then, it is possible to estimate variance $\hat{R}_T(t)$ by $(\hat{R}_T(t))^2 \widehat{Var}(log(\hat{R}_T(t)))$.

The Nelson-Aalen (NA) estimator $\hat{Z}_T(t)$ of the cumulative hazard function, $Z_T(t)$, which was justified by Nelson (1969), is also a step function represented by

$$\hat{Z}_T(t) = \sum_{i:t_{[i]}\leq t} \left\{ \frac{1}{r_i} \right\} \tag{3.3}$$

There is some difficulty in theory for the cases with ties. Different methods have been proposed for ties cases based on different assumptions. However, this is not covered in this report due to the numerous methods.

The asymptotic variance is presented by

$$\widehat{Var}(\hat{Z}_T(t)) = \sum_{i:t_{[i]}\leq t} \left\{ \frac{m_i}{r_i^2} \right\} \tag{3.4}$$

Further, the NA estimator can be used to derive the reliability function using the basic relation by

$$\hat{R}_T(t) = exp(-\hat{Z}_T(t))$$

3.3 Semi-parametric models

Semi-parametric models, as a compromise between parametric and non-parametric methods, consider only a partial specification of the reliability, probability density, or hazard function of the failure time distribution. This allows to model the covariates, which is the interest of the analysis, by assigning the parameters for it while the base part of the model remains non-parametric form. Cox hazard model is an example of semi-parametric model, known as *propor-*

tional hazards model. The hazard function at time t with covarietes x is expressed by

$$z(t \mid x) = z_0(t) exp(\beta^T x)$$

Where, $z_0(t)$ is the baseline hazard function and modelled non-parametrically; $exp(\beta^T x)$ is the exponential function of the covariates, x and β the parameters of this function.

Chapter 4

Case study - statistical analysis

Chapter 4 presents the case study and applies methods and real observed data of subsea control modules. In agreement with the company's confidentiality requirements, we do not provide the names of the fields and other confidential information.

4.1 Objectives of analysis

An operator of the offshore fields decided to assess the performance of the production control system, which is shown in figure 4.1. The production control system is a complex system and consists of topside controls, power equipment, Subsea Control Modules (SCM) and sensors as well as subsea electrical and hydraulic distribution equipment. The dependency causes the complexity of the system analysis and will require model simulation. Therefore our analysis is narrowed to one component of the system: The Subsea Control Modules (SCM), shown in figure 4.3. The objectives of the analysis are to use database on failure times and failure free times to decide whether the components satisfy specification or need a major modification. Additionally we estimate the replacement rate, to determine if the rate increases with operational time in hours, so we can predict the number of future replacements.

Subsea Control Module (SCM)

Subsea Control Modules are commonly used to provide subsea well and subsea manifold control functions during the production phase. There are two typical essential functions of SCM

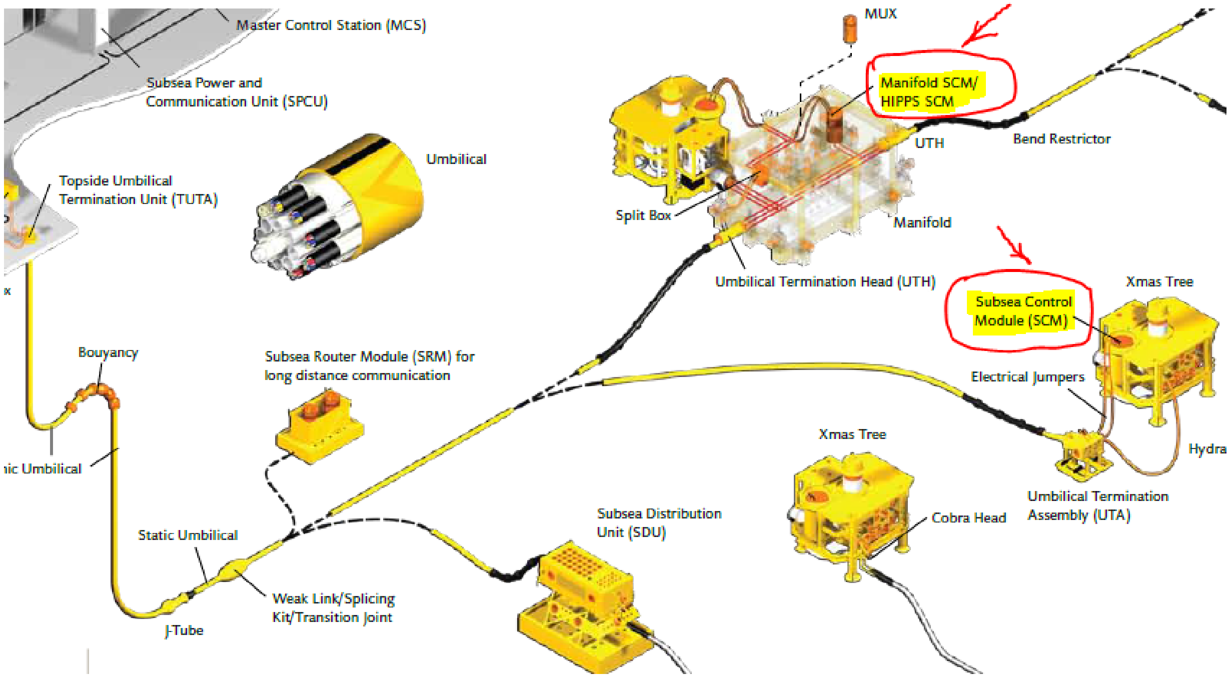


Figure 4.1: Production Control System (FMCTechnologies)

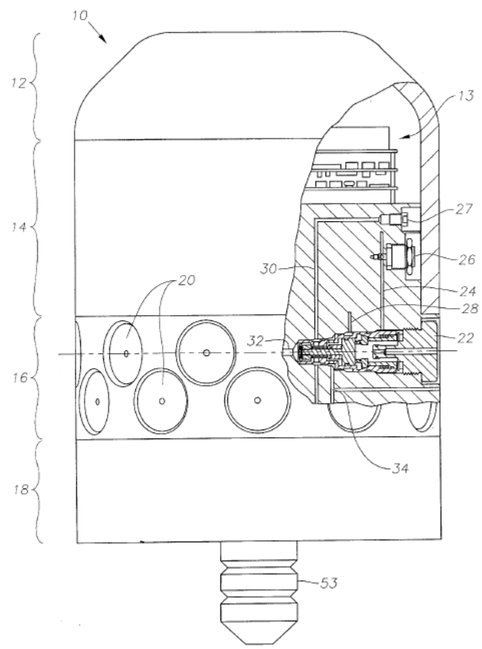


Figure 4.2: General arrangement drawing of Subsea Control Module (SCM) (Parks and Smith, 2000)

namely:

- To control the valves, such as production tree actuators, downhole safety valves, flow control choke valves, shut-off valves, manifold diverter valves, chemical injection valves, etc.
- For monitoring functions, such as measuring pressure, temperature and flowrate in downhole, and in production tree and manifold; sand probes; and choke positions.

A SCM is mounted directly on the wellhead or manifold subsea equipment as it is highlighted and marked in red in Figure 4.1. Such proximity allows for quick response times of valve actuations. SCM receives electrical power, communication signals and hydraulic power supplies from surface control equipment by umbilical hoses and cables, linking surface equipment to subsea equipment. According to general arrangement drawing in Figure 4.2, SCM **10** consists of three primary sections: a pilot module **14** enclosed by pressure dome **12**, a valving module **16** and a base module **18**. The work principle of SCM can be described as follows: SCM receives communication signals from surface, which are further processed by SCM electronics **13** that transmits electrical power to solenoid pilot valve **26** to actuate control valve **22**. Control valves **22** transmit hydraulic power to end devices such as subsea production tree valve actuators, choke valves and downhole safety valves. The status of control valves and their end devices are read by pressure transducers **27** located on the output circuit of the control valves. A SCM may be installed and retrieved by a remote operated vehicle (ROV).(Parks and Smith, 2000; API17A)

4.2 Statistical analysis

4.2.1 Database and assumptions of the analysis

The data was collected from five different regions of the North and South Atlantic Ocean in a period of more than 20 years. The database provides records for each component and their corresponding serial number. The records show three possible events: the failure time of the component, a time at which preventive maintenance was performed, and a time at which the component was withdrawn from service. Based on these, the time to failure or failure free operational times of each component is known. The feasible approach for analysing the event data

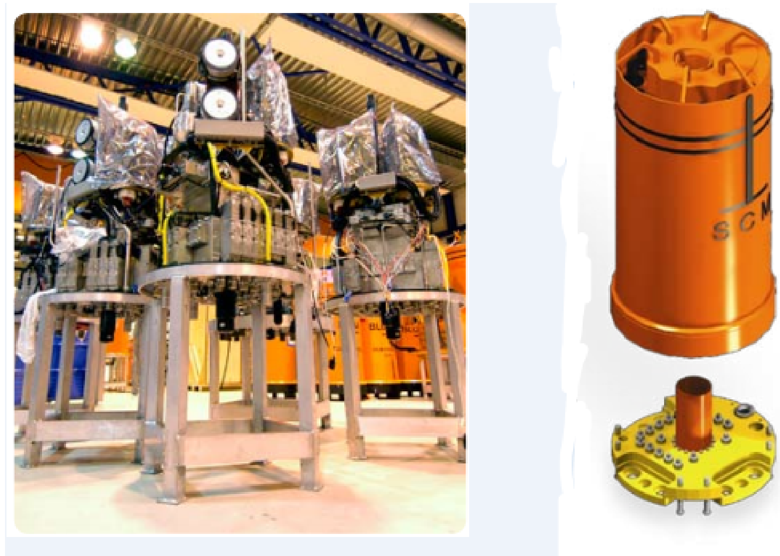


Figure 4.3: Subsea Control Module (SCM) (FMCTechnologies)

is subject for statistical techniques to identify the tendency of failures. The procedure is implemented and demonstrated in Minitab, the statistics software developed at the Pennsylvania State University.

When a failure of the component occurs in service, the SCM is replaced by a new module or repaired and assumed to be in as good as new state and the system is returned back to service. The time taken to repair the system is not taken into consideration as these times are short compared with the average time between failures.

There are additional information corresponding to each SCM serial number: operator, field, version, well or manifold, serial number, model, manufacturer, failure mode, failure effect, failure cause, failure cause category, failure class, remedial action, exposure time [hrs], depth from RKB [m]. An example of these information of the database is in Excel sheet presented in Figure 4.4. Commercial consideration does not allow to present data set, and the example shows only possible set for representation only. However, we appreciate the possibility to analyze the data obtained from real offshore facilities, which provides the fundamental importance for performing reliability analysis and emphasize inherent features.

Database consists of 911 records, of this, 81 records are failures and 830 records are right censored.

	A	B	C	D	E	F	G	H	I	J	K	
1	Operator	Field	Well or Manifold	Tag Number	Version	Serial Number	Exposure Time (hrs)	Manufacturer	Model	Failure Date	Failure Mode	Fa
2	North Sea	Name	well No	#	#	#	#	#	#	01.01.1998	Internal leakage - utility medium (ILU)	No im
3	West Africa	Name	Manifold No	#	#	#	#	#	#		External leakage - utility medium (ELU)	Opera
4	North America	Name		#	#	#	#	#	#		Failure in electronics/coms (FIE)	
5	South America	Name		#	#	#	#	#	#		Loss of electric power supply (LEP)	
6												

Figure 4.4: Example of the Excel sheet from the database

Table 4.1: Distribution of failures per SCM system

No. of failures per system	0	1	2	3	4	5	6	7	Total
Frequency of manifold's system	46	13	2	3	0	1	0	0	65
No. of system failures	0	13	4	9	0	5	0	0	31
Frequency of wellhead's system	94	20	6	1	2	0	0	1	124
No. of system failures	0	20	12	3	8	0	0	7	50
Total no. of failures	0	33	16	12	8	5	0	7	81
Mean no. of failures per system									2.33

Remark: The censoring time is a component's operational time after which the component is retired from service or its latest time if still in service.

We start SCM reliability study by tracing Tag numbers, which represents the repairable system, and not by individual serial numbers of the components. Tag number indicates a unique position of process equipment to enable identification. Under one Tag number it is possible to replace different SCMs with different serial numbers in long operational period due to failures, renewals or preventive maintenance. An example of a subset of the repairable systems with two and more failures is shown in Figure 4.5. The numbers were changed for numerical values by taking into account commercial consideration.

There are two places of SCM installation as presented in section 4.1: subsea manifold and wellhead. They are highlighted and marked in red in figure 4.1. The records of the database have the identification of installation place. Totally, the database has 189 Tag numbers, 124 of them are installed in wellheads and 65 of them are installed in manifolds. The distribution of the number of failures per place of installation is given in Table 4.1. Considering the total number of data records and numbers of failures according to place of installation we can notice the company's maintenance strategy. The total number of records for subsea manifold SCM is 692, from this 31 records are failures and 661 records are right censored. Same for the wellhead

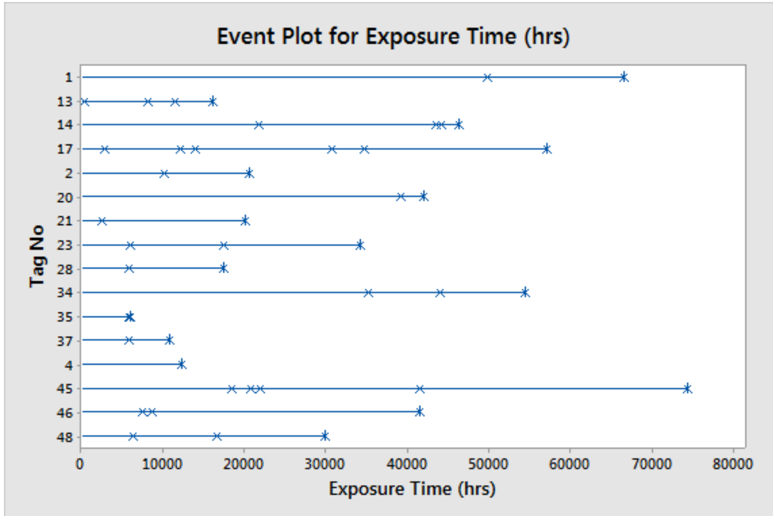


Figure 4.5: Example of the data from the repairable SCM

SCM, total number of records is 219, from this 50 records are failures and 169 records are right censored. Right censoring represents preventive maintenance. It can be concluded that 96% of all records for manifold SCM are preventive maintenance actions performed, while for wellhead SCM this number is only 77%.

The failure records contains identified failure modes. Seven possible failure modes of SCM were identified by the company's qualitative analysis, which are presented by

- Internal leakage - utility medium (ILU)
- External leakage - utility medium (ELU)
- Failure in electronics/coms (FIE)
- Loss of electric power supply (LEP)
- Loss of sensor/indicator reading (LSR)
- Failure to land/connect/lock/test (FTL)
- Other (OTH)

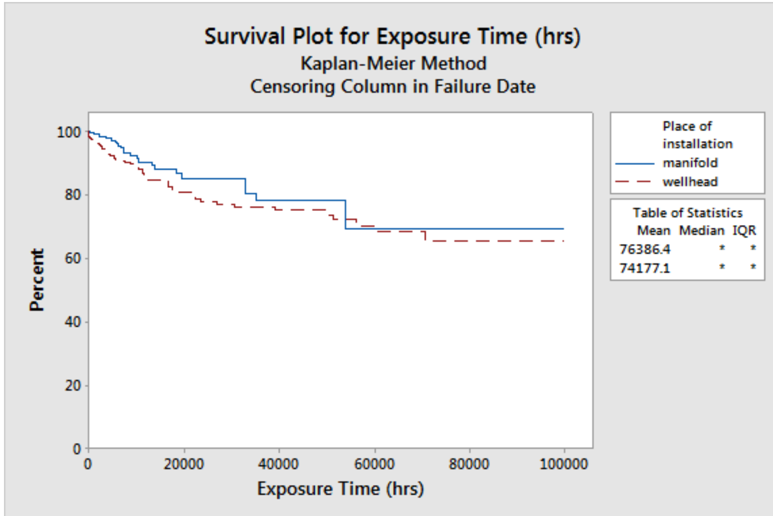


Figure 4.6: Reliability functions of the two groups. Kaplan-Meier method.

4.2.2 Comparison of Manifold SCM and Wellhead SCM

The first step is to validate the data for analysis. One of the main covariate in database is the place of SCM installation. These two types of SCMs can have different operational regimes, because they are installed in different equipment, while having same working principles. This subsection presents comparison analysis of these two groups of observations in order to validate the data as one merged data set for analysis.

We start the comparison with the non-parametric reliability analysis, since our observations consist mostly of right censored data. This allows to investigate if they are similar in order to combine them for analysis because a bigger number of observations reduce the variation in a statistical confidence interval. Non-parametric Kaplan-Meier(KM) estimators for the reliability (survivor) functions are obtained by equation 3.1. These functions are the step functions and are given in figure 4.6. The graph indicates the difference of the reliability of the two groups in first period from 0 to 40000 hours, after that, the survival curves have no big difference between the two groups. The results of the Kaplan-Meier(KM) estimators of the two groups are shown in Table 4.2 and are given by step in period of 10000 hours for better comparison. The difference in period from 0 to 40000 hours is up to 11 percents and it is reduced after that. This indicates the bad performance of "wellhead SCM" group in initial period of operation. The database does not have records regarding the operational regimes of this two groups, which can be a covariate

Table 4.2: The Kaplan-Meier(KM) estimator of the reliability function

	Manifold SCM		Wellhead SCM		Difference
Time	Reliability	Standard Error	Reliability	Standard Error	
10000	0.948276	0.0109913	0.887531	0.0220934	0,06
20000	0.875332	0.0303568	0.802735	0.0288593	0,07
30000	0.875332	0.0303568	0.767058	0.0316817	0,11
40000	0.803387	0.0485781	0.747389	0.0337842	0,06
50000	0.803387	0.0485781	0.734722	0.0355072	0,07
60000	0.718820	0.0910382	0.701701	0.0408739	0,02
70000	0.718820	0.0910382	0.678311	0.0457167	0,04
80000	0.718820	0.0910382	0.643525	0.0550373	0,08
90000	0.718820	0.0910382	0.643525	0.0550373	0,08
100000	0.718820	0.0910382	0.643525	0.0550373	0,08

for modeling the behaviour of the components.

For a formal check of a possible difference one can test the hypotheses $H_0 : R_1(t) = R_2(t)$ for all t versus $H_1 : R_1(t) \neq R_2(t)$ for at least one t. Log-Rank test statistics result obtained by Minitab for comparison of survival curves is presented in Table 4.3

Table 4.3: Test statistic of the groups.

Method	Chi-Square	DF	P-Value
Log-Rank	3.14313	1	0.076

$P(\chi_1^2 > 3.14313) = 0.076$ with significance level $\alpha \geq 0.05$.

So we do not reject the null hypothesis (H_0), that the difference between the survival curves is not statistically significant and we validate grouping the data for further analysis.

4.2.3 Model choice for failure data

In this subsection we determine which model is the appropriate, whether a homogeneous Poisson process or a non-homogeneous Poisson process. We use Minitab to calculate the tests for trend considering failures only and using the times between system renewals.

Trend test

There are 140 systems with no failures, 33 systems with one failure and hence 16 systems for which the **Laplace trend test statistic** U can be done to investigate a trend of failure occurrence

Table 4.4: Test statistic of the repairable systems.

	Trend Tests				Parameter	
	MIL-Hdbk-189		Laplace's		Estimates	
	Test Statistic	P-Value	Test Statistic	P-Value	Shape	Scale
Tag No 1	0.58	0.505	0.86	0.391	6.87156	60144.6
Tag No 13	9.76	0.270	-0.51	0.607	0.819623	2954.14
Tag No 14	1.74	0.116	1.72	0.086	4.60447	34277.8
Tag No 17	17.21	0.284	-1.60	0.109	0.813638	5223.23
Tag No 2	1.41	0.987	-0.02	0.982	2.83272	16141.2
Tag No 20	0.15	0.140	1.49	0.137	27.4757	41000.5
Tag No 21	4.11	0.256	-1.29	0.198	0.973424	9832.17
Tag No 23	4.82	0.613	-0.77	0.442	1.24508	14152.1
Tag No 28	2.22	0.660	-0.59	0.556	1.80452	11834.0
Tag No 34	1.30	0.277	1.11	0.265	4.61978	42892.9
Tag No 35	0.06	0.056	1.64	0.102	70.9953	5989.24
Tag No 37	1.20	0.904	0.17	0.868	3.32612	8709.92
Tag No 4	0.01	0.012	1.71	0.087	342.332	12335.0
Tag No 45	8.95	0.692	-1.08	0.282	1.11670	17599.7
Tag No 46	6.58	0.319	-1.50	0.133	0.911343	12451.5
Tag No 48	4.27	0.742	-0.56	0.573	1.40608	13657.0
TTT-based	188.76	0.119	-0.97	0.334		
Pooled	64.36	0.927	-0.79	0.432	0.892191	11978.0

(ref. Table4.1). The results of calculations of test statistic are shown in Table 4.4.

The pooled test statistic U is negative (-0.79) indicating that the systems are on average, deteriorating. The pooled test statistic is not significantly different from zero and we shall assume that there is no trend.

For a formal check of a possible trend one can test the hypotheses H_0 : No trend in data (homogeneous Poisson process) versus H_1: Trend in data (non-homogeneous Poisson process). Laplace pooled test statistic result obtained by Minitab is $P(\chi^2_{64}) = 0.432$ with significance level $\alpha \geq 0.05$.

So we do not reject the null hypothesis (H_0), and there is not enough evidence to reject the homogeneous Poisson process model. Although the power-law process may still be appropriate. Table 4.4 contains 4 trend tests: MIL-Hdbk-189 (The military handbook test)(pooled), MIL-Hdbk-189 (TTT-based), Laplace (pooled), Laplace (TTT-based). The pooled tests deal with different possible MTBF for each system to test the trend. While the TTT-based tests deal with the data from a homogeneous Poisson process (HPP) with the same MTBF for each system to check

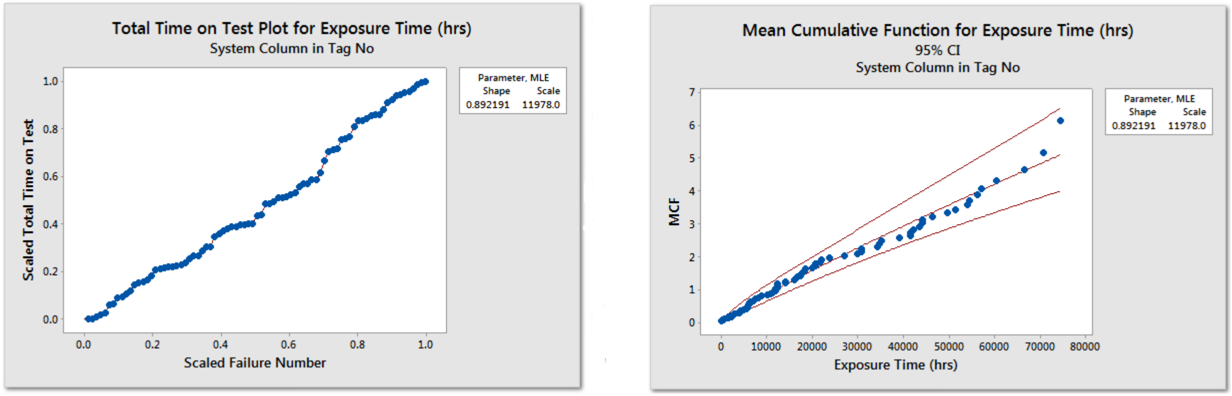


Figure 4.7: TTT and Nelson plots of the failure data

a trend in data or it can indicate that systems are heterogeneous. A relatively large difference in p-values between TTT-based tests and the pooled tests may indicate heterogeneity between systems (support.minitab). Thus we perform two types of tests to compare both P values and we observe big difference in MIL-Hdbk-189 tests only. Therefore we analyze the systems separately. Further we made separate test statistic for each Tag number and we see from Table 4.4 no Laplace's P value is lower than significance level $\alpha = 0.05$. and mean of the Us is positive (0.0506) and very close to 0 and same with MIL-Hdbk-189, except Tag number 4. The data for Tag number 4 are too sparse with only two failures which is insufficient for accurate results.

Total time on test (TTT) plot of the systems failure data is obtained and shown on the left side of the Figure 4.7. The plot indicates the constant failure rate and the curve is lying close to diagonal.

On the right side of the Figure 4.7 is shown **the mean cumulative rate of occurrence of failures (CROCOF)** function. The points on the plot are Nelson-Aalen estimators, which are obtained by equation 3.3. This plot also indicates the constant failure rate and the curve with 95% of confidence interval is lying close to the diagonal. The system is steady if the Nelson-Aalen plot is approximately linear (Rausand and Høyland, 2004).

Parametric model

Further, we fit parametric model for reliability analysis of SCM, considering previously performed trend test, which showed no dependency in failure occurrence. Firstly, we need to define the best fitted distribution. Figure 4.8 is the minitab result of testing the data samples to fit to the

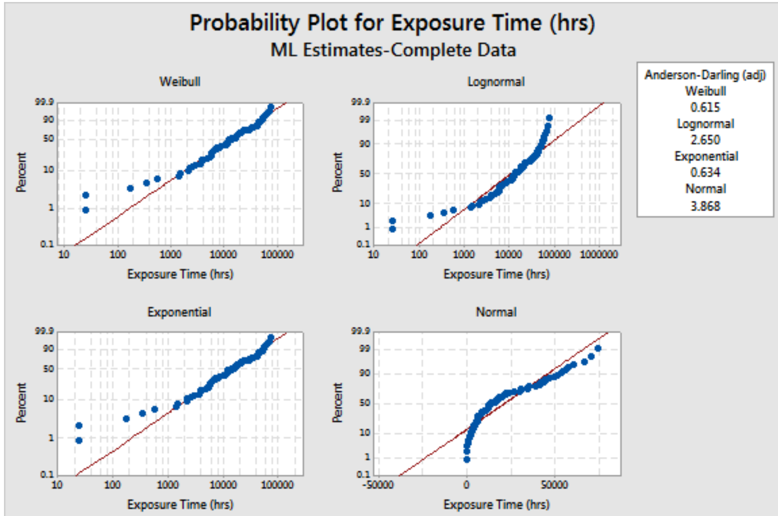


Figure 4.8: Probability plots of distributions for the failure times of SCM

population of the specific distributions. Graph shows the Weibull and Exponential distributions which are the best fitted in compare with Normal and Lognormal distributions. In addition to the graphical method, the Anderson-Darling goodness-of-fit tests shows same formal results. The Anderson-Darling statistic evaluates how well the data follow a particular distribution. The smaller statistic points the better “goodness-of-fit” of a sample data for a specified distribution. It is also possible to use the Anderson-Darling statistic in t-statistic to test if the data come from the chosen distribution, using the corresponding p-value.(Anderson, 2011; support.minitab).

The Weibull distribution is a common choice for reliability modeling. Maximum Likelihood Estimation (MLE) method is used in our calculations and allows to estimate values of parameters of the Weibull distribution. Maximum likelihood estimations for the Weibull distribution of the SCM failure function are presented in Table 4.5.

Table 4.5: MLEs of the parameters of the Weibull distribution for the failure times of the SCM

Component	Shape	Standard error	Scale	Mean(MTTF)	Median
SCM	0.957579	0.0864255	20601.2	21003.8	14049.7

However, we performed trend test for occurrence of failures and parametric estimation but we have not taken into consideration any censored failure times. Cox and Lewis (1966) noticed: "To treat failure as a point event occurring at a well-defined instant of time is often a serious oversimplification. Whenever there is a steady degradation of performance and the criterion

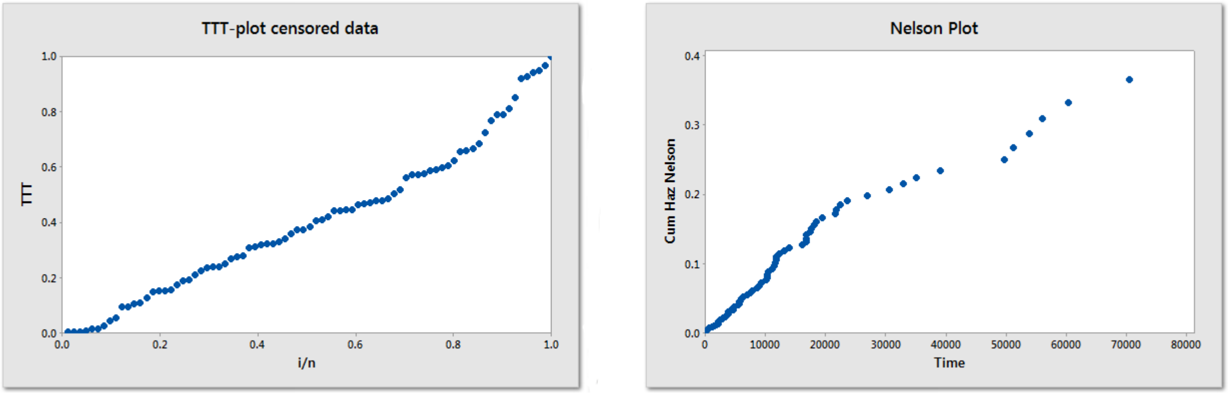


Figure 4.9: TTT and Nelson plots containing censored data

of failure is rather arbitrary, appreciable information may be lost by studying only the time to failure".

4.2.4 Fitting models to censored data

The SCM database contains 91% of right-censored failure times. Subsea equipment is considered as high reliability with robust design product. It will be a serious oversimplification to study only failure events of the systems. Trend test of failure occurrence in Section 3.2.3 showed that the systems are stationary. In this subsection we treat inter arrival times between the records as assumed to be independent of other inter-arrival times and identically distributed.

Trend test

Total time on test (TTT) and cumulative hazard function (Nelson) plots containing censored data are shown in Figure 4.9. We can notice the slight improvement at the end of the plots, though generally the functions are linear and lying close to diagonal. These plots indicate close to constant SCM failure rate.

Non-parametric model

Further we perform non-parametric reliability analysis of the SCM, since our observations consist mostly from right censored data. Non-parametric Kaplan-Meier(KM) estimators for the reliability (survivor) functions are obtained by equation 3.1 and variance by equation 3.2. These

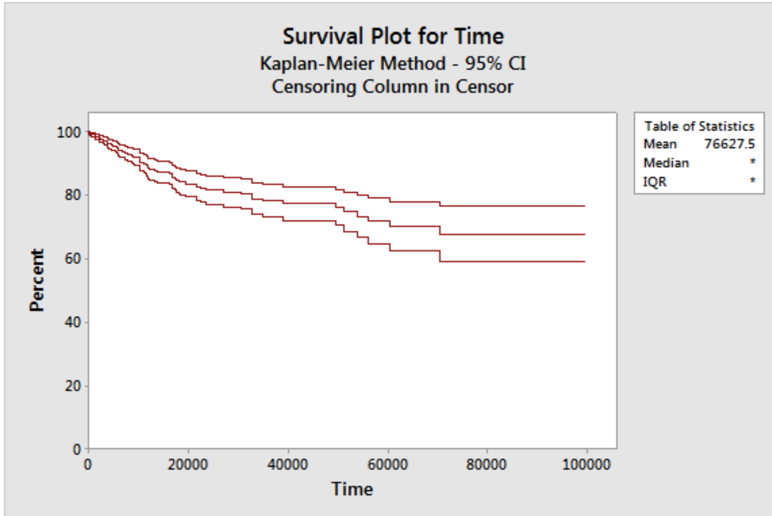


Figure 4.10: Reliability function of the SCM with 95% CI. Kaplan-Meier method.

functions are the step functions with 95% confidence interval and given in figure 4.10.

Parametric model

As alternative we fit parametric model for reliability analysis of SCM. Firstly, we need to define the best fitted distribution. Figure 4.11 is the minitab result of testing the data samples to fit to the population of the specific distributions. In this case of considering censored data, graphs show the Weibull and Lognormal distributions which are the best fit in comparison with Exponential and Normal distributions. Also smaller statistic of Anderson-Darling goodness-of-fit test indicates the Weibull and Lognormal distributions as the better fitted.

Weibull distribution is the only distribution represented in two cases as the best fitted for the data. We estimate parameters for the Weibull distribution that we can compare the cases further. Maximum likelihood estimations for the Weibull distribution for the SCM are presented in Table 4.6.

Table 4.6: MLEs of the parameters of the Weibull distribution for the failure times of the SCM considering the censored times.

Component	Shape	Standard error	Scale	Mean(MTTF)	Median
SCM	0.770006	0.0628633	246075	286873	152879

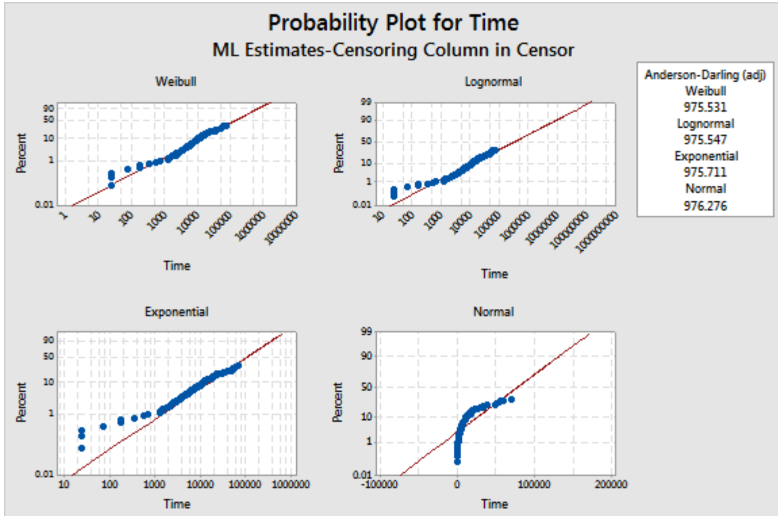


Figure 4.11: Probability plots of distributions for the failure and censored times of SCM.

Survival regression

The previous subsections consider only lifetime data analysis. This subsection analyzes additional information that is available from the database. Typically a database can consist from lifetime data and information regarding component's properties or its environment, known as covariates as discussed in Section 2.7.1. The term covariates is also used to cover factors, which are qualitative information. Survival regression analysis allows to find significant covariates which explain the reliability of an item, thereby obtaining new knowledge about failure mechanisms. In our study we use the Weibull regression model. The result is shown in Figure 4.12. The four factors are analyzed: operator, manufacturer, place of installation and Tag number. These four factors are common for the two places of installation, other variables presented in the database are specific for each of these two places. The variable "operator" describes the geographical place (field), i.e. one out of the five places in Atlantic Ocean. The variable "manufacturer" describes a manufacturer of SCM, which is one out of five operated brands. The variable "Wellhead/Manifold" indicates one out of two possible place of SCM installation. The variable "Tag No" indicates a unique position of process equipment to enable quantification and a hierarchical classification. These variables are factors with 5, 5, 2 and 189 levels respectively, which we used in analysis as dummy variables (coded for confidentiality). The only highlighted factor "manufacturer" in Figure 4.12 is only statistically significant at $p < 0.05$. The available database

Regression with Life Data: Exposure Tim versus Operator, Manufacturer, ...

```
Response Variable: Exposure Time (hrs)

Censoring Information  Count
Uncensored value          81
Right censored value     830

Censoring value: Failure Date = 0

Estimation Method: Maximum Likelihood

Distribution:   Weibull


Regression Table
```

		Standard			95.0% Normal CI	
Predictor	Coef	Error	Z	P	Lower	Upper
Intercept	10.5567	0.946354	11.16	0.000	8.70187	12.4115
Operator	-0.0743525	0.187460	-0.40	0.692	-0.441768	0.293062
Manufacturer	0.705696	0.203928	3.46	0.001	0.306005	1.10539
Wellhead/Manifold	0.109956	0.423184	0.26	0.795	-0.719469	0.939381
Tag No	-0.0069282	0.0077213	-0.90	0.370	-0.0220618	0.0082053
Shape	0.809574	0.0722911			0.679592	0.964417

```
Log-Likelihood = -1017.668
```

Figure 4.12: Estimates of Weibull regression model with covariates

with lifetime records is not sensitive to distinguish the geographical location of the oilfields and possible place of installation, hence the non-significance of the operator and place of installation covariates. The statistical regression analysis shows that the brand of SCM is significant factor affecting the reliability of SCM.

As the next step of regression analysis, we can divide sample data for two groups. The division is based on the places of SCM installation to investigate other significant covariates and to analyze more the "manufacturer" variable. The first group for analysis is SCMs installed in subsea manifolds. The results of the Weibull regression model is shown in Figure 4.13. As we can see from the result, no significant covarietes presented influences the lifetime of the component. The shape parameter of the Weibull distribution (0.99) is very close to 1 and indicates the constant failure rate in this group of components. The variable "manufacturer", that was mentioned earlier, is not statistically significant in this model. The second group for analysis is SCMs installed in subsea wellheads. The results of the Weibull regression model is shown in Figure 4.14. As we can see from the result, the covariate "manufacturer" is only statistically significant at $p < 0.05$. The other covariates do not influence the reliability of the component. The variable "RKB" indicates the depths of the installation from rotary Kelly bushing (RKB). This

Regression with Life Data: Exposure Tim versus Operator, Manifold, ...

Response Variable: Exposure Time (hrs)

Censoring Information	Count
Uncensored value	31
Right censored value	661

Censoring value: Failure Date = 0

Estimation Method: Maximum Likelihood

Distribution: Weibull

Regression Table

Predictor	Coef	Standard Error	Z	P	95.0% Normal CI Lower	95.0% Normal CI Upper
Intercept	11.7340	1.65731	7.08	0.000	8.48568	14.9822
Operator	-0.259069	0.285142	-0.91	0.364	-0.817937	0.299799
Manifold	0.0451682	0.0709474	0.64	0.524	-0.0938861	0.184222
Version	0.0211039	0.0200304	1.05	0.292	-0.0181550	0.0603628
Model	-0.0073273	0.143321	-0.05	0.959	-0.288232	0.273577
Manufacturer	0.151830	0.303400	0.50	0.617	-0.442823	0.746483
Shape	0.991720	0.126129			0.772915	1.27247

Log-Likelihood = -400.236

Figure 4.13: Estimates of Weibull regression model with covariates for manifold SCM group

Regression with Life Data: Exposure Tim versus Manufacturer, Operator, ...

* NOTE * 201 cases were used
* NOTE * 18 cases contained missing values

Response Variable: Exposure Time (hrs)

Censoring Information	Count
Uncensored value	47
Right censored value	154

Censoring value: Failure Date = 0

Estimation Method: Maximum Likelihood

Distribution: Weibull

Regression Table

Predictor	Coef	Standard Error	Z	P	95.0% Normal CI Lower	95.0% Normal CI Upper
Intercept	8.52486	2.43742	3.50	0.000	3.74760	13.3021
Manufacturer	1.22796	0.507261	2.42	0.015	0.233743	2.22217
Operator	0.366396	0.481575	0.76	0.447	-0.577472	1.31027
Field	-0.138706	0.219821	-0.63	0.528	-0.569547	0.292134
RKB - Tubing Hgr. (m)	0.0015987	0.0011356	1.41	0.159	-0.0006271	0.0038245
Shape	0.679626	0.0883715			0.526731	0.876903

Log-Likelihood = -574.541

Figure 4.14: Estimates of Weibull regression model with covariates for wellhead SCM group

variable is not recorded in 18 cases and extracted from analysis, as we can see from note in Figure 4.14. The shape parameter of the Weibull distribution is 0.68 and less than 1, and it indicates high initial hazard rate in this group of components.

In addition, the two separate groups of SCM maximum likelihood estimations for the Weibull distribution without covariates are presented in Table 4.7

Table 4.7: MLEs of the parameters of the Weibull distribution for the failure times of the SCM groups.

Installation	Shape parameter	Standard error	Scale parameter	Mean(MTTF)	Median
Manifold	0.962592	0.112725	172721	175667	118028
Wellhead	0.578513	0.0738139	339770	537019	180319

4.2.5 Manufacturer effect on SCM reliability

This subsection analyzes further the statistical significant factor "manufacturer". This factor is five levels of possible manufacturers. Brands are enumerated from 1 to 5, from less reliable to most reliable. It is coded for confidentiality.

Non-parametric model

Non-parametric Kaplan-Meier(KM) estimators allows graphical method of reliability comparison of different SCM brands. The graph is given in Figure 4.15. In period from 0 to 20000 hours the graph shows steep decline in reliability of brands number 1, 2 and 3. After that the reliability of brand 3 remains stable, that can be explained by an infant mortality period in operation with a decreasing failure rate. In contrast, the curves of brands 1 and 2 continue to decline up to the total failure of their sets. The reliability of the brands 4 and 5 look similar and have uniform reliability reduction from 100% up to 80% in period from 0 to 100000 hours.

Parametric model

The results of parametric model analysis are shown in Table 4.8. This presents the number of failures, censored data per manufacturer and the maximum likelihood estimations of the shape and scale parameters of the fitted Weibull distribution.

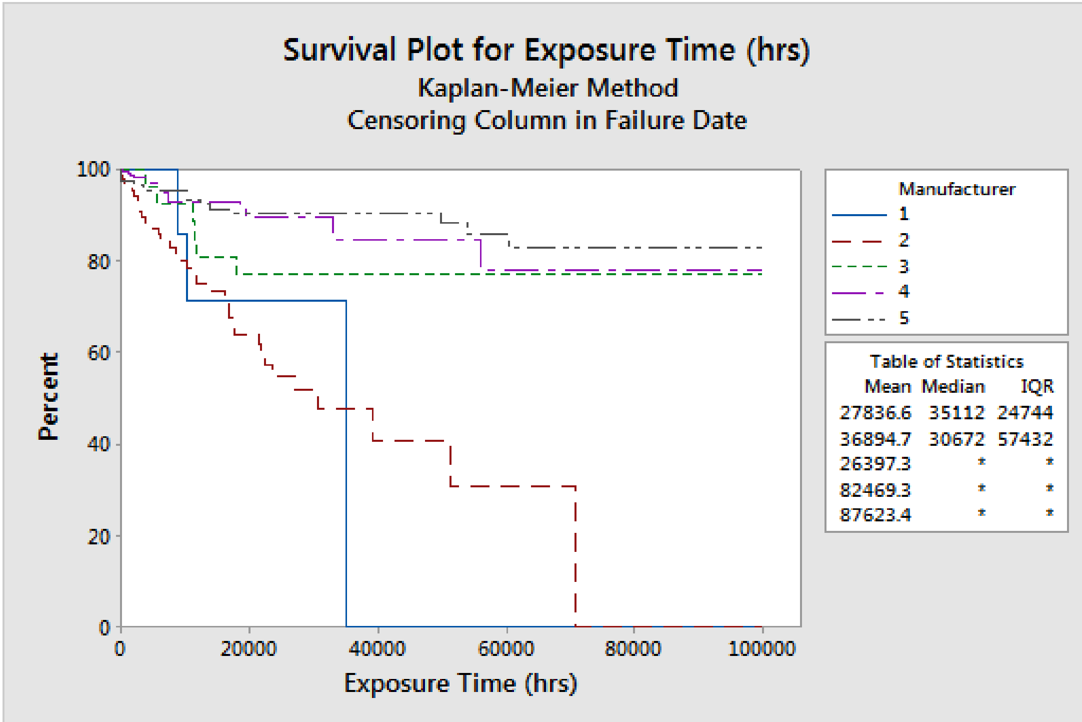


Figure 4.15: Reliability functions of the different brands of SCM. Kaplan-Meier method.

This analysis has identified the most contributed brands for failures. The brand 1 has only 3 failures. With such sparse data the standard error is high and result is not precise. The shape parameter shows considerable deterioration and median is under 27000 hours. The two brands 2 and 3 have failure times which can be fitted with shape parameter 1 with constant failure rate. The medians of 2 and 3 are contained in the interval 30000-53000 hours. The brands 4 and 5 are most reliable SCMs, which exhibit a high initial hazard rate and can be fitted by Weibull distributions with shape parameters of about 0.8 and 0.4 respectively and medians of about 20 and 237 years.

Survival regression

The result of the Weibull regression model is shown in Figure 4.16. We analyze only one factor and expand by all five brands to reveal the influence of each of them on the SCM reliability. We took brand number 1 as a basis for comparison. The coefficients show the difference in brands. Negative coefficient of the brand 2 indicates negative impact on the reliability of the total data set, while other three brands are improving reliability. The brands 4 and 5 are statistically signif-

Table 4.8: MLEs of the parameters of the Weibull distribution for the failure times of the SCM manufacturers.

Manufac-turer	No. of failures	No. of censored	Shape parameter	Standard error	Scale parameter	Mean (MTTF)	Median
1	3	10	2.0724	0.8500	31552	27948	26437
2	34	56	0.9019	0.1276	47506	49928	31642
3	6	21	1.1710	0.4511	72430	68580	52965
4	24	629	0.8524	0.1174	300534	326390	195507
5	14	114	0.4251	0.1067	5623724	15941748	2374436

Regression with Life Data: Exposure Time (hrs) versus Manufacturer

```
Response Variable: Exposure Time (hrs)

Censoring Information  Count
Uncensored value          81
Right censored value     830

Censoring value: Failure Date = 0

Estimation Method: Maximum Likelihood

Distribution:   Weibull


Regression Table

                          Standard                      95.0% Normal CI
Predictor         Coef       Error      Z      P       Lower      Upper
Intercept      11.1284    0.740588  15.03  0.000     9.67683    12.5799
Manufacturer
 2           -0.253705    0.761427  -0.33  0.739    -1.74607    1.23866
 3            0.645619    0.892108   0.72  0.469    -1.10288    2.39412
 4             1.72542    0.792241   2.18  0.029    0.172655    3.27818
 5             2.14977    0.807201   2.66  0.008    0.567685    3.73185
Shape         0.793009   0.0708628                  0.665603   0.944803

Log-Likelihood = -1012.492
```

Figure 4.16: Estimates of Weibull regression model with one factor

icant and have great positive influence on the whole SCM population.

The estimated model of the lifetime T can be written mathematically by,

$LnT = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \beta_3 * x_3 + \beta_4 * x_4 + \frac{1}{\alpha} W$, where W is Gumbel (0,1),

$LnT = 11.1284 - 0.2537 * x_1 + 0.6456 * x_2 + 1.7254 * x_3 + 2.1498 * x_4 + \frac{1}{0.793} W$

We introduce the null hypotheses for formal check and to obtain comparison of full Weibull regression model in Figure 4.16 and reduced Weibul regression model in Figure 4.12. We use significance level 5% for test.

Thus we got Log-likelihood values for considered models:

The log-likelihood for full Weibul regression model -1017,668

The log-likelihood for reduced Weibul regression model -1012,492

Null hypothesis: reduced Weibull regression model is sufficient. Log-likelihood statistic: $2*(-1012,492+1017,668) = 5,18 < 7.815 = \chi^2_{3,0.05}$. So we cannot reject null hypothesis that the reduced Weibull regression model is sufficient.

4.2.6 Failure rates

In previous subsections we started from trend investigation of the failure occurrences. It was done by establishing a Nelson-Aalen plot and Laplace trend test statistic. We conclude that the ROCOF is close to constant and as the result, the intervals between failures are identically distributed. After that we assume that records of SCM database are independent. Based on it, we fitted data to the Weibull distribution and found the MLE of the scale and shape parameters from the data set. The goodness of fit is considered to be adequate and we can use this model for further analysis.

The failure rate function tells us how likely it is that an item that has survived up to time t, will fail during the next unit of time. The survivor function for the Weibull distribution is $R(t) = Pr(T > 0) = e^{-(\lambda t)^\alpha}$ for $t > 0$, where λ is a scale parameter and α is a shape parameter. By use of the relationship of functions shown in Table 4.2 the failure rate function is given by

$$z(t) = \frac{f(t)}{R(t)} = \alpha\lambda^\alpha t^{\alpha-1}$$

The results of failure rates calculations are shown in Tables 4.9, 4.10 for the eight possible cases. The first three cases are represented in the Table 4.9 and the first case takes into account the censored data. The second and third cases show the failure rates for the two groups of SCMs installed in different equipment. The rest cases (4 to 8) shown in table 4.10 represent the failure rates for the different manufacturers and the results significantly differs. The graphs in Figures 4.17 and 4.18 show visually the difference in cases and manufacturers. The majority of the cases are with decreasing failure rate. The failure rate for the manufacturer number 1 is not shown in the graph, because the values are too far from other cases.

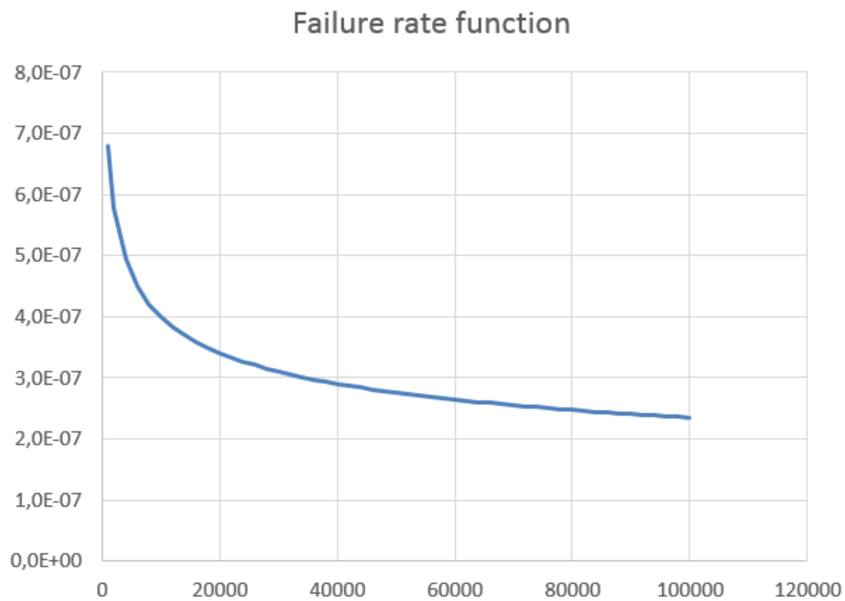


Figure 4.17: Failure rate function for SCM

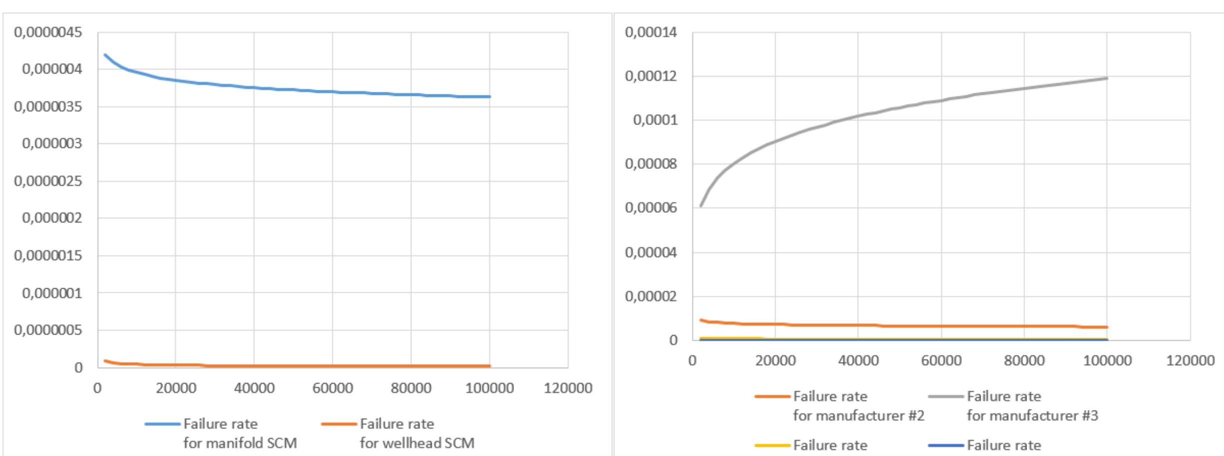


Figure 4.18: Failure rate function by groups for SCM

Table 4.9: Failure rates per hour by groups for SCM

$\alpha = shape$	0,770006	0,962592	0,578513
$\lambda = \frac{1}{scale}$	4,0638E-06	5,78968E-06	2,94317E-06
Time [hours]	Total	manifold SCM	wellhead SCM
1000	6,79E-07	4,31E-06	1,17E-07
10000	3,99E-07	3,95E-06	4,42E-08
20000	3,40E-07	3,85E-06	3,30E-08
30000	3,10E-07	3,80E-06	2,78E-08
40000	2,90E-07	3,76E-06	2,46E-08
50000	2,76E-07	3,72E-06	2,24E-08
60000	2,65E-07	3,70E-06	2,08E-08
70000	2,55E-07	3,68E-06	1,95E-08
80000	2,48E-07	3,66E-06	1,84E-08
90000	2,41E-07	3,64E-06	1,75E-08
100000	2,35E-07	3,63E-06	1,67E-08

Table 4.10: Failure rates per hour by SCM manufacturers

$\alpha = shape$	2,0724	0,9019	1,171	0,8524	0,4251
$\lambda = \frac{1}{scale}$	3,16937E-05	2,105E-05	1,38064E-05	3,32741E-06	6,27284E-08
Time [hours]	manufacturer 1	manufacturer 2	manufacturer 3	manufacturer 4	manufacturer 5
1000	0,24	9,74E-06	5,41E-05	1,05E-06	8,22E-10
10000	2,80	7,77E-06	8,02E-05	7,46E-07	2,19E-10
20000	5,88	7,26E-06	9,03E-05	6,73E-07	1,47E-10
30000	9,08	6,98E-06	9,68E-05	6,34E-07	1,16E-10
40000	12,36	6,78E-06	1,01E-04	6,08E-07	9,86E-11
50000	15,70	6,63E-06	1,06E-04	5,88E-07	8,67E-11
60000	19,10	6,52E-06	1,09E-04	5,72E-07	7,81E-11
70000	22,53	6,42E-06	1,12E-04	5,60E-07	7,15E-11
80000	25,99	6,34E-06	1,14E-04	5,49E-07	6,62E-11
90000	29,50	6,26E-06	1,17E-04	5,39E-07	6,19E-11
100000	33,02	6,20E-06	1,19E-04	5,31E-07	5,82E-11

4.2.7 Failure modes

The failure records of the database contains identified failure modes. Seven possible failure modes of SCM were identified by the company's qualitative analysis. They are listed in Section 4.2.1. One can use this information for the possible improvement of the SCM reliability and scheduling required preventive maintenance as part of the scope of reliability centered maintenance (RCM). The analysis performed in this subsection covers the case with merged data set of all SCM available in the database. The principle of analysis for the different cases, for example for one defined manufacturer holds same procedures as presented further.

The Kaplan-Meier estimators of the reliability function for the different failure modes of SCM are presented in Table 4.11. The analysis shows the contribution of each failure mode to the SCM reliability. The survival estimators are derived for each failure mode considering only related failure records and counting all other failure modes as censored data.

Table 4.11: The Kaplan-Meier(KM) estimators of the reliability function for the SCM failure modes.

Failure Mode	No. of failures	$R(10000)$	$R(30000)$	$R(50000)$	$R(70000)$	$R(90000)$
Failure in electronics/coms (FIE)	27	0.973	0.941	0.925	0.907	0.871
Internal leakage - utility medium (ILU)	27	0.970	0.934	0.926	0.926	0.926
External leakage - utility medium (ELU)	19	0.990	0.945	0.937	0.877	0.877
Loss of electric power supply (LEP)	3	0.998	0.994	0.982	0.982	0.982
Loss of sensor/indicator reading (LSR)	1	1	1	0.991	0.991	0.991
Other (OTH)	4	0.995	0.990	0.990	0.990	0.990
Failure to land/connect/lock/test (FTL)	0	1	1	1	1	1
Total	81	0.928	0.818	0.773	0.710	0.682

To achieve a target of system reliability, one can use this analysis to define which components require reliability improvement. For example in our case, the target can be set to 0.95 reliability at 30000 hours of SCM operation. As we can see from Table 4.11 the overall SCM reliability is 0.818 and we are 95% confident that the true reliability is between 0.774 and 0.862. It indicates that the actual reliability is worse than our target. From the analysis we can determine that the three failure modes FIE, ILU, ELU are the most contributors to reliability reduction. Improvement is required for components responsible for these failure modes. Reliability allocation technique can be used to determine required improvement to meet the overall SCM reliability target. This technique is not discussed in our report.

4.2.8 Comparison with OREDA

OREDA handbook presents average failure rates for different types of process equipment of the OREDA project participants (Veritas, 2009). SCM is considered as a unit of the control system. OREDA project have their own defined failure modes which is not corresponding with our database. Therefore comparison is done in level of equipment unit (i.e. SCM) and not in component level. OREDA failure rates for the control system are presented as a general group which comprises of six subgroups represented by place of installation. For the comparison with our database only two subgroups are applicable. The two subgroups of OREDA failure rates are shown in Table 4.12. All the failure rates presented by OREDA are assumed to be exponentially distributed with parameter λ. This mean that the failure rate function is constant and independent of time which is presented by $z(t) = \lambda$.

OREDA handbook consider two possible cases of estimation of failure rate λ:

For **homogeneous sample**, when failure data from identical items that have been operating under the same operational and environmental condition. For this case λ is given by:

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

Multi-sample it is when the aggregated data for an item may come from different installations with different operational and environmental conditions. The merge of these "more or less" homogeneous samples which have different failure rates and confidence intervals can cause a problem in estimation of the "average". The method for treating this case with different failure rates of samples is called OREDA estimation method. This method does not explicitly assume any parametric family for prior failure rate distribution. OREDA estimator is superior to other methods for this case because it considers a number of conditions as presented in

Spjøtvoll (1985).

The procedure for failure rate calculation of the multi-sample OREDA-estimator according to Veritas (2009) is:

Average failure rate by pooling the data

$$\hat{\theta}_1 = \frac{Total\ no.\ of\ failures}{Total\ time\ in\ service} = \frac{\sum_{i=1}^{k} n_i}{\sum_{i=1}^{k} \tau_i}$$

Next is

$$S_1 = \sum_{i=1}^{k} \tau_i$$

$$S_2 = \sum_{i=1}^{k} \tau_i^2$$

$$V = \sum_{i=1}^{k} \frac{(n_i - \hat{\theta}_1 \tau_i)^2}{\tau_i} = \sum_{i=1}^{k} \frac{n_i^2}{\tau_i} - \hat{\theta}_1^2 S_1$$

$$\hat{\sigma}^2 = \frac{V - (k-1)\hat{\theta}_1}{S_1^2 - S_2} S_1$$

Calculate the final estimate θ^* of the mean failure rate by:

$$\theta^* = \frac{1}{\sum_{i=1}^{k} \frac{1}{\frac{\hat{\theta}_1}{\tau_i} + \hat{\sigma^2}}} * \sum_{i=1}^{k} \left(\frac{1}{\frac{\hat{\theta}_1}{\tau_i} + \hat{\sigma^2}} * \frac{n_i}{\tau_i} \right)$$

Standard deviation for the mean of the failure rate:

$$SD = \hat{\sigma}$$

The lower and upper limits of an approximate confidence interval for the failure rate of a component from this item class under similar conditions, is given by(Lydersen et al., 1987):

$$\theta^* \pm u_{0.05} \sqrt{\hat{\sigma}_{\theta^*}^2 + \hat{\sigma}_{\lambda}^2}$$

The result of the failure rate estimations of our data set according to above procedure is shown in the second part of Table4.12.

Table 4.12: Failure rates of the SCM from two sources.

Source	Subsea control module	Failure rate per 10^6 hours Lower	Mean	Upper	SD	n/τ
OREDA (Veritas, 2009)	Manifold	3.57	13.07	33.79	7.55	13.07
	Wellhead	12.22	23.83	38.59	8.13	23.47
Database	Manifold	0	12.12	105.13	2.78	6.35
	Wellhead	0	91.57	335.23	10.23	7.33

As we can see from the comparison in Table 4.12, the manifold SCM groups have close mean values using the OREDA estimate method. However, the standard deviation in our case is much smaller due to large number of our data records. Similarly, failure rate $\lambda = n/\tau$ of fitted exponential distribution of our database is almost twice smaller than the OREDA data. Nevertheless the big range of OREDA estimator of our data case, from 0 up to 105.13, indicates big variance of failure rates in different data sets that are merged for analysis. This was shown and discussed in the example of Weibull fitted model presented in the previous subsections.

In contrast with the other group, Wellhead SCMs' estimators are totally different. The mean estimator of our data case is almost four times higher than OREDA's. Similar to previous group, the range of the estimator is significantly large. In general, the same distribution of failure rates between two groups shows that the wellhead group fails more often than the manifold's.

The large difference of our result in exponential failure rate n/τ and mean of OREDA estimation method indicates the problem of validation data records for our analysis. Thorough work should be done in the process of gathering, validating and grouping data for analysis. Due to commercial confidentiality and limitation in information access to the database, our comparison is done based on available access.

4.3 Conclusion

In this chapter we performed statistical analysis of SCM reliability. SCM is considered as the critical subsea equipment. The analysis shows good fit of the Weibull distribution for subsystem reliability and the calculated Weibull parameters using the maximum likelihood estimation (MLE) technique. The result of parametric analysis shows that all population of SCM, except one manufacturer tolerate infant mortality. Considering the significant subsea repair cost, this finding should prompt serious consideration to improve the reliability performance of SCM through system testing and burn-in procedures. Special attention should be given to the investigation of root causes of subsea electronics module (SEM) and directional control valves (DCV) failures. The implementation of improvement during the different stages of design, manufacturing, qualification testing, installation and operation will reduce the risks and increase production availability.

The analysis of covariates revealed the single factor influencing reliability. Before starting analysis, we expected to see the different reliability performance influenced by environmental impact, since the database presents a wide variety of geographical regions of operation. Consequently, we can conclude that subsea conditions are similar all over the World Ocean therefore, environmental condition impact was not detected by the analysis. The detected factor influencing the reliability is brand of manufacturer. Finally, we derived the failure rates for different groups of SCM using different methods.

Further analysis may investigate failure mechanisms by considering consequence of failures and a multi-state failure analysis with degraded states of system functionality. These objectives require thorough reliability data input discussed in chapter 2, which we do not have due to our limitations. Based on these facts, the recommendation to the company will be to adapt minimal requirements of data acquisition according to ISO-14224 (2006).

Chapter 5

Functional failure analysis (FFA)

Any technical system consists of number of components working together to perform a set of required functions. One of the responsibilities of reliability engineer is the prevention of system failures. It is necessary to identify all relevant functions and the performance criteria in order to reveal all potential failures.

5.1 Functional analysis

According to BS-4778 (1991), system failure is the termination of its ability to perform a required function. The Functional failure analysis (FFA) is more related to qualitative system analysis and has the following objectives:

1. Identification and description of the system's required functions.
2. Description of the input interfaces required for the system to operate.
3. Identification of system's functions.
4. Identification of the system failure modes.

To achieve this steps, FFA form is used and the form contains information necessary to perform this activity. Identified failure modes are ranked by criticality, which depends on both the frequency/probability of the occurrence of the system failure mode, and the severity of the failure.

A functional analysis is an important part of a technical system reliability analysis. Relevant functions of subsea control module is identified in order to reveal all potential failures.

The analysis shall to identify all functions and sub-functions related to an intended function of a system in a different operational situations. This helps to understand a system work and reveal all potential failures. Functions and sub-functions of a system are varying with their importance and relevance. Rausand and Høyland (2004) classify functions by their role and importance for analysis purposes by the following:

1. **Essential functions:** The functions required to fulfill the intended purpose of the functional block.

2. **Auxiliary functions:** The functions that are required to support the essential functions.

3. **Protective functions:** Functions that are intended to protect people, equipment and the environment from damage and injury.

4. **Information functions:** Functions that comprise condition monitoring, various gauges and alarms.

5. **Interface functions:** Functions that utilize interface between the functional blocks in the system and also with functional blocks outside the system.

Such thorough method of classification is practical for a complex system as an aid in identification of all relevant functions. SCM is a small system with a few system functions and a simple case for reliability analysis.

Functional block diagram

Structured analysis and design technique (SADT) is a common used approach for functional modeling. In a SADT diagram block element represents *function* and arrows represent *input, control, mechanism and output* required for supporting the function. Figure 5.1 shows established SADT diagram of the SCM. IEC-60812 (2006) recommends to begin the analysis from construction of functional block diagram for serving a basis for FMECA.

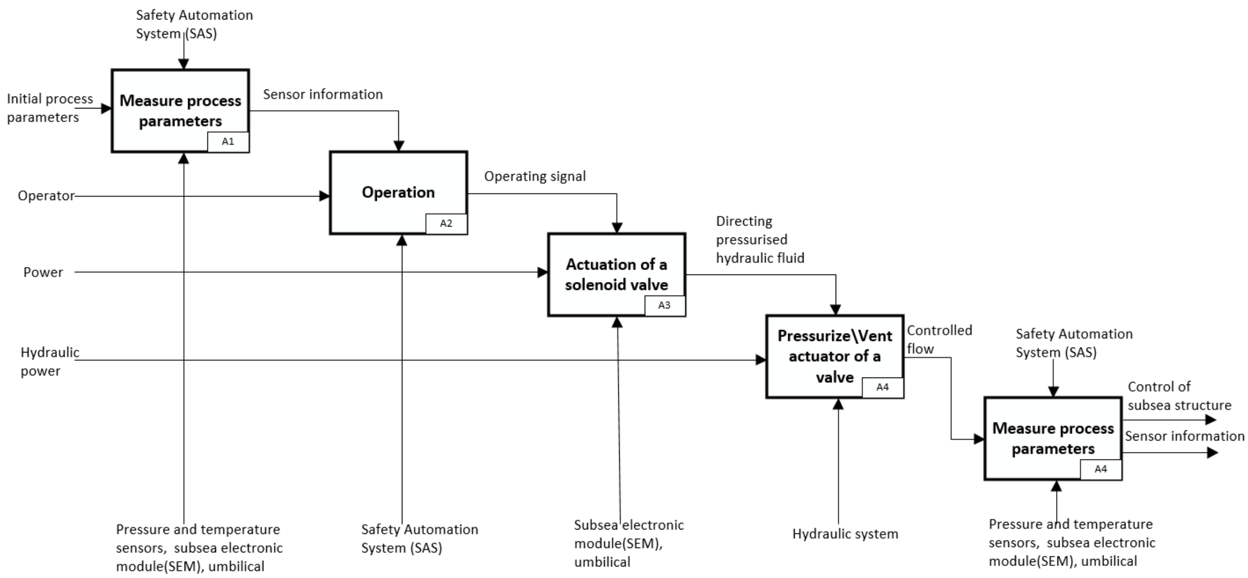


Figure 5.1: SADT diagram for Subsea Control Module.

SCM functions

SCM is part of the production control system and operated in continuous operational mode. Figure 5.2 shows schematics of SCM operation. Subsea Control Module is marked in red and consists of subsea electronics module, solenoid valves and hydraulic system. More detailed internal arrangement and operational principle are reviewed in Chapter 4.1. NORSOK U-CR-005 (1995) imposes minimal requirements for the SCM functions. The essential functions are divided and listed for two subsystems:

1. Functions of the communication and subsea electronic module:
   - Receive and execute commands from the Safety Automation System
   - Collect and transmit subsea sensor parameters to the Safety Automation System
2. Functions of the control module hydraulic system:
   - Direct pressurized hydraulic fluid to specific valve actuators through dedicated directional control valves, thus causing the valve to open.
   - Vent pressurized hydraulic fluid from specific valve actuators through dedicated directional control valves, thus causing the valves to close.

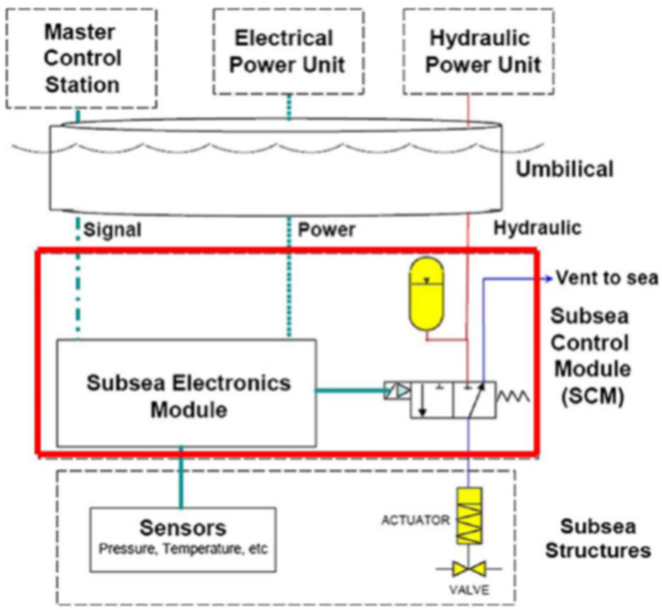


Figure 5.2: Schematics of Subsea Control Module operation.

Function tree

"A function tree is a hierarchical functional breakdown starting with a system function or a system mission and illustrates the corresponding necessary functions on lower levels" (Rausand and Høyland, 2004). Functional breakdown structure is usually used during the design phase of a product, while component top-down approach is more common for existing facilities. The objective of function tree construction is to visualize the sub-functions and required components to fulfill essential functions of the system. The function tree for the SCM is presented in Appendix B. The rectangles in diagram illustrate the function and sub-functions. Required components are identified and listed for essential SCM functions.

5.2 Failure analysis

Identification of all the failure modes is a big challenge in the analysis. Each function may have several failure modes and no formal procedure exists for identification and classification of the possible failure modes. (Rausand and Øien, 1996)

Understanding the scope of analysis and boundaries of system as well as the definitions of system's states or events are essential for engineers when identifying failure modes and causes.

Further we present key terms and definitions according to IEC50(191) (1990).

☞ **Failure**: The termination of an items ability to perform a required function.

☞ **Fault**: The state of an item characterized by its inability to perform a required function, excluding the inability during preventive maintenance or other planned actions, or due to lack of external resources.

A failure is the event according to definition, while fault is a state resulting from a failure. Now it is important to understand designation of **Failure mode**, which is a description of a fault. It indicates how we can observe the fault. According to IEC standard, "fault mode" is a more appropriate term but in practice "failure mode" is more used.

☞ **Error**: Discrepancy between a computed, observed or measured value or condition and the true, specified or theoretically correct value or condition.

An error is not a failure because function performance is in acceptable level. Though failure can be fallowed by error due to degradation process and if no preventive action is taken. Hence an error is often called *incipient failure*.

For technical system it is important to avoid failures or re-occurrence of failures and identification of the failure cause become a necessary step for this.

☞ **Failure cause**: The circumstances during design, manufacture or use that have led to a failure.

According to definition it has categorization by phases of system's life cycle: design, manufacturing and operation.

☞ **Failure mechanism**: The physical, chemical or other process, which has led to a failure.

This term can be understood as the initial failure cause on the lowest level of a system, component level. However, this level of identification is not sufficient to evaluate possible remedies. Remedial actions can be decided for underlying and fundamental causes, which are called the *root causes*.

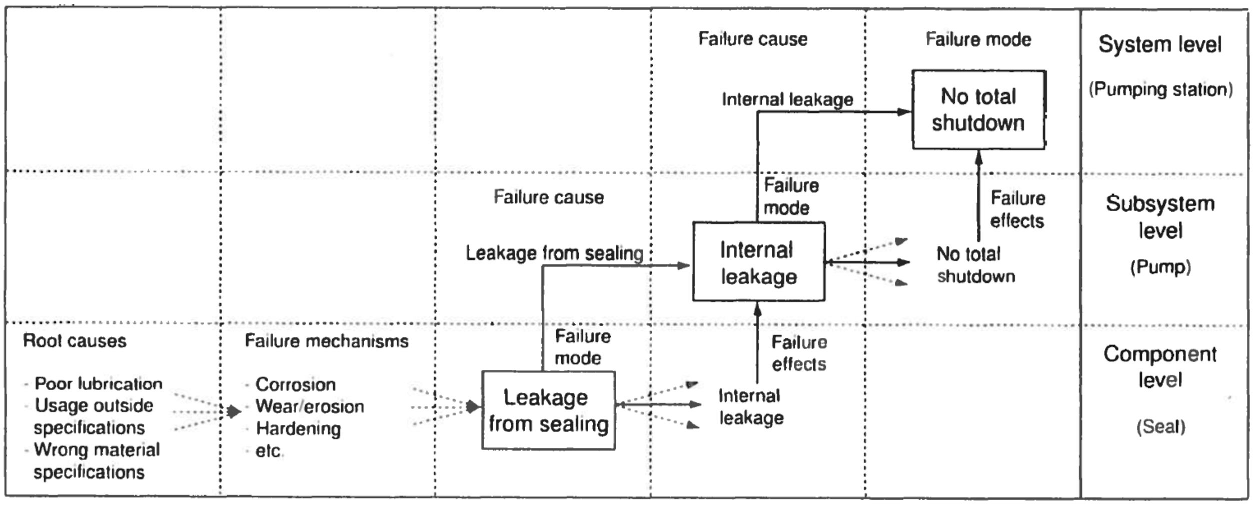


Figure 5.3: Relationship between failure cause, failure mode, and failure effect. (Rausand and Øien, 1996).

It is important to specify the level of a system structure being analyzed. Figure 5.3 shows relationship between terms for a pump hardware structure breakdown. Terminologies are dependent on a level of analysis, as for example the failure effect on the lowest level equals the failure mode on the next higher level.

Failure modes, effects and criticality analysis (FMECA)

FMECA is the methodology used to design and identify the potential failure modes for the system components. It assesses the risk associated with identified failure modes in order to rank the issues in terms of importance and consequently carry out corrective actions to address the most serious concerns. FMECA provides a knowledge base of failure mode and corrective action information that can be used as a resource to develop preventive maintenance. This tool was used to classify failures according to their influence on mission success and safety. In order to present a general definition of FMECA, there is need to identify some common features. Identification of all potential failure modes of the system is one of the features. It gives the description of what is wrong and what we need to prevent or fix (Smith and Mobley, 2011).

The ranking process of the FMECA can be accomplished by utilizing existing failure data or by a subjective ranking procedure conducted in this project with an understanding of the system using risk matrix shown in Figure 5.4. The FMECA worksheet for SCM is presented in

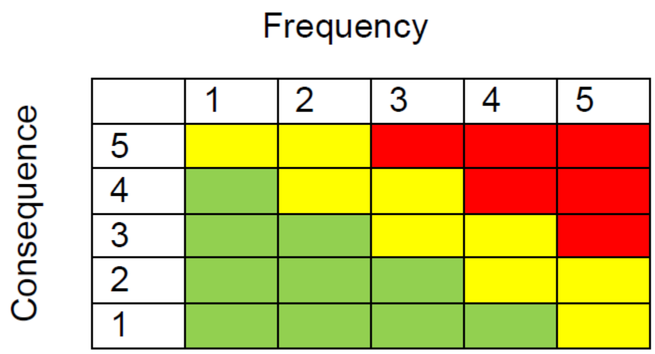


Figure 5.4: Risk matrix

Appendix C. Failure modes are identified by evaluating the output of functions, in addition SCM failure modes in OREDA Handbook(Veritas, 2009), and ISO-14224 (2006) are utilized. Based on the analysis, 11 out of the 26 failure modes require further risk reducing measures. According to the ALARP principle, if a measure can be beneficial for risk reduction, it should be implemented. Based on this statement, further analyses should be performed for the failure modes in the yellow zone.

Chapter 6

Quantitative reliability assessment of a system

Quantitative reliability assessment of a system can be performed by number of methods stated in IEC-62308 (2006). SCM is rather simple system consisting of a number of components working in series. Markov technique is presented in this chapter as a feasible approach for modeling the reliability and availability of a system. In addition, analytical method is discussed for the SCM as a part of safety instrumented system.

6.1 Markov method

This section is focused on continuous-time Markov chain. A continuous-time Markov chain is also called a *Markov process* and it is stochastic processes to model systems with several states and the transitions between the states. This method allows to model the reliability and availability of a system.

A system can be in several states, for example: operating (it can be defined capacity of production - 100%, 80%...), standby, failed. For some detailed analysis, the interest can be distinguishing the various failure modes of a system, and they can be presented as states. However, complexity of a system results in increasing number of states and hence increased computation time.

Markov process has property that the transition between states is independent of anything

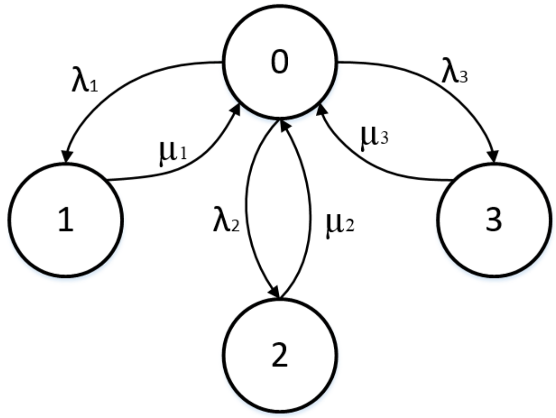


Figure 6.1: State transition diagram of the SCM.

that has happened in the past. It corresponds to exponential distribution for the transition probabilities. A practical consequence of this, is that we can not model long-term trends or seasonal variations. We assume that all operational conditions are relatively stable.

Case study

Figure 6.1 introduces Markov chain state transition diagram of stochastic process $\{X(t), t \geq 0\}$. $X(t)$ denotes the state $\{0, 1, 2, 3\}$ of the process at time t. Our case study is SCM which has three types of failures according to OREDA Handbook (Veritas, 2009): critical $\{$X(t)=1$\}$, degraded $\{$X(t)=2$\}$, and incipient $\{$X(t)=3$\}$. We are interested in the long-run (steady-state) probabilities that are the values of $P_X(t)$ when $t \to \infty$. These asymptotic probabilities are often called the *steady-state probabilities* for the Markov process (Rausand and Høyland, 2004).

We assume that SCM is operated on a continuous basis. The failure rates are $\lambda_1, \lambda_2, \lambda_3$ respectively to type of failure. When SCM fails, a repair action is started to bring the SCM back into operation after any failure. The repair rates are μ_1, μ_1, μ_1 respectively to type of failure. The rates are taken from OREDA Handbook (Veritas, 2009).

The corresponding transition matrix is

$$\mathbb{A} = \left\{ \begin{array}{cccc} -(\lambda_1+\lambda_2+\lambda_3) & \lambda_1 & \lambda_2 & \lambda_3 \\ \mu_1 & -\mu_1 & 0 & 0 \\ \mu_2 & 0 & -\mu_2 & 0 \\ \mu_3 & 0 & 0 & -\mu_3 \end{array} \right\}$$

Kolmogorov forward equations is presented in matrix terms as

$$\dot{\mathbb{P}}(t) = \mathbb{P}(t) * \mathbb{A}$$

Thus the steady-state probabilities **P**$= [P_0, P_1, P_2, P_3]$ are satisfy the equation,which is called the *state equation* for the Markov process:

$$[P_0, P_1, P_2, P_3] * \left\{ \begin{array}{cccc} -(\lambda_1+\lambda_2+\lambda_3) & \lambda_1 & \lambda_2 & \lambda_3 \\ \mu_1 & -\mu_1 & 0 & 0 \\ \mu_2 & 0 & -\mu_2 & 0 \\ \mu_3 & 0 & 0 & -\mu_3 \end{array} \right\} = [0,0,0,0]$$

From above we obtain the following system of equations:

$$-(\lambda_1+\lambda_2+\lambda_3)P_0 + \mu_1 P_1 + \mu_2 P_2 + \mu_3 P_3 = 0$$

$$\lambda_1 P_0 - \mu_1 P_1 = 0$$

$$\lambda_2 P_0 - \mu_2 P_2 = 0$$

$$\lambda_3 P_0 - \mu_3 P_3 = 0$$

$$P_0 + P_1 + P_2 + P_3 = 1$$

Using the fact that sum of all probabilities equals to 1, the solution is

$$P_0 = \frac{\mu_1\mu_2\mu_3}{\mu_1\mu_2\mu_3 + \lambda_1\mu_2\mu_3 + \lambda_2\mu_1\mu_3 + \lambda_3\mu_1\mu_2}$$
$$P_1 = \frac{\lambda_1\mu_2\mu_3}{\mu_1\mu_2\mu_3 + \lambda_1\mu_2\mu_3 + \lambda_2\mu_1\mu_3 + \lambda_3\mu_1\mu_2}$$
$$P_2 = \frac{\lambda_2\mu_1\mu_3}{\mu_1\mu_2\mu_3 + \lambda_1\mu_2\mu_3 + \lambda_2\mu_1\mu_3 + \lambda_3\mu_1\mu_2}$$
$$P_3 = \frac{\lambda_3\mu_1\mu_2}{\mu_1\mu_2\mu_3 + \lambda_1\mu_2\mu_3 + \lambda_2\mu_1\mu_3 + \lambda_3\mu_1\mu_2}$$

Table 6.1: Obtained results

System State	State description	Failure rate $\lambda_i[hours^{-1}]$	Repair rate $\mu_i[hours^{-1}]$	Steady-State Probability	Average Hours in State per Year
0	Operating	-	-	0.9997	8757
1	Critical failure	5.3E-6	3.9E-2	1.281E-4	1,123
2	Degraded failure	11.26E-6	6.9E-2	1.594E-4	1,396
3	Incipient failure	3.87E-6	35.7E-2	8.401E-6	0,074

Table 6.1 shows obtained results of probabilities solution by inserting OREDA failure rates and active repair time. One of the meaning of the steady-state probabilities is the mean proportion of time the system stays in the state concerned.

"The average, or long-term **availability** of the system is the mean proportion of time when the system is functioning" (Rausand and Høyland, 2004). In our case, it is state 0 and the system availability is equal to 0.9997, which means that the system will function approximately 8757 hours per year.

"**Frequency of system failures** ω_F is the steady-state frequency of transitions from a functioning state to a failed state"(Rausand and Høyland, 2004). It can be written for our model as

$$\omega_F = P_0 * \lambda_1 + P_0 * \lambda_2 + P_0 * \lambda_3 = 20.424E-6\ hours^{-1}$$

Some other parameters could be derived from Markov process such as visit frequency, mean duration of a visit, mean duration of a system failure, mean time between system failures, mean functioning time until system failure.

6.2 Analytical method

6.2.1 Reliability performance measures

"A safety-instrumented function (SIF) is a function that has been intentionally designed to protect the equipment under control (EUC) against a specific demand." (Rausand, 2014) A safety instrumented system designed to perform one or more SIFs. Reliability performance of SIF specified by safety integrity level (SIL).

Subsea control module is a subsystem of safety instrumented system which performs a number of safety-related control functions. Reliability of this functions should be evaluated in accordance to process industry standards. The measures for reliability quantification specified by standards are:

- Average probability of (dangerous) failure on demand (PFD_{avg})
- Average frequency (per hour) of dangerous failures (PFH)
- Hazardous event frequency (HEF)
- Risk-reducing factor (RRF)
- Spurious trip rate (STR)
- Safe failure fraction (SFF)

IEC-61508 (2010) distinguish three operating modes in which a SIF is performed:

- Low-demand mode of operation (i.e., demands occur no more often than once per year)
- High-demand mode of operation (i.e., demands occur more often than once per year)
- Continuous mode of operation (in this mode, the SIF continuously prevents the occurrence of a specific type of hazardous events)

Standard does not specify clear boundaries and criteria for classification, also practitioners have a lot of discussion regarding the issue. According to IEC-61508 (2010) the reliability performance of a SIF that operates in low-demand mode can be expressed by the average probability of (dangerous) failure on demand, PFD_{avg} , and the reliability performance of a SIF that operate in high-demand/continuous mode be expressed by the average frequency of dangerous failures per hour, PFH.

Subsea production process requires continuous control to prevent the occurrence of dangerous situations. SCM as a part of production control system performs a safety related control functions. The functions of SCM are analyzed in Chapter 5 and as we conclude this may be operated not on a continuous basis, only when the demand occurs: an example is to activate a necessary valve. Rausand (2014) classifies a safety-related control function into a proactive safety-related function with objective of controlling the safety of process system and said to operate in continuous mode. As a conclusion, our choice of analytical method for reliability assessment is the average frequency of dangerous failures per hour (PFH).

6.2.2 Average Frequency of Dangerous Failures (PFH)

PFH as per the IEC 61508 standard indicates the average frequency of dangerous failures to perform required function per hour. The PFH can be considered a function of time, PFH(t), and it is similar to the rate of occurrence of failures (ROCOF) of repairable system. Based on the same concept of the ROCOF, the average PFH within the given time interval can be similarly expressed as

$$\mathrm{PFH_{avg}} = \frac{1}{\tau}\int_0^{\tau} \omega(\mathrm{t})\mathrm{dt} = \frac{\mathrm{E[N}(\tau)]}{\tau} \tag{6.1}$$

"The ROCOF is an unconditional failure rate of an item at time t and is often denoted by $\omega(t)$. When the ROCOF is restricted to dangerous SIF failures, we have:"(Rausand, 2014)

$$PFH(t) = \omega(t)$$

Considering a single element as a SCM, and assume no more than one failure during a stated period, we get

$$E[N(\tau) = 0 * Pr(N(\tau) = 0) + 1 * Pr(N(\tau) = 1) = (1 - e^{-\lambda\tau}) \approx \lambda\tau$$

Inserting this in to equation 6.1, it results in

$$PFH_{avg} = \frac{1 - e^{-\lambda\tau}}{\tau} \approx \lambda$$

It is natural to see this result, in case of continuous mode operation of a single component, occurrence of dangerous event would be immediately after when the component has failed. One more feature of continuous operation is that it is likely a demand occurs before the undetected fault is revealed. Hence advisable to proof-test systems with redundancy. This makes it possible to reveal faults of redundant element even if the SIF is functioning.

For more complex system, simplified approximation formulas is presented by

$$PFH_{avg}^{koon} = \frac{Pr(M = n - k + 1)}{\tau} = \binom{n}{n-k+1} \lambda^{n-k+1} \tau^{n-k}$$

The user also can choose any other appropriate method for reliability analysis from the following:

- Reliability block diagram approach
- Simplified approximation formulas (based on reliability block diagram models)
- Approximation formulas provided in IEC 61508-6
- The PDS method (SINTEF, 2013b)
- Fault tree analysis
- Markov approach
- Petri net approach

The choice depends on the architecture of the SIS, and the testing and operational strategies of a system.

Chapter 7

Summary and Recommendations for Further Work

7.1 Summary and Conclusions

The main objective of this Master thesis is to study some practical aspects and elements of statistical methods in reliability analysis with focus on the case study. We estimated the failure rate of Subsea Control Module based on the company's reliability database. Further, the estimated failure rate has been compared to OREDA Handbook to see the difference between application of parametric model which shows the behaviour of the component and the OREDA's constant "average" failure rate.

This thesis applies available methods and models of reliability and lifetime analysis by performing functional analysis, failure analysis, and reliability assessment of the SCM. Different literature was used to understand reliability concepts and its application in various forms of required analysis. In chapter two, we identified that in carrying out a reliability analysis, it is important to follow a strategy according to Cox and Snell (1968) in order to identity a suitable and feasible approach for the analysis.

We reviewed the development cycle of statistical methods starting with pure mathematical parametric models which evolved into reliability tools (non-parametric and semi-parametric models). Some of the identified statistical data analysis methods were further used to derive the failure rate of an SCM for equipment performance assessment. This was achieved in chapter four by the following steps: investigating failure trends by establishing a Nelson-Aalen plot and Laplace trend test statistic. These tests show that the ROCOF is close to constant (no trend in the ROCOF) and as the result, the intervals between failures are identically distributed. With an assumption of independent records of the SCM database, we found the MLE of the scale and shape parameter of the Weibull distribution. The goodness of fit is considered to be adequate and we proceeded to finding the failure rate. In addition, we calculated the failure rate using the OREDA's procedure for results comparison reasons.

In chapters five and six, we showed the further utilization of failure rates for in-dept reliability assessment of systems. Qualitative assessments like the functional failure analysis using FMECA is considered the usual method for simple systems. Failure rate is the basic data input for performing quantitative reliability assessments. We showed how it can be used to calculate the availability and frequency of system failures using the Markov approach and simplified formula.

7.2 Discussion

The literature review presented in this work covers only selected theoretical approaches. More focus was centered on the practical aspects of reliability and this was driven by the case study.

The failure distribution analysis carried out using the failure and censoring times from the database record, shows a high hazard/failure rate at the initial phase of operation. Therefore, improvement of the reliability performance of the SCM through system testing and burn-in procedures should be implemented considering the high subsea equipment repair cost. Based on the result of the analysis, a systematic remedial measure is necessary during the life cycle phases with feedback from the plant's operations site.

The covariates analysis using variety of data collected from different geographical regions of operation reveals that there is no environmental impact on the reliability performance. However, it shows that brands from different manufacturers have different reliability performance hence the main influencing factor.

Finally,we derived the failure rates for different groups of SCM and also using different methods. Failure distribution analysis seems more informative and models the behavior of the system while the OREDA estimator comprise of multi-sample data in one ’average’ number with wide confidence interval.

This thesis gave me a better understanding of the importance of defining the study objectives before selecting the appropriate reliability analysis approach for a given system.

7.3 Recommendations for Further Work

In the course of this master’s thesis, some interesting aspects of reliability analysis which more clarification and better understanding are needed, were unveiled.

- There is a need to design a standardized systematic approach to identify failure causes, failure mechanisms and root causes of any system being analyzed which will be a great input for methods like FMECA and RCM.

- Further analysis may be required for databases (e.g. OREDA) which contains multi-state failure modes to identify the transition rates between the degraded states and the total failure. This information could be used as an input for residual useful life analysis (RUL) and condition monitoring.

Appendix A

Acronyms

ALARP As Low as Reasonably Practicable

CMMS Computerized Maintenance Management Software

FMECA Failure modes, effects and criticality analysis

HAZOP Hazards and Operability Analysis

LCC Life Cycle Costing

MLE Maximum Likelihood Estimation

MTTF Mean time to failure

OREDA Offshore Reliability Data

QA Quality Assurance

RAMS Reliability, availability, maintainability, and safety

RCM Reliability centered maintenance

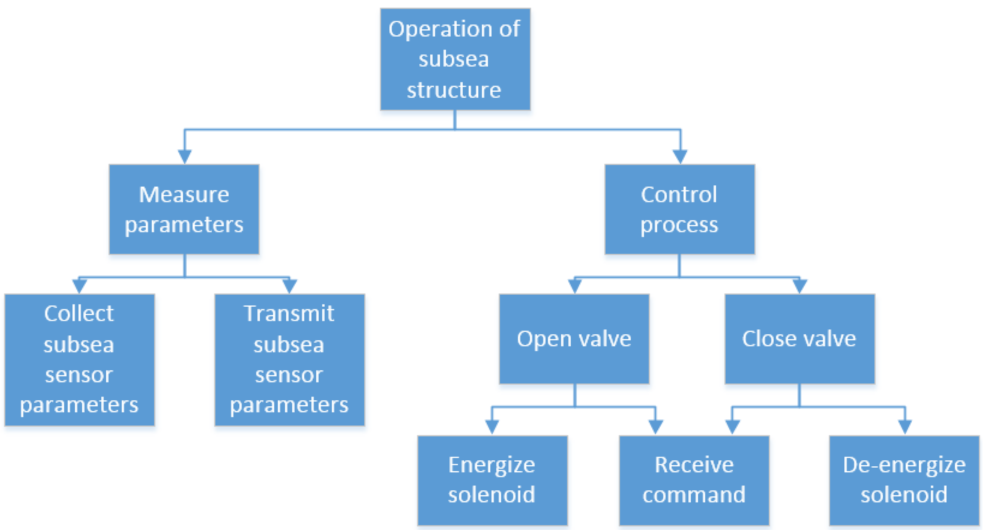
ROCOF Rate of occurrence of failures

SCM Subsea control module

SEM Subsea Electronics Module

Appendix B

Function tree



Components for "Measure parameters" function:

- Module base plate
- Power supply unit
- Power/signal coupler
- Subsea electronic module

Components for "Control process" function:

- Module base plate
- Power supply unit
- Power/signal coupler
- Subsea electronic module
- Solenoid control valve
- Accumulator-subsea
- Hydraulic coupling
- Chimical injection coupling
- Filter

Figure B.1: Subsea Control Module function tree.

Appendix C

FMECA worksheet

.

				Description of potential failure			Potential failure effect						Severity		
FM Code	Component	Device function	Operational mode	Potential Failure mode	Potential Failure cause	Failure detection method	On the subsystem	On the overall system	Existing safeguards	Corrective action	Occurence	O	E	S	Criticality
1,1	Accumulator -subsea	Provide utility medium	Operation	External leakage - utility medium	Aging of seals, corrosion, material fatigue	Continuous monitoring	Reduced capacity	Delayed valve actuation on demand	System pressure monitoring	Flushing, retrieve SCM	2	2	2	2	
1,2				Internal leakage - utility medium	Aging of seals, corrosion, material fatigue							1	1	1	
1,3				Fail to function on demand	Clogging, debris, external impact							3	1	3	
1,4		accumulating utility medium	Standby	External leakage - utility medium	Aging of seals, corrosion, material fatigue							2	2	2	
1,5				Internal leakage - utility medium	Aging of seals, corrosion, material fatigue							1	1	1	
2,1	Chimical injection coupling	Allow flow	Operation	External leakage - utility medium	Aging of seals, corrosion, material fatigue, external impact	Continuous monitoring	Loss of utility medium	Shutdown of subsea structure	Robust design	Flushing, retrieve SCM	2	2	2	2	
2,2				No flow	Clogging, debris, external impact		Blocked line	Depended on chimical. Shutdown or no effect.	Installation and operation procedures			3	1	3	
3,1	Filter	Filter utility medium	Operation	No flow	Clogging, debris, external impact	Continuous monitoring	Unable to filter	Depended on configuration. No effect.	operation procedure	Flushing, retrieve SCM	2	1	1	1	
4,1	Hydraulic coupling	Allow flow	Operation	External leakage - utility medium	Aging of seals, corrosion, material fatigue, external impact	Continuous monitoring	Loss of utility medium	Shutdown of subsea structure	Robust design	Flushing, retrieve SCM	2	3	2	2	
4,2				No flow	Clogging, debris, external impact		Blocked line		Installation and operation procedures			4	1	3	

Figure C.1: Subsea Control Module FMECA.

5,1	Module base plate	Provide interface between SCM and subsea structure	Operation	External leakage - utility medium	Aging of seals, corrosion, material fatigue, external impact	Continuous monitoring	Loss of utility medium	Shutdown of subsea structure	Robust design and operation procedures	Retrieve SCM	3	3	2	2
5,2				Structural deficiency	Wear, fracture, corrosion, material fatigue		Loss of structural integrity				2	4	1	3
6,1	Power supply unit	Provide uninterrupted power supply	Operation	Fails to supply power	Short circuit, software failure, wire break	Functional test	No power accumulated	Shutdown of subsea structure, SCM lacks power supply	Robust design and operation procedures	Retrieve SCM	2	4	1	3
6,2		Control and distribute power		Fails to distribute power		Continuous monitoring	No power					3	1	3
7,1	Power/signal coupler	Connection and transmition subsea sensor parameters and topside	Operation	Short circuit	Design, wire break, installation	Continuous monitoring	Loss of power/signal connection	Loss of interface beetween structures	Robust design, installation and operation procedures	Retrieve SCM	3	3	2	2
7,2				Transmission failure		Functional test						4	1	3
8,1	Solenoid control valve	Close/open a valve in controlled subsea structure	Operation	External leakage - utility medium	Fatigue, corrosion, contamination, coil "melted", Electric power not disconnected or no electric power supply	Functional test	No hydraulic power supplied to consumers	Shutdown of subsea structure	Robust design, installation and operation procedures	Redandancy for avoiding retrieval of SCM	3	2	2	1
8,2				Fail to function on demand								3	1	2
8,3				Internal leakage - utility medium								3	1	3
8,4				Plugged/choked								3	1	3
9,1	Subsea electronic module	Receive and execute commands from the topside	Operation	Control/signal failure	Short circuit, software failure, wire break, no power, leakage	Functional test, Continuous monitoring	Loss of control and signals	Shutdown of subsea structure	Robust design, installation and operation procedures	Redandancy for avoiding retrieval of SCM	3	3	1	3
9,2				Fail to function on demand								3	1	3
9,3				Insufficient power								2	1	1
9,4		Collect and transmit subsea sensor parameters to the topside		Short circuit								2	1	1
9,5				Spurious operation								2	1	1
9,6				Combined								3	1	2

Figure C.2: Subsea Control Module FMECA (continued).

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