NTNU
Norwegian University of
Science and Technology

Master's thesis

2019

Endre Hordnes Aspen

Master's thesis

NTNU
Norwegian University of
Science and Technology
Faculty of Engineering
Department of Mechanical and Industrial Engineering

Endre Hordnes Aspen

Maintenance Optimization for Subsea Pump Systems: a Contribution Based on Modelling and Comparative Study

June 2019

NTNU
Norwegian University of
Science and Technology

NTNU
Norwegian University of
Science and Technology

Maintenance Optimization for Subsea Pump Systems: a Contribution Based on Modelling and Comparative Study

Endre Hordnes Aspen

Mechanical Engineering
Submission date: June 2019
Supervisor: Professor Anne Barros, MTP
Co-supervisor: Christopher Lassen, Aker Solutions

Norwegian University of Science and Technology
Department of Mechanical and Industrial Engineering

Preface

This master thesis was carried out in the spring of 2019, as a report for the course TPK4550, which is the final work of a five-year master's degree in mechanical engineering with a specialization in reliability, availability, maintenance and safety engineering, at Norwegian University of Science and Technology (NTNU).

The thesis was written in collaboration with Aker Solutions, and the idea of this joint effort was established in the summer 2018 after a 9-week internship at their headquarters at Fornebu, Bærum.

The topic was discussed and proposed in collaboration with main supervisor Professor Anne Barros and co-supervisor Christopher Lassen at Aker Solutions, and the idea of investigating maintenance optimization for subsea pump systems was decided.

Trondheim, 2019-06-10

Endre Hordnes Aspen

Acknowledgment

First of all, I would like to thank Professor Anne Barros for the great feedback and useful insight on this thesis' topic. Her expertise in the field of maintenance optimization and prognostics is genuinely inspiring.

I would also like to show my gratitude to Christopher Lassen at Aker Solutions for the opportunity to investigate such an interesting topic and for the help provided during the thesis' work. His knowledge in the subsea and RAMS field has been both inspiring and helpful.

A special thanks are also given to Åge Hofstad and Tarje Olderheim at Aker Solutions for their great help on understanding the practical aspects of subsea pumps and the challenges they face in the industry.

My fellow students, both in the RAMS specialization and from mechanical engineering, should also be thanked for creating a pleasant work environment for both professional and non-professional discussions and the help provided during this semester.

Lastly, I want to thank Marvin Rausand for creating the Latex template for the RAMS group as it has made the writing process a thrill.

E.H.A.

Summary and Conclusions

Subsea pump systems are prone to high competition between industry actors. High availability and profitability are essential parameters for operators when purchasing subsea equipment. Implementation of the best maintenance strategy is an important aspect when ensuring that these parameters are reached.

Aker Solutions is an oil and gas service company that delivers production equipment to energy companies. They have been developing and manufacturing reliable subsea pumps for a long time and are interested in further developing the maintenance strategies implemented for such systems.

This thesis aims to investigate the current maintenance approaches used by the industry for subsea pump systems and to investigate the optimal maintenance strategy for these systems.

Literature studies on maintenance methodology and state of the art in subsea maintenance were performed to investigate what strategies and challenges was met by the industry. One of the biggest concerns is how costly unplanned intervention of subsea equipment is, due to the loss of production. This downtime can be lengthy due to the need for specialized vessels and operators. These are usually external companies with long waiting lists, and their service needs to be rented.

A simulation tool that compares maintenance strategies were developed. This tool takes several operation, system and environmental inputs and simulates system lifetimes, that results in an average cost for each maintenance strategy. These results are then compared to find the most economical strategy.

The components in the system were divided into two sub-classes, those prone to degradation that can be modelled and those that could not. The degradation model used is the same model Aker Solutions use for estimations on sand wear of components. The expected life of the components not prone to sand wear was modelled based on failure data.

To make this simulation tool applicable for other input parameters an interface was developed. This also makes the simulation tool usable for engineers with little knowledge of maintenance modelling and computer science.

The most commonly used maintenance strategies in the industry are age-based maintenance with a five-year renewal interval, and a condition-based approach combined with a run-to-failure approach. These are implemented into the simulation tool as well as a corrective and an ideal maintenance strategy for comparison.

The optimal strategy is decided based on its cost, this is decided as downtime of the system leads to production loss, which can be translated to a cost, and as the intervention to renew the system has a related cost.

The tool is built on a Monte Carlo simulation, that simulate several lifetimes of the system. It was decided to use Monte Carlo simulation due to how well it models complex systems with a

lot of components.

The main objective of this thesis was to compare the effects of implementing different maintenance strategies for a subsea pump system.

Several simulations were performed with different input parameters, and all results showed that the age-based maintenance strategy with a five-year renewal interval is the most economical strategy. The results only differed when the sand concentration in the system was doubled. Then the condition-based maintenance strategy proved to be cheaper. This was due to the reliability of the components not prone to sand wear, as their combined reliability was low, the system usually failed before the condition monitored components. Hence, a low renewal interval was more economic.

The results of this thesis have a high uncertainty due to the degradation model and input data. The degradation model has an uncertainty of around 50% in their results. The input data used for the lifetime modelling of components is mostly based on data for topside pumps as no other data was available.

The simulation tool created can be improved and expanded by implementing other strategies and degradation models. If supplied with real operational data, it could also give more realistic results.

This thesis also serves as an introduction to maintenance modelling and optimization, as it presents the relevant theory and approaches used by the industry and academia. It provides a framework and an insight on how to build a simulation tool.

Sammendrag

Undervannspumpesystemer er utsatt for høy konkurranse mellom industriaktører. Høy tilgjengelighet og lønnsomhet er viktige parametere for operatører når man kjøper undervannsproduksjonsutstyr. Implementering av den beste vedlikeholdsstrategien er et viktig aspekt når man skal sikre at disse parameterne nås.

Aker Solutions er et olje- og gasserviceselskap som leverer produksjonsutstyr til energiselskaper. De har utviklet og produsert pålitelige undervannspumper i lang tid, og er interessert i å videreutvikle vedlikeholdsstrategiene implementert for slike systemer.

Denne oppgaven tar sikte på å undersøke de nåværende vedlikeholdsmetodene som brukes av industrien for undervannspumpsystemer og å undersøke den optimale vedlikeholdsstrategien for disse.

Litteraturstudier om vedlikeholdsmetodikk og den nyeste teknologien i vedlikehold for undervannsproduksjonssystemer ble utført for å undersøke hvilke strategier og utfordringer som ble møtt av næringen. En av de største utfordringene er hvor kostbart uplanlagt intervensjon av undervannsutstyr er, og produksjonstap er den største bidragsyteren til dette. Nedetiden kan være lang på grunn av behovet for spesialiserte fartøy og servicearbeidere. Disse leies vanligvis eksterne selskaper med lange ventelister.

Et simuleringsverktøy for vedlikeholdsstrategier ble utviklet for å sammenligne flere vedlikeholdsstrategier. Dette verktøyet tar inn flere operasjons-, system- og omgivelsesdata og simulerer en livssyklus for pumpen, noe som resulterer i en gjennomsnittlig kostnad for hver vedlikeholdsstrategi. Disse resultatene blir deretter sammenlignet ved å finne den mest lønnsomme strategien.

Komponentene i systemet ble delt inn i to underklasser, de utsatt for slitasje som kan modelleres og de som ikke kunne. Nedbrytningsmodellen som brukes er den samme modellen som Aker Solutions bruker til estimering av sandslitasje på komponenter. Forventet levetid for komponentene som ikke er utsatt for sandslitasje ble modellert basert på feilratedata.

For å gjøre dette simuleringsverktøyet anvendbart for andre parametere enn de brukt i oppgaven ble det utviklet et brukergrensesnitt. Dette gjør også simuleringsverktøyet nyttig for ingeniører med lite kunnskap om vedlikeholdsmodellering og programmering.

De mest brukte vedlikeholdsstrategiene i industrien er aldersbasert vedlikehold med et femårig fornyelsesintervall, og en tilstandsbasert tilnærming kombinert med en kjør-til-ødelagt-tilnærming. Disse implementeres i simuleringsverktøyet, samt en korrigerende og en ideell vedlikeholdsstrategi for sammenligning.

Den optimale strategien er bestemt basert på kostnadene, dette avgjøres da nedetid av systemet fører til produksjonsstap, som kan oversettes til en kostnad, og kostnadene for å reparere systemet slik at det kan fortsette produksjon.

Simuleringsverktøyet er bygget på Monte Carlo-simuleringer, som simulerer flere levetider

for systemet. Det ble bestemt å bruke Monte Carlo simuleringer på grunn av hvor godt det modellerer komplekse systemer med mange komponenter.

Hovedformålet med denne oppgaven var å sammenligne effektene av å implementere ulike vedlikeholdsstrategier for et undervannspumpsystem.

Flere simuleringer ble utført med forskjellige inngangsparametere, og alle resultater viste at den aldersbaserte vedlikeholdsstrategien med et femårig fornyelsesintervall er den mest økonomiske strategien. Resultatene var bare forskjellig når sandkonsentrasjonen i systemet ble doblet. Deretter viste tilstandsbasert vedlikeholdsstrategi seg å være billigere. Dette skyldtes påliteligheten av komponentene som ikke var utsatt for sandslitasje, da deres kombinerte pålitelighet var lav stopper systemet å fungere vanligvis før de tilstandsovervåkede komponentene. Derfor var et lavt fornyingsintervall for systemet mer økonomisk.

Resultatene av denne oppgaven har stor usikkerhet på grunn av slitasjemodellen og parameterene som er brukt. Nedbrytningsmodellen har en usikkerhet på rundt 50% i resultatene. Parameterene som brukes for levetidsmodellering av komponenter, er hovedsakelig basert på data for pumper innstallert på plattformer over vann, ettersom ingen andre data var tilgjengelige.

Det opprettede simuleringsverktøyet kan forbedres og utvides ved å implementere andre strategier og nedbrytningsmodeller. Hvis virkelige driftsdata gjøres tilgjengelig kan det også gi mer realistiske resultater.

Denne oppgaven gir også en introduksjon til vedlikeholdsmodellering og optimalisering, da den presenterer relevante teorier og tilnærminger som brukes av industrien og akademia. Den gir også et rammeverk og et innblikk i hvordan man bygger et simuleringsverktøy.

Contents

List of Figures

List of Tables

Abbreviations

ABAO As Bad As Old

AbM Age-based Maintenance

AGAN As Good As New

AHP Analytic Hierarchy Process

AKSO Aker Solutions

AUV Autonomous Underwater Vehicles

BFS Barrier Fluid System

BOE Barrels of Oil Equivalent

BST Binary Search Tree

CAPEX Capital Expenditures

CbM Condition-based Maintenace

CCbMAbM Combined Condition-based and Age-based Maintenance

CCbMCrM Combined Condition-based and Corrective Maintenance

CM Condition Monitoring

CPM Condition and Performing Monitoring

CrM Corrective Maintenance

DD Data-driven

FTA Fault Tree Analysis

HaW Hydro-abrasive Wear

IMR Inspection, Maintenance and Repair

KPI Key Performance Indicator

MCS Monte Carlo Simulations

MEG Mono-Ethylene Glycol

MMBOE Million Barrels of Oil Equivalents

MTBF Mean Time Before a Failure

MTTF Mean Time To Failure

NOK Norwegian Krone

NTNU Norwegian University of Science and Technology

OPEX Operational Expenditures

OREDA Offshore and Onshore Reliability Data

O&G Oil and Gas

PDF Probability Density Function

PG Planning Game

PM Preventive Maintenance

PrM Predictive Maintenance

PVR Pressure Volume Regulator

R&D Research and Development

RAMS Reliability, Availability, Maintainability, and Safety

RAM Reliability, Availability and Maintainability

RBD Reliability Block Diagram

ROV Remotely Operated Vehicle

RUL Remaining Useful Life

TbPM Time-based Preventive Maintenance

Chapter 1

Introduction

1.1 Background

Requirements for the oil and gas industry have become stricter in later years from governmental and public safety authorities as well as from economic actors due to lower oil prices. The industry has had an increased focus on sustainability in operations to adapt to these requirements, meaning an increased focus on the life cycle of production equipment and maintenance policies.

Aker Solutions is an oil service company that sells subsea equipment to the oil and gas industry. Most of the subsea equipment they offer are operated with a run-to-failure maintenance strategy with some condition monitoring implemented, but other possible strategies have been proven to be more beneficial and cost-effective. Comparing such alternative strategies rapidly with few parameters could be an effective way to investigate benefits and differences between them without performing time-consuming analysis.

The availability of operational data is growing due to increased collecting and new models to analyse these data, and due to this, predictions of failures are getting easier. This makes it so it should be possible to better tailor maintenance strategies to production systems than what is done today.

As the energy industry is competitive and technological merits can prove very profitable, the reason to cooperate is low, seen from the energy companies view. This makes it, so they are not always interested in sharing operational data with the oil service companies from whom they buy their equipment.

This master thesis describes and develops a simulation tool that can be used to compare and present possible maintenance strategies for subsea pump systems. Such a tool should help to justify to the clients how different strategies could perform in a life cycle. The output of the simulation tool is understandable without a vast knowledge of maintenance modelling as a research field.

1.2 Problem Formulation

Subsea pump systems are prone to high competition between industry actors. High availability and profitability are essential parameters for clients when purchasing such systems. Aker Solutions have been delivering reliable subsea pumps for a long time and are interested in investigating possible improvements in the maintenance strategy for such systems. In this process, increased access to operational data could prove helpful.

Aker Solutions are, therefore, interested in a tool that can investigate possible alternative maintenance strategies for their subsea pump systems. A literature study of the current state of subsea maintenance for subsea pumps should be performed. Further on analysis of such maintenance strategies should be performed based on simulated data and result in tangible results.

1.3 Project Description and Plan

1.3.1 Project Description

This thesis consists of the development of a simulator that can be used as a comparison tool for different maintenance strategies for subsea production equipment, with the main focus on subsea pump systems.

This project is done in collaboration with AKSO and the final product delivered is made with their customers and product portfolio in mind. The simulator developed can be used as a demonstration tool in client meetings to compare possible maintenance strategies for generic subsea pump systems.

To develop this simulator, a literature review of relevant maintenance theory and optimization models, component degradation and prediction models is performed. Only models implemented in the program are deeply studied and presented. Models that are not selected are discussed less thoroughly.

A literature review of the state of the art of subsea maintenance is presented. This is done to investigate what technology is currently available and what is viewed as possible approaches by the industry and academia. As an introduction to this literature review generic maintenance theory and strategies are presented.

A generic pump system model which is used for the simulations is presented and discussed, and the simulation tool is made based on this model. The results of the thesis are mainly written based on the generic model showed. As this is a master thesis, the results are also interpreted and given generic results.

1.3.2 Project Plan

The first part of the thesis will be to present the system under study and to develop a system structure to be analyzed and modelled. Then a literature review of maintenance strategies and current state of maintenance in subsea will be presented to understand what strategies are relevant for this type of system.

The second part will be to investigate maintenance modelling and optimization theory. This is done to understand how to build the simulation tool for comparing maintenance strategies. In the same process, a review on degradation and prediction approaches will be done to be able to simulate the degradation of parts in the system.

The last part of the project will be to develop the simulation tool. This is started right away as the time frame of this part of the project is unclear. This is due to the lack of knowledge about the amount of help needed and how time-consuming the work is. This will then be tested and produce comparing of different maintenance strategies applied to the system. Notes and ideas for the thesis writing will be done simultaneously for the other parts of the thesis work.

1.3.3 Objectives

The main objective of this master thesis is to compare the effects of implementing different maintenance strategies to a subsea pump system. To do this, several sub-objectives must be completed.

1. Develop a model of a subsea pump system and collect all relevant data for such a system.
2. Discuss relevant literature on generic maintenance theory to find possible maintenance strategies for such a system.
3. Perform a literature review of the current state of maintenance for subsea equipment and discuss its challenges.
4. Discuss and present theory and studies on maintenance modelling and optimization, and on degradation and prediction models of subsea components to understand what can be performed for a subsea pump system.
5. Build a simulation tool for comparing different maintenance strategies that are implemented and can be implemented for subsea pump systems and present the background theory for such a tool.
6. Discuss results and findings.

1.3.4 Goal

The two main goals of the master thesis are to study the current situation of subsea maintenance and to develop a tool that can effectively compare different maintenance strategies for a subsea pump system. An added value to this thesis could be to showcase to Aker Solutions clients that providing more operational data can improve the equipment's profitability.

This demonstration tool should be built based on relevant maintenance and prediction models as well as on degradation models used in the industry. The tool should have inputs such as the structure of the system (e.g. RBD), failure data of components, run time, desired maintenance strategy, cost of maintenance activities, degradation models and possibly others or less.

The output from the program would be relevant plots, cost of desired maintenance strategy and comparisons with other strategies. The results should be visually presented and understandable by any user.

1.4 Limitations

The scope of this thesis is limited to a generic subsea pump system that is part of a subsea compression system. This pump system is then given a generic description based on design commonly used in the industry, as initial design drawings and reports from Aker Solutions may be subject to confidentiality.

There has not been granted any access to operational data of a subsea pump. All data used is, therefore either simulated or based on public data sources.

The simulation tool is developed in MATLAB, and no other programs are investigated. Some parts of the code could be made to run faster with another program or present the results better, but MATLAB is used due to its capability to implement stochastic models. Some programs are similar to the developed simulation tool and are used in the industry, but access to these is not available, and comparisons between them are not made.

The quality and availability of relevant literature could be a limitation, as the subject of maintenance optimization and implementation of predictive models are newer topics. This leads to a decreased availability of reliable literature.

1.5 Actors Involved

1.5.1 Norwegian University of Science and Technology

Professor Anne Barros supervised the Master thesis on behalf of NTNU and made sure that the thesis was up to the quality and standards that NTNU and the faculty required. She was also the primary person to rely on for help and guidance on the topic and general theory.

1.5.2 Aker Solutions

Aker Solutions was the industrial partner for this Master thesis, *"Aker Solutions is a global provider of products, systems and services to the oil and gas industry. We create solutions to unlock energy safely and sustainability for future generations."* (AKSO, 2018).

Christopher Lassen was the primary contact from AKSO, and he served as co-supervisor. He provided papers and research from AKSO as well as an industrial view on the problems and discussions. He also made sure that the project delivered the results required and gave input on how the study could create value for AKSO.

Experts and other employees in AKSO were also helpful. Contact with these was made in the last year as some time was spent at Aker Solutions offices at both Fornebu, Bærum and Tranby, Lier. Some of these were Åge Hofstad, Chief Engineer Pumps and Tarje Olderheim, Tech Lead Hydraulic. Hofstad has knowledge on the subsea pumps delivered by AKSO and on their current maintenance strategies, and challenges and Olderheim gave a great insight into the degradation of components in subsea pumps.

1.6 Approach

The model of the generic subsea pump system will is made in collaboration with Aker Solutions specialists on subsea pumps, they have hands-on experience from the industry and made expert judgements on what was included and neglected. The relevant failure data was mostly be based on the OREDA database, as this is most commonly used in the industry. Degradation data was based on experts input on what numbers are most commonly used in the industry.

The literature review on maintenance theory was based on articles found in NTNUs database for academic articles, papers and books, Oria (2019), as well as on previous knowledge on books and compendiums studied in earlier courses in the study program. The Oria (2019) database was also used for the literature review on the current maintenance situation for subsea equipment and the discussion on theory and studies on maintenance modelling and optimization, degradation modelling and prediction models of subsea components.

The degradation model used is the same as some use in the industry. This was, therefore, also built on discussion and input from Aker Solutions employees. The numbers and parameters for this model were based on commonly used numbers in the industry.

The simulation tool was made in MATLAB as it is provided free access to by NTNU for all students. MATLAB has build-in the mathematical framework required for such simulations, and as it produces visual as well as numerical results, it was suited for this problem-solving. Lastly, MATLAB is commonly used by engineers, so there exists a lot of support and guides for it online.

For the overall project, there were regular meetings with all supervisors. This was to ensure progress and sufficient workload for the thesis. Collaboration and discussions with other students on similar topics are also an essential part of the thesis work.

1.7 Structure of the Report

The rest of the report is structured as follows. Chapter 2 gives an overview of the system and study case, which is a generic subsea maintenance pump. This is made generic in collaboration with Aker Solutions employees who have been part of AKSO and making subsea pumps for many years. Chapter 3 is a theoretical study of maintenance strategies, and definitions and effectiveness of maintenance is discussed. Chapter 4 is a state of the art literature review of subsea maintenance. The evolution towards condition-based maintenance, the current and future state subsea maintenance is also discussed. Challenges related to subsea maintenance is presented as well as some studies that compare different subsea maintenance strategies. Chapter 5 is a literature review on maintenance optimization; it creates a framework and presents all relevant approaches to perform the modelling of the simulator. In chapter 6 the theory from chapter 5 is discussed and applied for the subsea pump system under study, as well as the degradation modelling, maintenance optimization and prognostics for the system. Chapter 6 is then summarized by presenting the results of maintenance comparison and discussing these. Lastly, in chapter 7 a summary and conclusion of the results from chapter 6 are presented as well as recommendations for further work.

Chapter 2

System and Study Case Overview

In this chapter, the main parts of a subsea processing facility will be presented, as well as a more detailed description of a subsea pump system. The most relevant components and sub-units will be discussed before a proposed system structure for the generic subsea pump system is presented. Lastly, the life-time modelling of components in the system is discussed.

2.1 Subsea Processing System

Figure 2.1 shows the layout of a subsea processing system, it consists of a scrubber, a compressor system, a pump system, a cooler and piping and valves connecting them together. The processing system's job is to increase the flow rate of gas and liquid in a subsea production.

2.1.1 Scrubber

The production fluids first run through the scrubber when entering the processing system. The scrubber is either a two-phase separator that separates gas from liquids or a three-phase separator that separate, gas, liquid and water. A subsea scrubber is most often vertically deployed. The main drawback of this design is that it is more difficult to clean, but as periodic cleaning of the scrubber is not an option this is not a drawback for subsea systems. The vertical deployment is an advantage in that it takes up less space, and limited space is a concern for subsea systems (SPE-International, 2019).

2.1.2 Compressor

The compressor increases the flow rate of the gas phase of the production. In short, this is done by a piston moving into a tube and pushing the fluid against a wall, hence increasing the pressure. The fluid is then released in front of the piston, and the velocity of the fluid is increased.

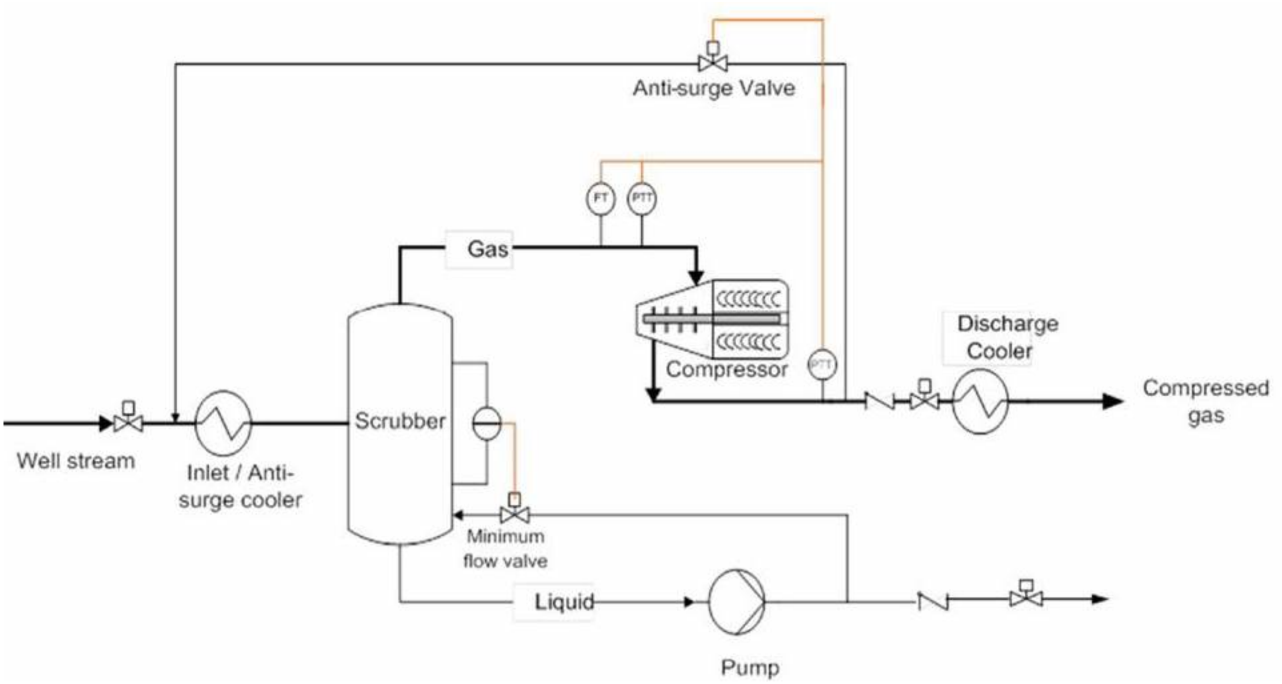


Figure 2.1: Generic subsea compression system (SPE-International, 2019)

Unique for AKSOs compressor modules is that every component is sealed inside an airtight enclosure, which in theory reduce the need for maintenance. The need for lubrication and power is low as the rotating machinery is run through a magnetic bearing.

2.1.3 Cooler

The processing system has a cooling system to lower the temperature of the production fluid for safe and efficient operations. The system is cooled by passive cooling, which is based on natural convection. This is done by running the fluid through a loop of tubing in direct contact with the sea water that then lowers the temperature of the fluid by the temperature difference. The length of the tubing loop is decided based on how much the temperature needs to be lowered to deliver a safe and efficient operations. This method of cooling fluids is possible due to the low temperatures at the seabed (Lima et al. (2011) and Winge Rudh et al. (2016)).

2.2 Subsea Pump System

The figure 2.2 presents the system layout of the pump system under study. It is taken from a presentation by Aker Solutions on subsea processing systems.

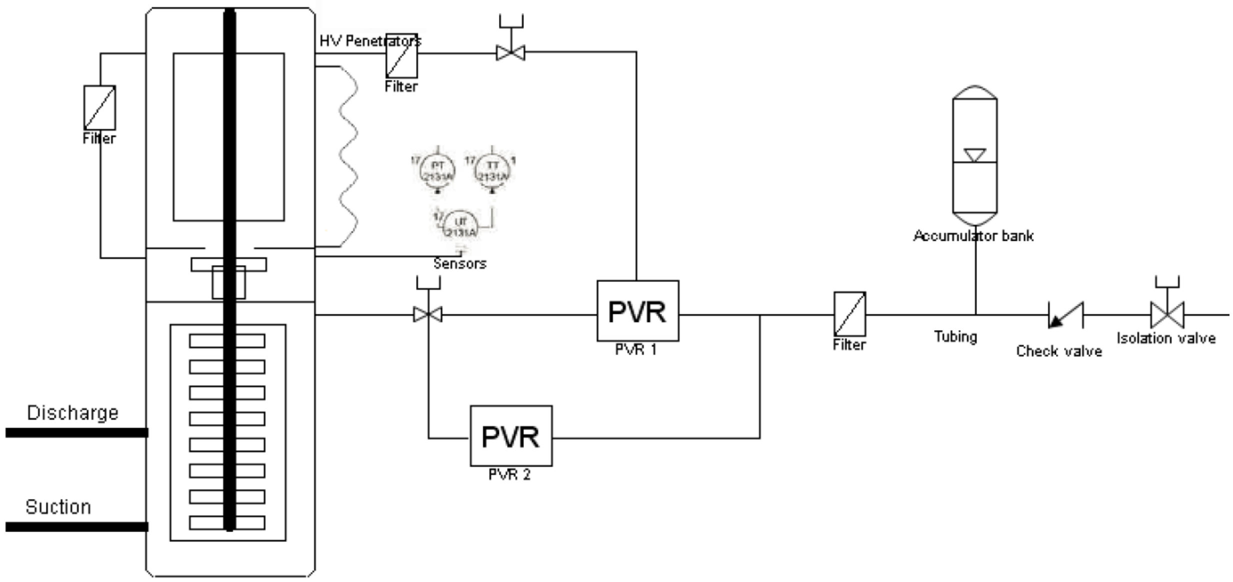


Figure 2.2: Subsea pump system

2.2.1 Pump

The pump unit is a centrifugal pump with eight impellers, that uses rotor dynamics to move liquids inside a pipe. Its function is to drain condensate, water and monoethylene glycol (MEG), which is added to the production fluid to lower its freezing temperature, from the separator and to boost the liquid phase of the hydrocarbons in the production line. It is driven by a pump shaft that goes through the pump horizontally and rotates. Holding this shaft in place are radial and axial (thrust) bearings. Mechanical and internal seals separate dynamic and static components. The throttle bush and the mechanical seal also separate the motor chamber from the pump chamber.

Impeller

The impeller part of the system can be divided into three sub-components. These are the impeller blades, inlet and outlet. They are all subjected hydro-abrasive wear by sand in the fluid. This type of degradation can often be monitored and estimated based on the sand in the fluid. The impeller blades can not directly cause a system failure, but sufficient wear of the blades leads to reduced production and is interpreted as a system failure by operators. Adequate wear of the impeller inlet and outlet can cause a system failure.

Pump Throttle Bush

The Pump throttle bush is a short tube that is part of the seal between the motor and the pump. It has some clearance between itself and the rotor for fluid to pass by. In this clearance hydro-abrasive wear of the throttle bush can occur. When degraded the clearance can get sufficiently big, and the pump system can fail.

2.2.2 Motor

The subsea motor is an electrical induction motor and is the driver unit of the pump. The power penetrator is connected to an energy source and supplies the motor with electricity where a current is sent through the stator. The stator creates a magnetic field inside the winding, and this creates a magnetic field that rotates the rotor, which is the rotating electrical component of the motor. This rotor has radial bearings for support. The motor can run hot, and a cooling system is therefore connected to the motor. Its function is to transfer heat out of the motor, prevent the motor from overheating. To do this, the cooler uses a cooling fluid that it passes through the motor and into long lines of external tubing. The tubing is in direct contact with the sea water and transfers heat from the cooling fluid to the sea. The cold cooling fluid is then transferred back into the motor. This method is similar to the passive cooling of the whole processing system but at a smaller scale.

2.2.3 Casing

The casing around is a pressure casing around the pump cartridge. It consists of several parts put together, and it is sealed with screws and flanges. It is there to protect the pump from the sea water and to lead the fluids inside through the pump and sustain the increased pressure on the fluids during operations. Inside the casing, the process and barrier fluids are detained and outside the sea water is pressing in. The casing is also tested for temperatures as these can increase due to the temperature of the pump and reduce the resilience of the casing material.

2.2.4 Barrier Fluid System

The barrier fluid system (BFS) consists of two redundant pressure volume regulators (PVRs), filters, an accumulator pack and two three-way valves. The function of the BFS is to maintain a constant over-pressure across the mechanical seal between the motor and the pump. This is done to ensure adequate high-pressure difference to prevent process fluid from entering into the motor cartridge. The PVRs are the main functioning unit of the BFS, and the accumulators contain the process fluid so that the BFS is not reliant on fluids from the umbilical or other parts of the system. The three-way valves are the actuators in the BFS as they operate as a switch between the two redundant PVRs when the operating one fails. The PVRs are therefor only operating one at a time with one of them on passive standby.

2.2.5 Sensors

There are three types of sensors used on the pump system: pressure and temperature transducers, accelerometers and flow meters. They are there to do condition monitoring and are monitored manually by operators. Measures are acted on by expert judgments and by comparing measures of several sensors. Several sensors are used to avoid acting on false measures from malfunctioning sensors.

Pressure and temperature transducers are a type of sensor that measures the pressure and temperature at specific locations in the process. A transducer is a device that transforms the measure into an electric signal that can be sent and analyzed in the control room.

The accelerometer is a device that measures the rate of change in velocity. For pumps, this is a method to measure changes in vibration. They are often attached to bearings or other rotating parts of the pump, where the vibrations are easily monitored.

The flow meter measures how fluids move through the system, and it is an easy way to find irregularities or failures in the system as the flow should be close to constant based on operations.

2.3 Generic Model of the Pump System

To optimize a maintenance strategy and perform reliability analysis on the pump system, a tangible model of the system must be presented.

The first thing to investigate is what model is best suited for modelling. To investigate these two of the most common reliability-related models will be discussed. These two approaches are fault trees (FT) and reliability block diagrams (RBD).

They are well-known models and are both applied in the industry. They can be quite complex, but also presents a real picture of how different parts of a system is constructed.

The FT present all possible component failures that lead to a specific system failure. It presents them through binary logic-gates and can be quantified. The RBD has a success-oriented approach instead of a failure-oriented, like the FT. All components are put together in a network illustrating how they together fulfil some system function. It is often advised to construct an FT first as this finds all possible events that can lead to failure and do mitigating measures accordingly. The model for this thesis is made first to understand how the components interact and to discover how different component failures can lead to a system failure (Rausand and Høyland, 2004).

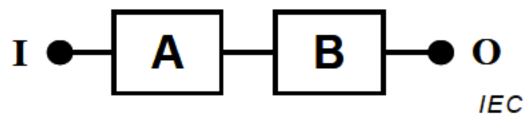
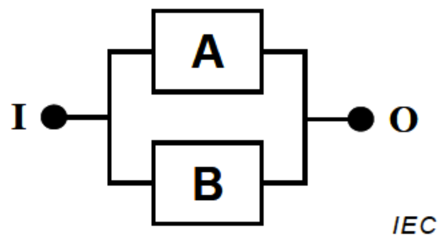
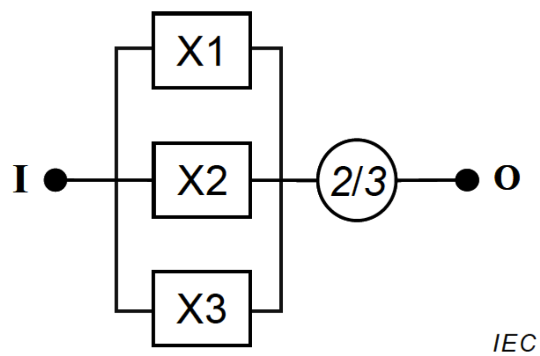
The RBD gives a better picture of how the system looks and works to fulfil its functions and can easily be transformed into an FT or other models if required. It is also presented to be beneficial according to the condition monitoring standard (ISO 17359, 2018). Based on this, the RBD proves better for this thesis.

2.3.1 Reliability Block Diagram

The RBD is a network of blocks where each block represents a component or a sub-system, that together fulfil some function or represents a system. It can show structures in series, parallel, k-out-of-n or as a combination of the three. The state of the system model can be quantified based on the state of each block, by binary failed or working states.

The different system structures of an RBD and their illustrations are presented in table 2.1.

Table 2.1: Reliability block diagram system structures

Structure	Definition	Symbol
Series	A structure of a system that is only functioning if all components in the series are functioning	
Parallel	A structure of a system that is functioning as long as one of the components in the parallel branches is functioning	
k-out-of-n	A structure of a system that is only functioning if k out of the n components in the parallel branches is functioning	

To use RBD modelling, there are some assumptions required. The system and each component only have a working and failed states, and all blocks are independent of each other. This limits some of the quantitative parts of the RBD modelling, but this does not affect the current scope of the model.

2.3.2 Approach

The RBD created for this thesis is a generic representation of a subsea pump system based on previous studies performed by AKSO. As this system is more generic and newer, some changes are made on a component level. By considering the function and component descriptions made earlier in this chapter, an RBD for the system can be made. The RBD presented is the network of the relationship between all the components and subsystems discussed earlier when the pump system is described.

The decision of which components to include was made as an iteration process together with AKSOs pump expert. Based on previous studies on similar systems, an RBD was developed. The data for these studies are based on simulations and testing data. The studies present reliability data and failure data for the whole pump system. Then the same data at the component level is presented. The components whom failure most often lead to a pump retrieval were considered for the RBD. Based on newer studies done on test pump modules and expert judgments from previous projects, some components are neglected.

2.3.3 Generic Model

Figure 2.3 shows the RBD of the generic model that can be used further in the thesis to analyze reliability and optimize maintenance strategy. It is generic, which means it is not necessarily an exact copy of a real system.

2.3.4 Limitations of the Model

To have a manageable model of the system under study, some simplifications are made. Not all components and sub-units are presented in the model as they are less relevant to the reliability of the system. These simplifications are again based on expert judgments and discussions.

- In a real pump system, there are three power penetrators in a 2oo3 structure, including common cause failures (CCFs). Individual failures are not very likely compared to CCFs. In the RBD the penetrators are presented as one block, which is a combination of the individual failures and the CCF. This is done as the CCFs are the most significant contributor to a penetrator failure.

- For the barrier fluid system, a simplification is made on the accumulators. They are all combined into one block and renamed to an accumulator pack. Looking at redundancy for them individually is not relevant as the most significant contributor to accumulator failures are common cause failures which will lead to a pump retrieval. A simplification of the two three-way valves is also made. They are combined into one block as they have the same probability of failure on demand and because the failure of one leads to failure of the barrier fluid system.

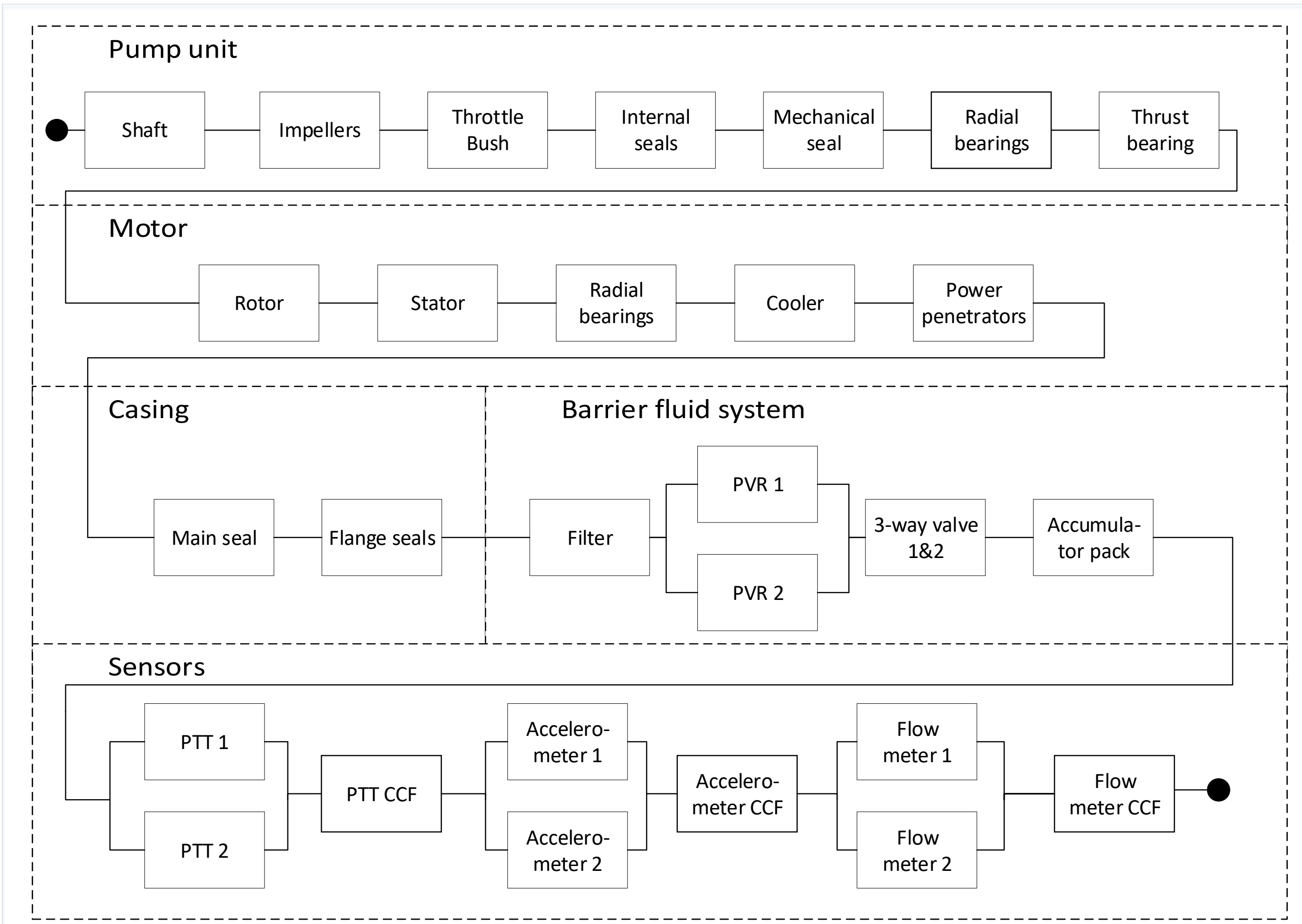


Figure 2.3: Reliability block diagram of pump system

- The impeller is shown as one block, but in reality, it consists of the inlet, outlet and blades of the impeller. These are all subject to hydro-abrasive degradation, and a failure of one of them leads to a system failure.

2.3.5 Life-time Modeling of Components

Components in a subsea pump are theoretically not supposed to degrade measurably and the pump, if in a perfect state when deployed, is supposed to run smoothly for a very long time. To do degradation modelling on such a system is therefore only possible in certain instances. An example of such a case is when the pump is used in production to pump hydrocarbons that contain sand. The sand then degrades some components in the system, and this is called hydro-abrasive wear. The sand entering the system can then be monitored, and degradation models for the components exposed to hydro-abrasive wear can be implemented to predict the degradation.

In this model, there are only two components that are subject to measurable and monitorable degradation. These are the impeller and the pump throttle bush. These will, therefore, be the subject of degradation modelling in this thesis.

For the other components in the model, the expected life will be based on life-time modelling and historical data for similar components. The historical data utilized are from the OREDA handbooks, which are commonly used in the Norwegian oil and gas industry.

Chapter 3

Maintenance Strategies

Maintenance has proven to be an essential aspect for a manufacturer when wanting to increase profitability. Production costs can be decreased, stability in production can be increased, and the sustainability of the business can be increased. These are some of the benefits implementation of the right maintenance strategy can produce. In this chapter, maintenance will be defined, and possible maintenance strategies for the subsea pump system will be presented.

3.1 Definition of Maintenance

Maintenance is defined in different ways in the literature, but there is a consensus on the interpretation of the word. Table 3.1 present the definitions from two relevant maintenance standards.

Table 3.1: Maintenance definitions

Standard	Definition
NS-EN13306 (2018)	Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function.
IEC 60050-192 (2015)	Combination of all technical and management actions intended to retain an item in, or restore it to, a state in which it can perform as required.

The definitions are similar, and they can be interpreted as having the same meaning. To better understand the word maintenance based on these definitions, it should be defined what is meant by *"performing as required"* and *"perform the required function"*. It is defined in the same two standards and can be expressed as the combination of some functions of an item that are necessary to fulfil some given requirement. For the generic subsea pump system, this requirement would be to move some amount of fluids every second and the function, how it does it, will be to increase the fluid's velocity.

The act of maintenance for the pump is therefor some actions performed to maintain its ability to deliver a given amount of fluids from point A to B by increasing its velocity.

3.1.1 Maintenance Strategy

Maintenance strategy is not defined or described in IEC 60050-192 (2015), but it is in NS-EN13306 (2018). It is defined as, *"Management method used to achieve the maintenance objectives"*. This can be interpreted as how the operator chose to perform maintenance actions based on the requirements of the maintained system. This is how it will be defined for further use in this thesis. As NS-EN13306 (2018) has definitions for all the strategies discussed and is more recently updated, it will be used for the rest of this chapter as a guideline.

In NS-EN13306 (2018) it is also stated that a decision maker should define their maintenance strategy according to the following four objectives:

1. *"to ensure the availability of the item to function as required, at optimum cost;*
2. *to consider the safety, the persons, the environment and any other mandatory requirements associated with the item;*
3. *to consider any impact on the environment;*
4. *to uphold the durability of the item and/or the quality of the product or service provided considering cost."*

All these objectives point to important aspects of subsea operations. Costs and quality of operations are essential for the industry to be profitable, and the safety and environmental aspect is equally important to be allowed to develop the industry.

3.2 Maintenance Effectiveness

By maintenance effectiveness, the understanding is to what degree maintenance is performed. It is a classification that describes what state the system or component is in after the maintenance has been performed. Pham and Wang (1996) present a five class overview of maintenance effectiveness:

- **Perfect repair or perfect maintenance:** the system or component is brought back to a state where it is *As Good As New* (AGAN), it is equally as good as when it first started. The failure rate and life-time distribution are the same as that of a new system or component.

- **Minimal repair or minimal maintenance:** the system or component is brought back to a state where it is *As Bad As Old* (ABAO), it is in the equal state to what it was right before it failed and the failure rate and life-time distribution is the same as that of an almost failed system or component.

- **Imperfect repair or imperfect maintenance:** the system or component is brought back to a state where it is in a state between AGAN and ABAO.

- **Worse repair or worse maintenance:** the system or component is brought to a state where the performance is worse than that of a failed one, but it is not in a failed state. The failure rate is often worse than that of a normal system or component, but it is functioning.

- **Worst repair or worst maintenance:** The system or component un-deliberately fail due to the maintenance action.

Imperfect, worse and worst maintenance or repair is often not performed deliberately but is a consequence of something not going according to plan in the intervention.

3.3 Maintenance Strategies

3.3.1 Corrective Maintenance

In Standard-NS-EN13306 (2018) corrective maintenance is defined *"Maintenance carried out after fault recognition and intended to restore an item into a state in which it can perform a required function."* Corrective maintenance is an unscheduled maintenance action to bring the system back to an operational state after the discovery of an unforeseen failure (Rausand and Høyland, 2004).
The corrective maintenance process can be summed up by the following five steps:

1. Discovery of the failure
2. Localization of the failure, trace it to a specific equipment/part in the system
3. Diagnosis of equipment to locate failed component
4. Replace or repair failed component
5. Investigating and testing that the system is back in an operating state

When a failure occurs, some action has to be done to restore the system to an operational state, and this is step four in the process. Too what operational state is determined by what corrective maintenance effectiveness is implemented, if the failed component is replaced the system will often be determined to be as good as new (AGAN) or the component can be repaired to some state where the system is determined to be ABAO. Lastly, the corrective maintenance can be performed by switching to a redundant component (Dhillon, 2002).

Some literature also differentiates between corrective maintenance and breakdown maintenance, but for this thesis, it is not relevant as corrective maintenance is defined as is.

3.3.2 Preventive Maintenance

Preventive maintenance (PM) is defined by Standard-NS-EN13306 (2018) as *"Maintenance carried out intended to asses and/or to mitigate degradation and reduce the probability of failure of an item"*. It is planned actions performed when the system is operating properly to prevent future failures and/or reduce the probability of a future failure. It is often performed regularly regardless of the system's condition. If a failure occurs prior to the PM, the system is restored to a functioning state, and the PM strategy is continued as if there had been no failure (Rausand and Høyland, 2004).

Preventive maintenance can be divided into the following sub-strategies:

Clock-based Maintenance

Clock-based maintenance is maintenance performed based on predetermined calendar dates regardless of the state of the machinery. If a component failed and was replaced or repaired a short time prior to the scheduled maintenance it will still be replaced/repaired on the predetermined date. In short, the maintenance program is followed regardless of the state of the components of the system. This makes it a strategy that is easily planned, as the dates are usually determined long in advanced (Rausand and Høyland, 2004).

In figure 3.1 below t_c refers to the preventive maintenance time interval and T is a failure time. Figure 3.1 shows a typical clock-based maintenance programs timeline.

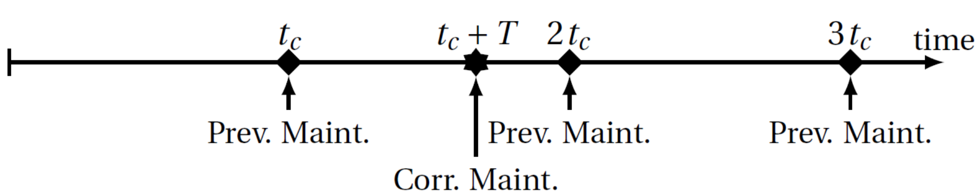


Figure 3.1: Clock-based maintenance timeline (Barros, 2018)

Age-based Maintenance

Age-based maintenance (AbM) is maintenance performed after a predetermined time interval or cycles of operations. This means it takes into consideration if an unexpected failure occurred, the lifetime of the new operating component will be fully utilized. It makes this strategy more efficient in terms of components, but less effective in terms of planning as the maintenance plan get shifted after a failure (Rausand and Høyland, 2004).

In Standard-NS-EN13306 (2018) predetermined maintenance is defined as *"Preventive maintenance carried out in according with established intervals of time or number of units of use but without previous condition investigation."*. This definition is similar and can be interpreted as the same as the age-based maintenance.

In figure 3.2 below t_a refers to the preventive maintenance time interval and T is a failure time. This figure demonstrates how a typical clock-based maintenance programs timeline would look like.

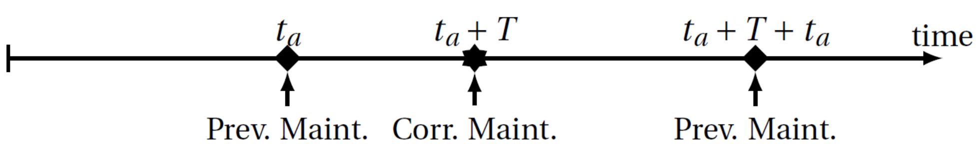


Figure 3.2: Age-based maintenance timeline (Barros, 2018)

Opportunity Maintenance

Opportunity maintenance is applicable for multi-unit systems, where the maintenance of one unit opens for the possibility to maintain other components that were not the cause of the failure. This is typically done when the cost of downtime is high, and the maintenance requires shutdown of the system (Rausand and Høyland, 2004).

Failure-finding Maintenance

Failure-finding maintenance is maintenance performed on a system to discover hidden failures. It is performed by doing testing or operational checks on the system, and it is considered preventive even though the failures have already occurred. This is because the failures are hidden and are not required to operate continuously and are therefore not discovered during normal operations. This type of maintenance is often performed on safety systems. A fire alarm test is a typical example of such a maintenance strategy (Rausand and Høyland, 2004).

Condition-based Maintenance

Condition-based maintenance (CbM) is defined in standard NS-EN13306 (2018) as *"Preventive maintenance which include assessment of physical conditions, analysis and the possible ensuing maintenance actions."*. It is defined as a sub-strategy of preventive maintenance where the condition of the system is considered when deciding on performing a maintenance intervention.

To do condition-based maintenance a condition monitoring (CM) system has to be implemented. A CbM system consists of a CM system that again consists of measuring (sensors), measurement acquisition, storage of these data and viewing of the data/measures.

The CbM system then views the data and do calculations of pre-determined key performance indicators (KPI) for the system under study. Lastly, these KPIs are used to perform prognosis on the future health of the system, often in terms of *remaining useful life* (RUL) (Eriksson and Antonakopoulos, 2014).

Figure 3.3 illustrates the building blocks of condition-based maintenance and condition monitoring.

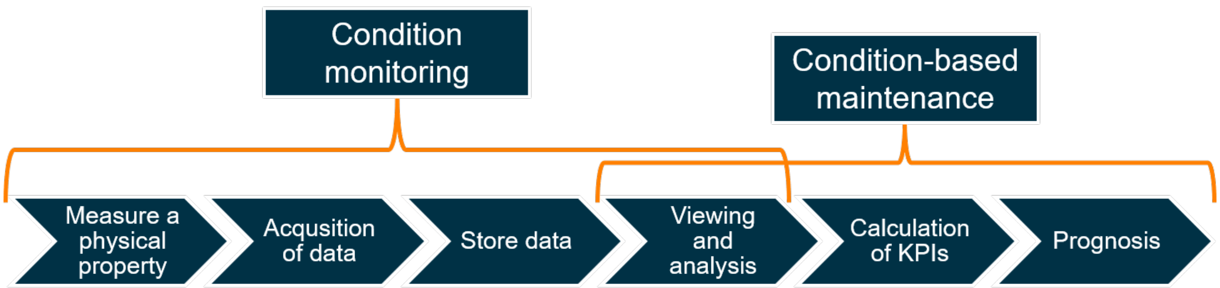


Figure 3.3: Condition-based maintenance and condition monitoring

Predictive Maintenance

Predictive maintenance (PrM) is a sub-maintenance strategy of condition-based maintenance as it utilizes condition data to optimize the best point in time of intervention (Schmidt and Wang, 2018). In Standard-NS-EN13306 (2018) it is defined as: *"Condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item"*.

Figure 3.4 shows the relationship between predictive maintenance and the other maintenance strategies.

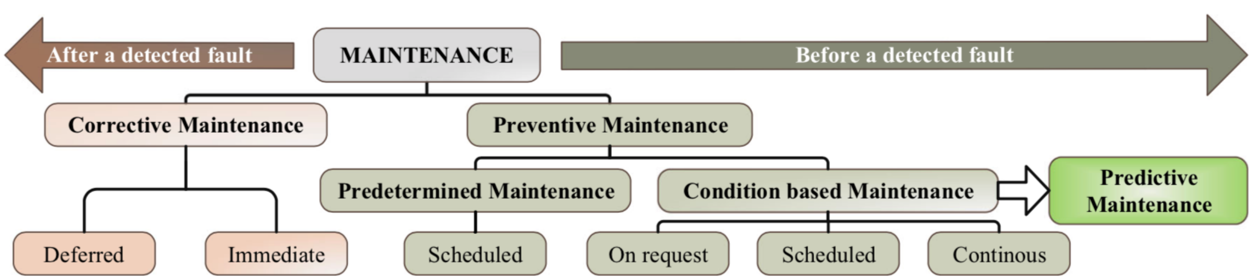


Figure 3.4: Classification of maintenance strategies including PrM (Schmidt and Wang, 2018)

To perform proper PrM a sufficient amount of reliable operational data on the state of the system must be provided. As technology has advanced the ability to collect such data has grown, making operators able to monitor the state of their systems continuously (Selcuk, 2017).

Condition Monitoring

Standard-NS-EN13306 (2018) defines condition monitoring as an *"Activity either manually or automatically, intended to measure at predetermined intervals the characteristics and parameters of the physical actual state of an item"*. It can be interpreted as the collection of information regarding the condition or state of a system. This information can be found either by operators inspections or sensors. As the technology is evolving and sensors are getting smaller and better, it is possible to perform continuous condition monitoring of a system and its components.

Condition monitoring for subsea equipment is still considered a novice technology in the O&G industry. It is already well implemented and used in the aerospace and railroad industry. Comparisons and lessons learned can be taken from these industries to help further develop the use in the O&G industry (Friedemann et al., 2008).

3.3.3 Ideal Maintenance

Ideal maintenance should also be mentioned as this is the optimal situation of when to perform maintenance. It is to perform preventive maintenance at an infinitesimal time before a failure occurs (Barros, 2018). Graphically it is presented in figure 3.5 below, where T_n refers to the nth failure time and Δt is this infinite decimal number ($\Delta t \rightarrow 0$).

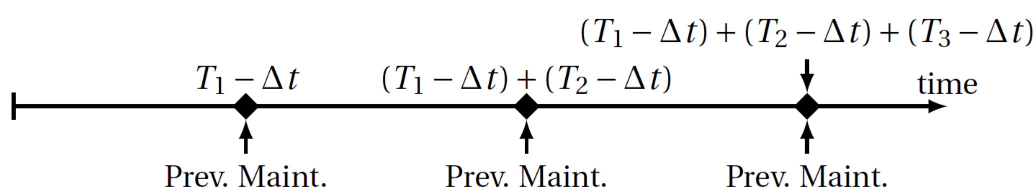


Figure 3.5: Age-based maintenance timeline (Barros, 2018)

Chapter 4

State of the Art of Subsea Maintenance

In the specialization project written prior to this master thesis an implementation of CbM for subsea pump systems was argued to prove beneficial (Aspen, 2018). In this chapter, the state of the art of CbM for subsea pump systems and subsea equipment, in general, will be discussed. Further on challenges related to subsea maintenance will be presented as well as the future of maintenance subsea. This chapter is a literature review on the current status of subsea maintenance and how the topic is evolving to understand better the needs and ambition the industry have with the implementation of CbM for subsea equipment.

4.1 Evolution to Condition-based Maintenance Subsea

From the first oil and gas production equipment was deployed subsea in the nineties, the complexity and monitoring of such systems have increased. Moving from simple systems with few valves and sensors to complex subsea processing systems with redundant sensors and analyzing tools (Friedemann et al., 2008). The increase in sensors leads to more data and information being available, which again can increase the benefits of condition and performing monitoring (CPM) systems (Hernæs and Aas, 2015), but condition monitoring subsea is a fairly novice technology and needs to evolve further to increase the availability of reliable data (Vaidya, 2010).

Production monitoring has been the focus of subsea operators from the beginning. In recent years the development towards diagnostics of machinery either based on monitoring of the status of components or based on calculations from operational data, have gotten an increased focus. Operators no longer only care about the status of production, but they are also interested in minimizing the need for maintenance, due to its high cost. By investigating the condition of the equipment itself, the need for maintenance can be reduced (Soosaipillai et al., 2013).

As technology is developing further, the sensors used for CM are getting smarter and better. The information technology and connection between sensors and the CM system is getting more reliable and faster. This makes the remote collection of condition monitoring data less costly as well as improving the diagnostic and prognostic results of the data (Zhu et al., 2015).

Harsher climates and greater depths have lead to an increased demand for high-reliability subsea systems (Markeset et al., 2013). As this decrease the need for interventions that are costly due to the need for specialized vessels and machinery. Due to this higher costs of interventions in deeper waters, the maintenance philosophy is decided in the design phase for subsea systems. Then contracts and long time plans for maintenance can be signed, and the economic aspect can be evaluated before production starts. The maintenance strategy is then decided in the front end engineering design (FEED) phase of the project (Markeset et al., 2013).

As more than 50 subsea pumps have been deployed anno 2014 (Eriksson and Antonakopoulos, 2014), a maintenance strategy that optimizes the new technology of more sensors and monitoring is the future of the industry.

4.2 Current Inspection, Maintenance and Repair of Subsea Pump Systems

Inspection, maintenance and repair (IMR) operations are considered very costly for subsea equipment. This is due to the need for specialized vessels and remotely operated vehicle (ROV) systems, and also due to the loss of production (Schjølberg et al., 2016). Because of this, operators want to keep downtime to a minimum to increase the profitability of their fields.

The commonly used operating time of a subsea pump system in the industry today is expected to be 5-10 years without any intervention Eriksson and Antonakopoulos (2014).

4.2.1 Subsea Inspection

As most subsea equipment is placed in water too deep for human divers, ROVs are more commonly used for inspection (Moreno-Trejo and Markeset, 2012) as well as for smaller interventions with simple tooling (Markeset et al., 2013).

Subsea visual inspections are performed to detect visible failures or failure development and verify the physical state of the equipment. During inspections, abnormal environmental conditions that affect the system can also be discovered. Abnormalities discovered by ROV inspections are usually external, but they can also detect sound and identify internal problems. Internal failure propagation is more relevant for pumps as they are vibrating machinery where failures occur within the system (Moreno-Trejo and Markeset, 2012).

The cost of ROV inspections and interventions are high due to the travel time (Schjølberg et al., 2016) and due to the need for specialized operators and tooling (Markeset et al., 2013).

The costs related to ROVs use have increased in recent years and are predicted to get higher in the future (Mai et al., 2017).

4.2.2 Subsea Maintenance Strategies

Subsea interventions require the use of specialized vessels and equipment. These are usually not owned by the operator of a field, and are services are often rented and is needed to be planned. Because of the costs associated with intervention and downtime, contracts with service companies are made in the design phase together with the decision on the maintenance strategy of the field development (Moreno-Trejo and Markeset, 2012).

There are two widely used maintenance strategies for subsea pump systems in the industry. Both of these maintenance strategies consist of having spare pump systems onshore and replacing these with the currently operational equipment on demand.

The demand for a replacement is commonly decided either by a corrective or age-based preventive maintenance policy. The corrective maintenance is performed either after an unexpected failure or by sufficient monitored fatigue on the system. This makes it a semi-CbM strategy, but mainly with a policy of changing when a failure occurs.

The age-based preventive maintenance interval is set to five years, and then the pump is retrieved and changed with the spare before maintenance is performed on the pump.

As these two strategies have developed, spare modules of sub-units in the system are also being made and kept in inventory, to reduce the repair time of the pump system. In the case of a motor failure, a motor module is also ready and can be put into the failed pump system, to shorten the repair time of the pump system by several months.

For subsea pumps, the change to the spare module can be performed in 48 hours if all vessels and tools are available. To make sure everything is available, the operators require one month of planning. This means that unforeseen failures usually lead to a one-month downtime of operations (Eriksson and Antonakopoulos, 2014).

4.2.3 Opportunistic Maintenance

Opportunistic maintenance is utilized in the industry, often in the form of modularization of several components. When one component in a module fails or is monitored to be sufficiently fatigued, the whole module is retrieved and replaced. Often the module is replaced right away by a spare module. In practice this is what is done on subsea pumps as well, if something goes wrong the whole unit is removed and replaced by a spare pump system (Soosaipillai et al., 2013).

4.2.4 Condition Monitoring

Condition monitoring subsea is done with sensors connected to parts of the system. It can either be direct by a reading of the condition of some components, e.g. a tear, or indirectly by calculating the state of a component based on other factors, e.g. temperature, power consumption, environment. Indirect condition monitoring and calculations based on empirical models are

the most common ways to utilize CM for CbM of subsea pumps (Eriksson and Antonakopoulos, 2014).
Typical parameters for CM in subsea pumps are:

- **Dynamic:** monitor how the machinery is vibrating out of its normal bounds. This is relevant for pumps as an increase in vibrations can be due to loose components inside the system that may lead to failures.

- **Particle analysis,** or ferrography is to look for sediments of machinery in the fluids going through the system. This is very relevant for centrifugal pumps as cavitation can occur, and the material loss can be analyzed.

- **Crack detection:** can be essential to look at for piping or other components where leakage or pressure drops can become an issue.

- **Temperature monitoring:** increased temperatures is an energy loss and can serve as an indicator for a developing failure in the system.

- **Electrical monitoring** is often used to investigate the state of electrical components or electric consumption. As increased electrical consumption could be an indication of a failure in the system.

- **Abrasion monitoring** is monitoring of degradation of components that are exposed to abrasion. Abrasion is short for hydro-abrasive wear, which means deterioration due to particles in the fluid. For a pump sand particles in the production fluid is considered a common challenge.

(Kaboli and Hashem (2016), Akula et al. (2017) and Levitt (2011))

4.2.5 Condition-based Maintenance

Condition-based maintenance is the utilization of the data collected from CM, as explained in chapter 3. From the literature, some examples of CbM implementation for subsea equipment is found. When it is used, it is often used by the implementation of a CPM system.

A CPM system is a monitoring system that has historical data, CM of components health and the performance of the system as input. Based on these parameters, the CPM investigates trends and find deviations in operations. It then uses this to propose maintenance and interventions. Experts then discuss and analyze the output from the CPM system and make decisions (Soosaipillai et al., 2013).

The CPM system takes a holistic approach as it considers the system's health, equipment's health, system's performance and its environment (Skytte af Sätra et al. (2011) and Hernæs and

Aas (2015)) and uses this information to find the overall performance and technical health of the monitored system.

In the CPM several KPIs are predetermined and can then be used to do prognostics and calculate the RUL of components and equipment. This prognostic is not performed by the CPM itself, but by experts and operators (Skytte af Sätra et al., 2011).

Requirements for the KPIs are that they need to be measurable, have a degradation limit (alarm bound) and a prediction of the degradation. The prediction of degradation is commonly for subsea pumps one month as this is the time it takes to plan an intervention with the lowest amount of downtime (Eriksson and Antonakopoulos, 2014).

Instead of using KPIs to assess the state of a component Vaidya (2010) argues assessing the technical health based on the technical condition, operational history and the design quality of a component. This is a more data-driven approach than KPIs as these are often discussed and decided by experts.

4.3 Theoretical Studies of Subsea Maintenance

Prior to the implementation of CbM for subsea equipment, several studies have been done to show its possible benefits. Studies have shown that CM implemented on component level increased availability and reduced the costs (Moreno-Trejo and Markeset, 2012). This is also argued to be expandable to systems by Serene and Chze (2015). Zhu et al. (2015) argues against that component CM can easily be expanded to a whole system, as economic dependencies of components must be taken into consideration. Because of this, a static joint maintenance interval should be determined and implemented. This is a shared optimized time interval for maintenance on the whole system for all components.

Serene and Chze (2015) also argues that an effective CM will increase detection and decrease the need for maintenance and that one of the ways to improve the effectiveness of a CM system is to specify the type and amount of data collected.

Eriksson and Antonakopoulos (2014) compares a corrective, preventive and a CbM maintenance strategy for subsea processing systems. Predictions in the CbM is based on some CM of components, but also on calculations based on operational data. As an example bearing life can be predicted based on the power usage of the system.

The calculations of the profitability of the three different maintenance strategies are simplified but show that a CbM strategy is more profitable than the two others. It is a simplified argument, but should still be mentioned as it shows the need for more research and testing of this strategy and logically it makes sense to intervene on a system based on its state rather than on some pre-determined time limit or after a failure. The increase in the utilization of components life and an increase in planned maintenance that reduce the downtime will increase the profitability of the operations.

Markeset et al. (2013) also argues that if a CM system is implemented and an operator can assume that the subsea system will fail in the near future preventive maintenance would be cheaper than running to failure.

4.4 Challenges of Subsea Maintenance

One of the challenges for service companies, like AKSO, is access to sufficient reliable operational data. As the energy companies usually are responsible for their operations, they also collect and analyze operational data them self. Most data on subsea equipment made in the industry is therefore based on the service companies own testing data collected prior to deployment.

Catastrophic and/or unforeseen failures are part of the aspect in failures of all systems. These types of failures often have no monitorable warning or degradation before failure, and they happen without warning. As CM is reliant on monitorable degradation occurring gradually over time, such failures are not possible to model with today's technology and maintenance strategies (Eriksson, 2010).

Another part of the failures that are not possible to model are failures in the initial phase of operations. These types of failures are known as *infant mortality*. They are often undiscovered failures that happened during deployment of equipment or due to faulty production (Rausand and Høyland, 2004).

Modularization is mentioned as a measure to increase the maintainability, but it also can be challenging to know when too much modularization will decrease the availability of the system. As smaller modules increase the maintainability of the system it also increases the number of connectors (e.g. process, power and control components) in the system, as all the modules need to be connected. As more components are added the reliability of the system decrease, as neither of the extremes, very big or small modules, are optimal something in between must be used to maximize the availability (Lima et al., 2011).

To makes sense of and fully utilize all collected data, and to use this data for prognostics is one of the challenges today. A lot of the data collected is collected for possible future use. To then use the prognostic modelling to perform just-in-time maintenance for the subsea systems is what has to be solved in the industry (Eriksson and Antonakopoulos, 2014). To have this process autonomous would also significantly improve the industries profitability as a lot of CM is done by sensors and analyzed by experts rather than an autonomous CM and PrM system.

New technology has been discussed as an important aspect of CbM implementation, but it also serves as a future challenge for subsea operations. As new sensors and measuring tools will be available the benefits of implementing this more modern technology could be great. The problem occurs when the system needs to be recovered, or intervention needs to take place to implement the new components. Operators must discuss if the added value of new technology is greater than the loss of operation time (Soosaipillai et al., 2013).

The practice of today can also be outdated in the future, as the lifetime of the subsea systems often is 30-50 years, routines and practices will most likely change. To have this mind, when planning and developing a long life system can make the system more dynamic to change.

As subsea pumps only have been used for the last decades, it is still considered a fairly novice technology and the availability of operational data is limited (Vaidya, 2010). Stipulated data must be used as no operational data for 50 years exists. Statistical modelling together with stipulated data (from e.g. OREDA) is used for RAM analysis (Hernæs and Aas, 2015).

4.5 Future of Subsea Maintenance

The subsea technology is evolving and will develop further in the years to come. Some of the emerging technologies that will impact the industry are being researched and talked about today.

One of these is the use of autonomous underwater vehicles (AUVs). There is a considerable research effort going on today to make this a viable solution for small interventions and inspections in the future.

AUVs will significantly reduce the time and cost related to such interventions as the vehicles could be stationed subsea and do routine check-ups and maintenance without operators action required (Schjølberg and Utne, 2015).

Improvements of CbM systems are being researched, both in the form of improved sensors, but also to make them autonomous and have less need for experts input.

Lastly, the reliability of components increase as the technology of machinery gets better. This will probably increase the reliability of subsea systems in the future.

4.6 Concluding Remarks

Maintenance strategies for subsea pumps are based on a run-to-failure approach or usually on a 5-year run-period before it is replaced by a spare.

Subsea equipment is often deployed in deep waters with a harsh and challenging environment. Because of this, operators want to minimize interventions on subsea equipment as they are expensive and if not planned lead to long periods without production.

Technology is evolving and more sensors and ways to measure parameters on a subsea system increase, which gives operators a better understanding of the condition of their equipment. A KPI measure for different parts of the system is often decided based on expert judgements.

The systems often have a holistic approach, and this means that several components measures are compared and evaluated together when decisions on intervention is made. These are then discussed when reaching some limit and interventions are initiated.

The CPM or today's CM systems have a diagnostic approach, they analyse the current state of equipment and components, and expert judgement is used to make maintenance decisions. A prognostic approach is not properly implemented in any subsea systems based on the literature reviewed.

Chapter 5

Maintenance Modeling and Optimization

Maintenance modelling and optimization require a lot of inputs both for the system and its operational profile. In this chapter, the essential inputs and possible approaches and methods to maintenance modelling and optimization for the thesis' problem are assessed.

5.1 Maintenance Optimization Framework

Van Horenbeek et al. (2010) present a methodology for optimization and maintenance modelling. Their approach is based on an extensive literature review of the subject. It gives an overview of all that can be done with maintenance modelling optimization. Figure 5.1 present the different inputs required to build a model. The most relevant parts of the methodology will be further discussed in this chapter.

The framework shows all the possible building blocks that may be required or utilized when choosing the right maintenance optimization method. It is made with the industry in mind so that it can be tailored for specific business cases.

By presenting already tested and well-documented methods, the user can be confident in the methodology chosen as a result of using this framework. Solutions provided by academia are often specific for the problem solved; this makes their methods challenging to reproduce for practical problems of the industry.

The framework is meant as a starting point for further development for a company and does not claim to be the only solution to finding the right maintenance method.

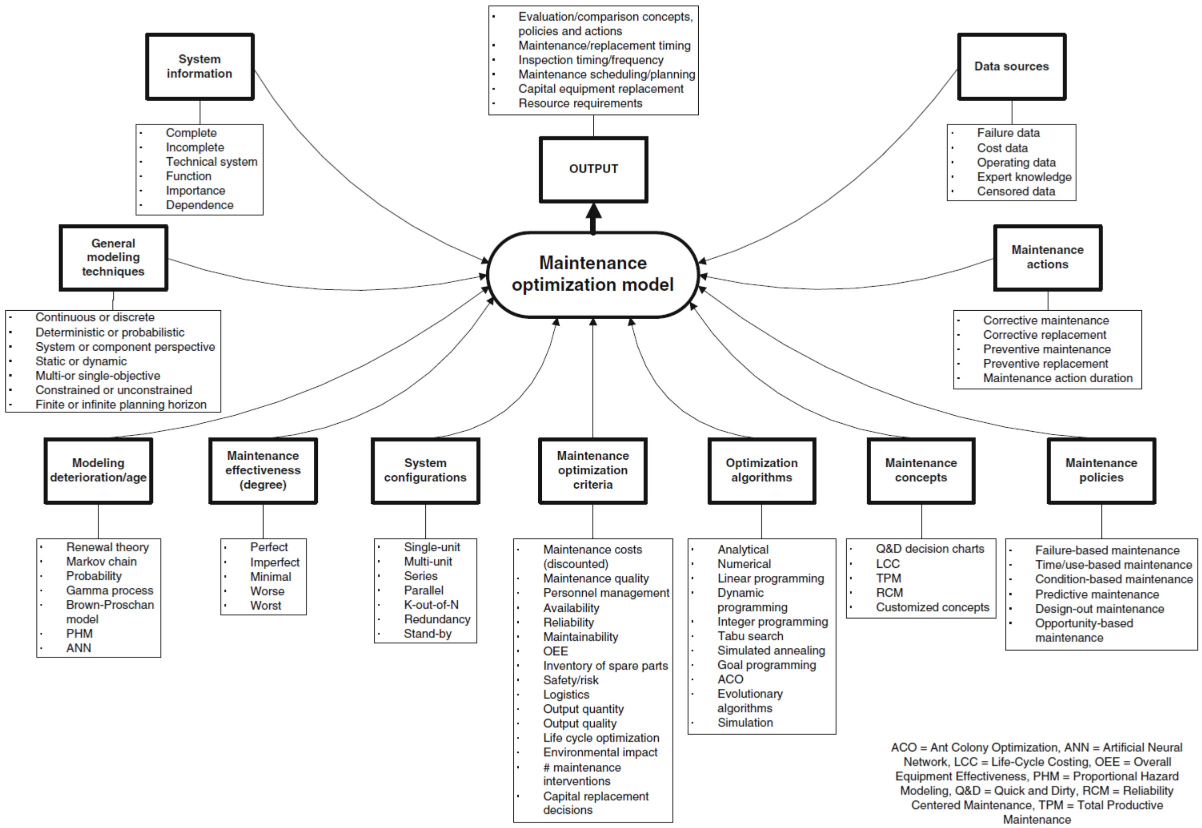


Figure 5.1: Maintenance optimization classification framework (Van Horenbeek et al., 2010)

5.2 Maintenance Modeling Optimization Criteria

To perform a maintenance optimization process there need to be parameters to optimize. These parameters in maintenance modelling are referred to as the maintenance criteria. In the literature, several criteria are presented such as cost, availability, safety, reliability, etc., but commonly these can be translated to a cost criterion (Barros, 2018).

Van Horenbeek et al. (2010), on the other hand, argues that the cost and availability criteria are too widely used, and that other criteria should be assessed. The choice of criterion should be more specific for each business case. They present a prioritization list of criteria based on what business case is being modelled. Table 5.1 shows the generic maintenance optimization criteria. Here they are presented with an associated KPI and optimizing the correct criterion is an essential part of maintenance optimization, and choosing the wrong one will lead to a suboptimal solution.

Table 5.1: Generic maintenance optimization criteria

Generic list of optimization criteria	
Maintenance costs (discounted)	Availability
Maintenance quality	Reliability
Personnel management	Maintainability
Inventory of spare parts	Environmental impact
Overall equipment effectiveness	Safety/risk
Number of maintenance interventions	Logistics
Capital replacement decisions	Output quantity
Life-cycle optimization	Output quality

5.3 Maintenance Optimization Methods

Maintenance optimization methods are chosen when all information about the problem is gathered. In the literature, several optimization methods are presented and Barros (2018) classify these into three main categories:

Exact methods: methods where all information about the different aspects of the optimization is known and is based on an analytical or an algorithmic resolution. It is therefore commonly applied to small-sized problems, and specific for maintenance when the mean of the optimization criterion is known.

Heuristics methods: methods where the optimization problem can be simplified by reducing the number of outcomes. Hence, fewer outcomes are investigated to find the optimal result, and it is therefore only applicable to specific problems.

Metaheuristics: are more of a set of concepts rather than a method. These concepts are adapted to work for different problems with few alterations.

Common for the heuristic and metaheuristic is that they are applied when the optimization has a certain amount of complexity, then the exact methods are not applicable.

5.4 Maintenance Modeling Methods

Maintenance modelling is to investigate the different maintenance actions on a system. There are several approaches to maintenance modelling, but mainly, they are categories into scenario-based, and state-transition approaches (Barros, 2018).

Cui (2008) present the ten most dominating factors when modelling maintenance. These are shown in the list below:

- Maintenance strategy
- System structure
- Maintenance degree
- Optimization criteria
- Distribution of components
- Shut-off rule (How many components must fail before a shut-down)
- System information (the type of inspection)
- Model types (discrete or continuous)
- Maintenance action distribution
- Other assumptions: independencies or dependencies

In the rest of this section, the generic methods, scenario-based and state-transition approaches will be presented and exemplified by two approaches to these methods, Monte Carlo simulations and Markovian method.

5.4.1 Scenario-based Approach

The scenario-based approach or method for maintenance modelling is performed by describing all the possible sequences of events that may occur during the study's time frame. The time frame is often a predetermined renewal interval of a component or a system. The challenge with doing this is the need to list all possible sequences of events, as well as its scalability.

The assessment method for a maintenance strategy can be analytical, with numerical calculations of integrals, or it can be done with discrete-event or Monte Carlo simulations (MCS), which is further elaborated in the next section.

Monte Carlo Simulation

The Monte Carlo simulation method is a scenario-based modelling approach, which is a statistical technique used to model stochastic (or probabilistic) systems and to predict the likelihood of outcomes.

By stochastic, it means that the parameters used are not deterministic. They have some randomized value, often decided by a PDF, and specific for MCS, these values change for every simulation. Then every process may be different due to stochastic parameters that change at some rate as time goes by or has some PDF around a mean outcome.

As the parameters on natural processes often are very complex when presented deterministic, an MCS can take a less complex process and assign stochastic parameters instead. Then a large number of simulations can be done to say something about how the process will develop over time.

MCS is performed by a number of simulations, for each simulation, a random number is generated, based on some PDF, for a component. This number is then stored, and the process is repeated thousands or even millions of times. After the MCS is completed, there is a large number of results from the simulations stored. These can then be used to say something about the probability of reaching some values when using the model. This result then has uncertainties or a statistical error as it is stochastic.

Limitations of MCSs are determined by the uncertainty in the numbers used and in the numbers generated. As every MCS will give different results, there is some uncertainty, and this can be reduced by increasing the number of simulations done in the MCS (Rubinstein and Kroese, 2016).

Figure 5.2 better illustrates the Monte Carlo simulation algorithm by a flow chart.

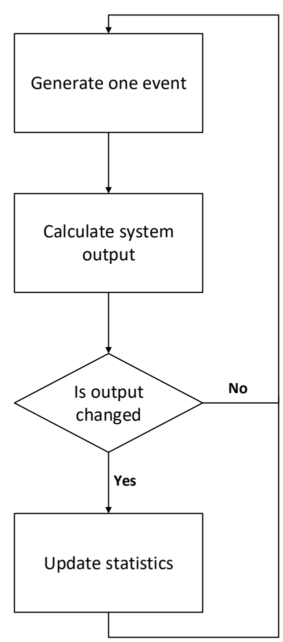


Figure 5.2: Main loop of MCS algorithm (Lei and Huang, 2017)

5.4.2 State-transition Approach

The state-transition approach for maintenance modelling is performed by describing the relevant system states and all transitions between these states. This is often built on a Markov process, as the Markov property makes the next state only dependant on the current state of the system. This makes the need for a complete knowledge of the systems life irrelevant. The assessment of the method can be done analytical or by simulations, just as the scenario-based. In the next section, the Markovian method is further discussed.

Markovian Method

The Markovian method is a stochastic process used in the state-transition approach of maintenance modelling. It is used to model the state-transitions of a system that can be in more than one state. The Markovian methods or Markov chains can be sorted into two types, discrete- or continuous-time. Continuous-time is most commonly used and will be discussed further. A continuous-time Markov chain is also known as a Markov process. The process possesses the *Markov property*, which means that the next state-transition of the process is only dependent on its current state. The future of the component is independent of its past and exclusively dependent on its present state (Rausand and Høyland, 2004).

Transition Rate Matrix and State Equation

A Markov process with continuous-time and finite state space size, N, is defined by the transition rates $A(i,j)$ from state i to j. The transition rates between each state are stored in matrix $\mathbb{A}$, which is known as the *transition rate matrix*.

$$\mathbb{A} = \begin{bmatrix} a_{00} & a_{01} & \dots & a_{0r} \\ a_{10} & a_{11} & \dots & a_{1r} \\ \vdots & \vdots & \ddots & \vdots \\ a_{r0} & a_{r1} & \dots & a_{rr} \end{bmatrix} \tag{5.1}$$

The probability for the process to be in state j at time t, given that it is in state i at time 0 is denoted $P_{ij}(t)$ and often simplified to $P_j(t)$. These probabilities are then arranged in a matrix for calculations, where the sum of every row is equal to 1, as the sum of all probabilities are 1.

$$\boldsymbol{P}(t) = \begin{bmatrix} P_0(t), & \dots & P_r(t) \end{bmatrix} \tag{5.2}$$

$$\boldsymbol{P}(t) \cdot \mathbb{A} = \dot{\boldsymbol{P}}(t) \tag{5.3}$$

$$\begin{bmatrix} P_0(t), & \dots & P_r(t) \end{bmatrix} \cdot \begin{bmatrix} a_{00} & a_{01} & \dots & a_{0r} \\ a_{10} & a_{11} & \dots & a_{1r} \\ \vdots & \vdots & \ddots & \vdots \\ a_{r0} & a_{r1} & \dots & a_{rr} \end{bmatrix} = \begin{bmatrix} \dot{P}_0(t), & \dots & \dot{P}_r(t) \end{bmatrix} \tag{5.4}$$

The state equation, formula 5.3, for the Markov process is an ordinary differential equation used to calculate the state probabilities.

State Transition Diagram

Markov processes are often illustrated by a node-graph called a *State transition diagram*. Here each node represents a state, and its connections are the transition rates between the states. The diagram is made by listing all possible system states and merging the same ones to make all nodes unique.

Figure 5.3 shows an example of a state transition diagram for a three-state Markov process. It illustrates a repairable system of two identical components in a parallel structure, with a *failure rate*, λ, and a *repair rate*, μ.

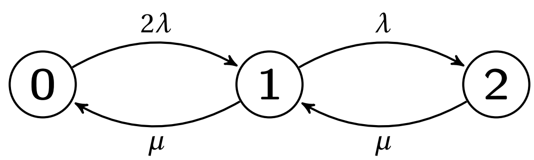


Figure 5.3: State transition diagram of two-component parallel structure

Steady-state Probabilities

To investigate the systems state probabilities in the long run, one can calculate the *steady-state probabilities*, these are the value of $P_j(t)$ when $t \to \infty$. Then the Markov process is said to be *irreducible* if a all states can be reached from every other state, then the time-derivative of $P_j(t)$, $\dot{P}_j(t)$ is equal to 0 and the state probabilities can be found by $P_j(t)$ satisfying the equation, 5.5.

$$\begin{bmatrix} P_0(t), & \dots & P_r(t) \end{bmatrix} \cdot \begin{bmatrix} a_{00} & a_{01} & \dots & a_{0r} \\ a_{10} & a_{11} & \dots & a_{1r} \\ \vdots & \vdots & \ddots & \vdots \\ a_{r0} & a_{r1} & \dots & a_{rr} \end{bmatrix} = \begin{bmatrix} 0, & \dots & 0 \end{bmatrix} \tag{5.5}$$

Multi-phase Markov Process

The multi-phase Markov process can be used to model systems where the state transition rates change over time. If these times are denoted $T_0 = 0, T_1, T_2, ..., T_n$, the time denoted between T_{i-1} and T_i, the system follow a homogeneous Markov process with a homogeneous transition matrix A_i. The probability of the process at time T_1 can then be calculated by formula 5.6.

$$\mu_{T_1} = \mu_0 \exp T_1 A_1 \tag{5.6}$$

Between T_1 and T_2 the process evolves with transition matrix A_2 with the initial law μ_{T_1} and the probability law of the process at time T_2 is then given by equation 5.7

$$\mu_{T_2} = \mu_{T_1} \exp(T_1 - T_2) = \mu_0 \exp T_1 A_1 \exp(T_1 - T_2) \tag{5.7}$$

This makes it possible to model more complex problems with the Markovian method. Interventions or other environmental aspects can affect the system, and this is now possible to model (Barros, 2018).

5.4.3 Maintenance Modeling Approach

The maintenance modelling approach is used when moving away from analytical modelling due to an increase in complexity and wanting to have fewer assumptions tied to the calculations, and the use of simulations opens for this (Alrabghi and Tiwari, 2016).

Alrabghi and Tiwari (2016) presents an approach on how to do maintenance modelling specific for different maintenance strategies on complex systems. Their approach is based on discrete-event simulation methods and is argued to integrate complex behaviours better and require fewer assumptions than analytical modelling methods.

Their approach to CbM is based on CbM with a periodic inspection. The system under study in this thesis is assumed to be under continuous condition monitoring, and the aspect of optimization of inspection intervals is therefore not relevant. The approach is well described and can still be utilized without the periodic inspections aspect.

Time-based Preventive Maintenance

Time-based preventive maintenance (TbPM) is defined by Alrabghi and Tiwari (2016) as age- and clock-based maintenance, which has been presented in chapter 3.4. As shown below TbPM is a combination of the two strategies rather than a subgroup of TbPM.

Their approach to model TbPM is a two-step process illustrated in 5.4 and is summarized as follows:

1. **Develop the simulation model**
   CrM and PM strategies and their variables are defined for all components, as well as reliability parameters (e.g. lifetime distribution) of components. As unexpected failures can occur before the renewal interval, CrM has to be defined. Variables for CrM includes repair times, costs, etc. and for PM renewal interval, repair times and costs.

2. **Manage the effects of Maintenance Actions on the same asset**
   In the second step, the maintenance action and how it affects production is modelled. Type of maintenance performed is decided based on the state of the system/component,

either CrM or PM. If the system has failed, CrM is performed, and its variables are added to the model. If the system is functioning PM will be performed and its variables are added to the model. If the system has just failed before the planned PM it is skipped, and the next PM will be run as planned. After this, the simulation goes back to step one and run again.

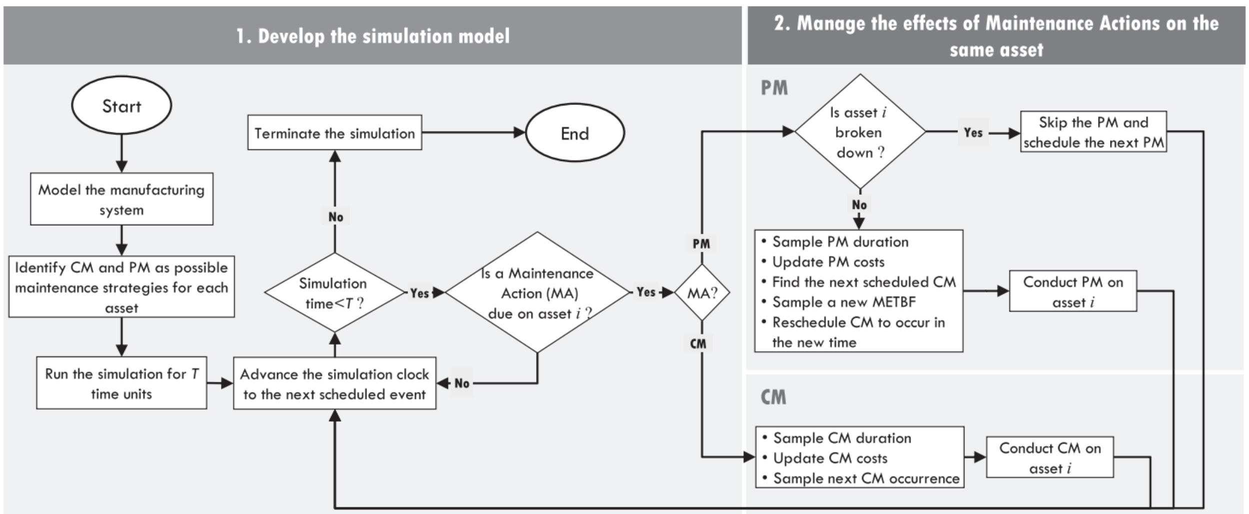


Figure 5.4: An approach for modelling time-based PM (Alrabghi and Tiwari, 2016)

Condition-based Maintenance

CbM, as described in chapter 3, is different from TbPM by not having a time parameter that defines when to perform PM, instead, it is based on the condition of the component. This condition is found by continuous monitoring and is a pre-set threshold value before intervention is started. The process is also illustrated in 5.5.

1. **Develop the simulation model**
   CrM and CbM are defined similarly to step one for TbPM modelling. CM is the same as for TbPM. CrMs variables are similar to TbPMs PM, but with added variables related to inspection (inspection cost, inspection frequency.. etc.).

2. **Manage the effects of Maintenance Actions on the same asset**
   This step will be similar to TbPM, but with some differences related to CbM. Components conditions are reset to as good as new after each CrM.

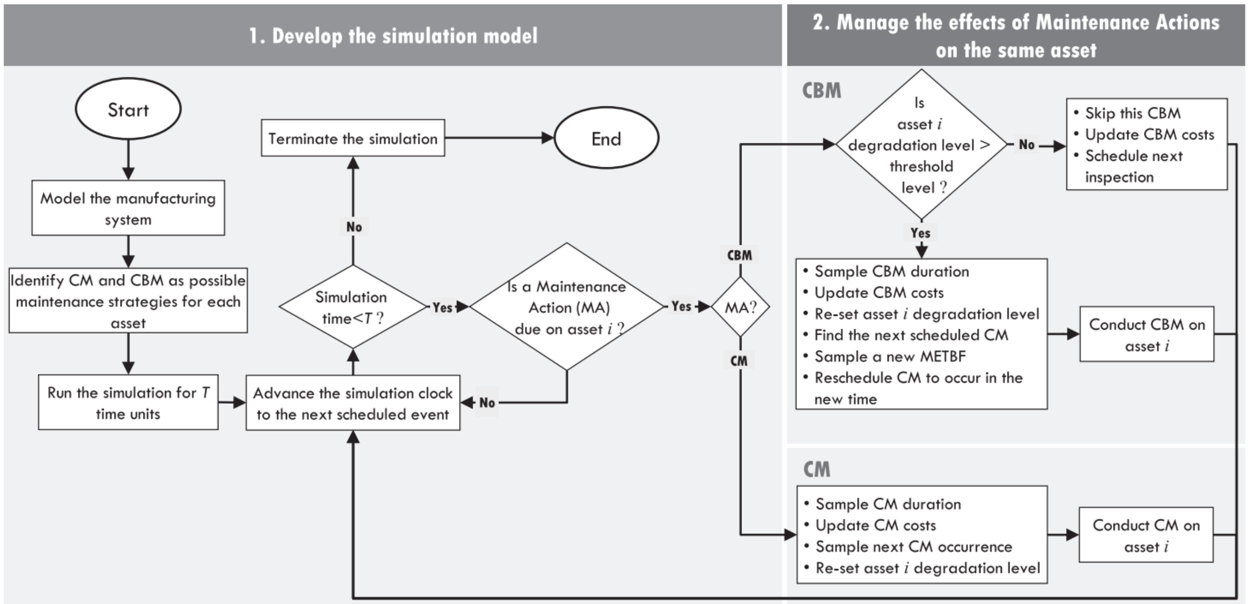


Figure 5.5: An approach for modelling CbM with periodic inspections (Alrabghi and Tiwari, 2016)

The last part of the second step related to CM can be skipped as the system under study is assumed to be continuously monitored.

5.5 Degradation Behavior

In the process of maintenance optimization the aspect of the degradation of a component, by itself or in a system, plays a vital role, and it is often the decision rule for when to do maintenance. It is therefore essential that the degradation process modelled is as close as possible to the real experienced degradation.

Zio and Compare (2012) present three classes to categorize the degradation behaviour of a component:

- **Physical models** are generally empirical or semi-empirical laws that establish the relationship between suitable variables and the degradation of the system or component. An example of such a model is the Paris-Erdogan model of crack propagation in mechanical components. The crack growth rate is linked to physical parameters of the component, such as loads, material and geometrical factors. Based on this, a model expressing the crack propagation as a function of these parameters is built. These models often demand in-depth knowledge of the failure mechanisms of the component and models to calculate loads and the lifetime of the component. In practice such degradation mechanics is unknown.

- **Stochastic models** have some inherent randomness and will produce different results with the same parameters and can be grouped into two sub-categories:
  1. *Directly* by investigating the behaviour of the degradation process of the component. Failure is assumed to occur when a component parameter reaches a certain threshold, this can be fixed, random, or when a certain event occurs, a random shock.
  2. *Indirectly* by describing how failure rates develop during the lifetime of the component. This can be difficult to conceptualize in practice, but theoretically, it is possible.
- **Experience-based models** are degradation models used when there is a lack of field data, and they are built on expert judgements and imprecise variables. The background for this type of models is the Fuzzy Logic theoretical framework, which tackles expert statements about degradation.

For both the physical and stochastic models, the need for field data is essential. These can be difficult to obtain, and commonly expert judgement is used to determine parameters in practice. The uncertainty of these two models can, therefore, be high. This is where the use of experienced-based models can be utilized.

5.6 Life-time Modeling

Lifetime modelling of components or systems are often done based on field data, collected from real operating systems. These can then be used to estimate or calculate the expected life of the component or system. This is commonly done in the Norwegian oil and gas industry through the OREDA database which collects failure data from industry operations and fit exponential distributions to all components and sub-units investigated. Mean time to failure (MTTF) is then found for all components, and this can be used to calculate the expected lifetime of a component and a system.

5.7 Prognostics

Failure prognostics is an essential part of maintenance modelling when condition monitoring is implemented. Prognostics have in the last ten years been in focus both by the industry and academia (Barros, 2018). It has been defined in several publications and standards, ISO 13372 (2012) define it as *"analysis of the symptoms of faults to predict future condition and residual life within design parameters"*. Byington et al. (2002) defines it as *"Prognostic is the ability to predict the future condition of a machine based on the current diagnostic state of the machinery and its available operating and failure history data"*. To interpret these definitions, prognostics is modelling a future failure of a component or system based on its history, current state and future operational environment.

Johnson et al. (2011) define prognostics as *"predicting the time at which a component will no longer perform its intended function."* and is focused towards the goal of prognostics, which is to predict a time of a future failure. This predicted time can be defined by the *Remaining useful life* or *life time* (RUL) of the component or the system.

Prediction uncertainties is an important part of prognostics because the prognostics are used as a base for decision making. If the predicted RUL has too high uncertainty, it does not apply to real-life components (Johnson et al., 2011). This is also argued in Heng et al. (2009) as the biggest challenge of prognostics; it's inherent uncertainty.

5.7.1 Remaining Useful Lifetime

In the compendium by Barros (2018) RUL is defined as *"RUL of the system at time t given all available information up to time t"*. It is often used as an indicator of life expectancy of a component and that all available information must be utilized when calculating it. The RUL can be presented as a mean value but is presented here as a time-dependent random variable.

The RUL(t_j) is a random variable corresponding to the RUL at time t_j, and the following formulae can then define it:

$$RUL(t_j) = inf\{h : Y(t_j + h) \in S_L | Y(t_j) < L, Y(s)_{0 \leq s \leq t_j}\} \tag{5.8}$$

$$P(RUL(t_j) > t| =) F_{RUL}(t_j) \tag{5.9}$$

Where Y(t_j) is the systems condition at time t_j, St_L is a set of failed or unacceptable states and h is some time greater than 0.

The RUL serves as a better estimator for maintenance optimization than reliability. This is because its uncertainty is reduced, and get smaller based on condition monitoring data of the system (Barros, 2018).

5.7.2 Prognostic Approaches

How to perform prognostics is often referred to as prognostic approaches or degradation modelling in the literature. Heng et al. (2009) argue for classification of prognosis approaches into data-driven (DD) and physics-based approaches. Vachtsevanos et al. (2007) have a similar classification, but by naming the physics-based approach as part of a more comprehensive model-based approach, as well as adding a third approach that is the probability-based. Heng et al. (2009) mentions this probability- or statistically-based approach as well, but rather as a different view on degradation that does not result in prognosis. The book Johnson et al. (2011) discuss five different approaches, but these are instead examples of a classification of the three that is experienced-based, evolutionary and physics-build. Vachtsevanos et al. (2007) also discuss this higher level view approach and they both present the same table of requirements and accuracy of the different approaches. Table 5.2 shows this table.

Table 5.2: Prognostics approaches and accuracy (Johnson et al. (2011) and Vachtsevanos et al. (2007))

Prognostic accuracy ⟶	Experienced-Based	Evolutionary	Physics-Based
Engineering model	Not required	Beneficial	Required
Failure history	Required	Not required	Beneficial
Past operating conditions	Beneficial	Not required	Required
Current conditions	Beneficial	Required	Required
Identified fault patterns	Not required	Required	Required
Maintenance history	Beneficial	Not required	Beneficial
In general	No sensors/no model	Sensors/no model	Sensors and model

Table 5.2 presents the three classifications, and based on the literature of the two books (Johnson et al. (2011) and Vachtsevanos et al. (2007)) and the article (Heng et al., 2009) a common ground can be found and be presented by three approaches: probability-based, data-driven and model-based approaches. These are presented and discussed in the following sections.

Probability-based Approach

The probability-based approach represents the experience-based approach in table 5.2 and it is used when precision and accuracy of the model is of less importance due to low levels of critically or low failure rates of the components. The need for condition monitoring is not present as the model is based on failure history and possible also the operational environment. The operational environment is a term for the operating hours and conditions (e.g. loads, stresses.) and the environmental conditions (e.g. temperature, vibrations) (Johnson et al., 2011). Based on a sufficient amount of data on these parameters, PDFs for them can be found, and the model is made based on these PDFs. The inaccuracy and precision can then be quantified by the confidence limits of the PDFs, which is an advantage even though these can be low. The PDFs can be presented as hazard functions, and their lifetime reliability can be exemplified by a bathtub curve (Vachtsevanos et al., 2007).

Another important aspect of this approach is that of alarm bounds, which can be decided by operators. These will determine whether the model gives too many alarms on the degradation threshold being passed or less. This again will affect the availability of the system.

Data-driven Approach

The data-driven approach is part of the evolutionary approach in table 5.2. These are approaches built directly from historical data which are then combined with current conditions, collected by condition monitoring of components, to do prognostics. It is popular in the industry as there is no need for a sophisticated model of the system to be utilized.

The historical data is used in pattern making or regression schemes to model the degradation. Understanding of how the failure modes are related to the specific measures together with the DD-model then create the decision making for this approach. These measures can be indirect, vibration measures that lead to some damage on other components, or directly measuring strain on a rod (Johnson et al., 2011).

An advantage of this approach is the simplicity in the calculations, as there is no complex model. It is, on the other hand, limited by this simplification as there has to be assumed stability in the degradation of the components and the system, as it is based on historical data. It therefore also struggle to tackle shocks and sudden changes (Heng et al., 2009).

Model-based Approach

The model-based and physics-based approach is used interchangeably in the literature. The two books, (Johnson et al., 2011) and (Vachtsevanos et al., 2007), are copies of each other on this topic and define it as follows: *"Model-based methods provide a technically comprehensive approach that has been used traditionally to understand component failure mode progression."*. It is modelled by calculating the degradation of a component based on operating and environmental conditions. The lifetime of the component is then assessed based on these calculations. Distribution for the RUL can then be modelled based on a combination of physical and stochastic modelling. Confidence intervals can also be found for the RUL due to the stochastic modelling. This demands requirements of condition monitoring and information on future operating environmental profile (Johnson et al. (2011) and Vachtsevanos et al. (2007)).

This approach is not always practical for industrial applications as fault types, and failure modes often are unique for all components. It gives high accuracy, and for specific problems like cost-based applications where the physics models are consistent for the whole system, it can be effective (Heng et al., 2009).

Chapter 6

Analysis and Optimization of Maintenance Strategy

In this chapter, all the maintenance modelling methodologies and approaches required to solve the thesis problem are discussed. Appropriate maintenance strategies and optimization criteria are examined to find what is best suited to solve the problem of this thesis. A comprehensive presentation of the degradation behaviour, modelling of the hydro-abrasive wear, is presented, and all relevant numbers and parameters for these are discussed and the data for the lifetime modelled components are presented. The assumptions and limitations of the model and analysis performed are also presented before the results from the completed work is presented and discussed. The results are summarized and concluded in the next chapter.

6.1 Modeling Approach and Methods

6.1.1 Maintenance Modeling Method

Chapter 5.4 listed several factors required for maintenance modelling. All the relevant factors for this modelling are listed and explained below, except maintenance strategy, optimization criterion and distribution of components which will be discussed later in the chapter.

- System structure: is the reliability block diagram presented and discussed in chapter 2.
- Maintenance degree: AGAN as the pump will be drawn and replaced by a spare pump when maintained.
- Shut-off rule (How many components must fail before a shut-down): is described by the RBD. If any component in the series fails, it leads to a system failure. There are some components in parallel structures, these are redundant components, and all components in the parallel must fail for the system to fail.

- System information (the type of inspection): is assumed to be ideal or perfect condition monitoring of the relevant components.
- Independences or dependencies: independence for all components are assumed (Should also be written in limitations).

Discussion of Modeling Approach

A method to model this type of problem could be done with a state-transition approach through a Markov process. There are information and data for the transition rates to all states and how the states affect the whole system. The degradation of some components, by hydro-abrasive wear, could be presented by transition rates found from simulating lifetimes of the degradable components. There are a lot of components in the system, and the state-transition diagram would be quite comprehensive. There is available software that could make this approach a possible way to model this problem but it might be easier and less comprehensive to do it with a scenario-based approach.

As discussed in chapter 5, the state-based approach can be made with Monte Carlo simulations. Then all stochastic variables can be better implemented, and the uncertainty of the results can be found. A flowchart of the code can be more tangible than the complex state-transition matrix of a Markov process. It is difficult to conclude on whether one of them will lead to better results than the other, but the approach of a Monte Carlo simulation is more practical for this problem, as it is less theoretical and more straight forward, as well as scalable and dynamic to changes.

The Monte Carlo simulation approach is therefore selected for solving this problem and a code for the simulation tool is made in MATLAB R2018b.

6.1.2 Maintenance Strategy

In the industry today, the two most common approaches to maintenance of subsea pumps are age-based maintenance with 5-year renewal intervals and corrective maintenance with some condition monitoring. As these are the ones used by the industry, they are relevant to investigate further.

The maintenance strategies to be analyzed are ideal maintenance, corrective maintenance, age-based with five years of renewal intervals and a corrective maintenance strategy with condition monitoring of hydro-abrasive wear. The condition monitoring of hydro-abrasive wear is idealized or perfect, which means it is assumed to always report the current state of wear and degradation of relevant components.

The analyze of a maintenance strategy is then to compare the costs related to a lifetime of each strategy when implemented for the subsea pump system.

A fifth maintenance strategy will also be investigated. This is a maintenance strategy where the condition-based and age-based are combined. This can be performed if age-based maintenance shows more profitable than condition-based maintenance.

6.1.3 Optimization Criteria

There are two optimization criteria for the subsea pump system, cost and availability, where the costs are related to intervention, maintenance type (corrective or preventive) and loss of production. For availability, it is relevant to investigate the percentage of time the system is operating and producing, but this is mainly relevant due to the loss of production. This means that the availability aspect can be translated to a cost perspective through the loss of production. The optimization criterion for this analysis is, therefore focused on cost, or more specific on average cost for a maintenance strategy per lifetime of the system.

6.1.4 Maintenance Optimization Method

The optimization method is based on the heuristic methods as simplifications are made due to a lack of complete system knowledge. The method is also specific for the system under study. The complexity of the system is simplified by investigating each component individually to find the failure date of each component. Based on this, an optimum maintenance strategy is detected based on the simulated cost for a lifetime of the system.

6.1.5 Prognostics

The prognostics are only calculated for the components where the degradation can be modelled. These are the components prone to hydro-abrasive wear, which are the pump impeller and the pump throttle bush.

As discussed in chapter 5, there are three approaches to prognostics, probability-based, data-driven and model-based. The approach used is a combination of the probability-based and the model-based approaches. First, a degradation for one year is found by an analytical and empirical model for hydro-abrasive wear, which is a model-based approach, this is based on stochastic and deterministic variables, and as it is based on stochastic variables one can argue that a stochastic approach is implemented in the modelled-based approach.

The yearly degradation found by the model is simulated several times, and a data set is created. A distribution is fitted to this data set and is used to find the maximum tolerated degradation before maintenance is required. This is often called an *Alarm bound* for the deterioration. It is selected for a limit that is before a failure occur to make sure it is sufficient time to plan and perform the maintenance.

This simulation and alarm bound are performed and found for all components prone to hydro-abrasive wear. Appendix B shows the code developed and figure C.1, Appendix Cshows a flow chart of the code.

6.2 Degradation Behaviour

The degradation behaviour of the relevant components, those prone to hydro-abrasive wear, has to be based on the modelling approaches presented in chapter 5. The modelling of this degradation is done by an analytical and empirical model for degradation. This is a combination of a physical and an experienced-based model of degradation. The physical model aspect is from the semi-empirical calculation of the degradation, but this model is also based on some expert judgement, which makes it experienced-based.

6.2.1 Hydro-abrasive Wear Modeling

Hydro-abrasive wear or sand erosion occurs on surfaces where fluids containing sand flows. The sand grains can hit structures or irregularities in the surface, which lead to wear.

Accurate generic methods for predicting abrasive wear in pumps are unavailable. Hence, expert judgements and rough estimations are used. This leads to uncertainties in model and its results, which is estimated by the author as up to 50%.

One approach to modelling hydro-abrasive wear is presented in Gülich (2010). This modelling method, together with testing is the basis of hydro-abrasive wear calculations done by Aker Solutions.

As Aker Solutions are basing there modelling of hydro-abrasive wear on Gülich (2010) it is most relevant to do the same. This thesis lacks the testing data, but modelling of the wear can still be done only by this method.

It is relevant to investigate the theory of this kind of modelling as it is one of the only ways to obtain degradation data and do prognostics on components prone to this type of degradation. Several factors are affecting the hydro-abrasive wear, these and the quantification of the wear are presented and discussed in the following subsections.

6.2.2 Parameters

Concentration of solids: The wear is proportional to the concentration of sand in the liquid over the surface. This concentration is also dependent on the life of the field and of fluid flows in the pump, as some flows may move the sand away from the surface and vice-versa. The concentration can be defined in several ways, but for this purpose, it is defined by kg/m^3.

Flow velocity is an essential parameter that highly increase the number of sand grains that hit the surface, which wears down the component faster. It also increases the kinetic energy of each sand grain, which further increase the wear produced by the sand. This is also why the wear is theoretically proportionate to the third power of the fluid velocity.
Flow patterns describes the local flow on the surface of the component. As this velocity can be higher than the velocity of the fluid, this can cause far more wear than the velocity of the fluid. But, this is not a quantifiable parameter as the local flow is challenging to measure.
Vortices generate high local flow near the walls and cause remarkable abrasive wear. Vortices are often created by local flow separation, for instance by some irregularities in the surface caused by a screw or a flange. This can be avoided to some degree by proper design.
Turbulence transports fluid perpendicular on to the main flow and carries solids towards the walls. This increases the wear based on turbulence intensity and the Reynolds number of the fluid.
Impingement angle of the fluid profoundly affect the wear. Ninety degrees impingement angle causes more of the particles to hit the surface and cause more wear than if it is a flow parallel to the surface.
Grain size: As the size of the sand particles increase, so does the wear, up to a certain point. As more mass increases the kinetic energy of the sand particle, it is also depended on the velocity and angle on impact. The sand grains are not all equal, so a distribution to randomize the sand grains diameter can be implemented.
Grain hardness and shape: the wear is proportional to the hardness of the sand. It is also proportional to the angularity of the grain. The shape also impacts how the sand flows and where it can cause wear, as the clearance is different within the system.
Material properties: abrasive wear is less likely to occur on hard surfaces, but the microstructure of the material is also crucial as it decides how the sand interact with the surface and cause wear.

Some of these parameters are immeasurable and cannot be implemented into the analytical calculations. This is why the book gives a limiting factor of +/-50% of the wear provided by the model.

6.2.3 Stochastic Parameters

The three most suitable parameters found to randomize are the sand concentration, sand grain size and the velocity of the fluid. The fluid flow velocity significantly impacts the hydro-abrasive wear as it increases the velocity of the sand over a surface.

As the field's life evolve the concentration and type of sand in the fluid varies. This can be taken into consideration to be randomized for a time period and then assume the sand to be equal for that given period of simulations. The velocity of the fluid will not be constant as it varies by the location in the pump as well as by the run speed.

These will also vary for each component in the system as the collection of sand in some locations as well as the flow velocity is different for all locations of the relevant components.

Grain size will not be deterministic as every grain of sand is different, but by assumption, sand grains can be stochastic with some distribution. During testing a particular sand type is used with a distribution provided by the supplier. Some assumptions are made about the maximum size and minimum size of the grains. Commonly the maximum size is used for calculations, as this is conservative. It can also be presented by a normal distribution which will be used for this model.

Sand concentration is differ during the lifetime of a field, but no distribution or data for this has been found. To assume that it is not constant is reasonable. Some normal distribution is therefore used. This is a simplification of the real scenario of sand concentration and also why it is common to use a conservative number.

Fluid velocity is assumed not to be constant as some variation in performance is expected. It also differs for the locations in the pump, but as it is such a significant factor in the calculations, a small difference can make a considerable impact on the wear.

6.2.4 Quantitative Estimation of Hydro-abrasive Wear

One analytical formula for hydro-abrasive wear is presented in Gülich (2010). As there are a lot of parameters that affect the wear rate and these again are influenced by parameters, the quantification of hydro-abrasive wear is subject to a considerable amount of uncertainties.

The analytical expression is combined with test data, empirical view, and the empirical/analytical expression is then used to provide input on the wear of components. This still gives a lot of uncertainty that is hard to quantify.

The analytical expression for the wear is made based on the impact of the parameters and is expressed in formula 6.1.

$$E_{R,a} \sim \frac{c_s d_s {w_{mix}}^3}{H_{Mat}\left(1+\frac{c_s}{\rho_s}\right)\left(1+f\left\{\frac{H_{Mat}}{H_s}\right\}\right)\Delta L} \tag{6.1}$$

The following parameters is represented in the analytical formula:

c_s = Solids concentration

d_s = Average solids diameter

w_{mix} = Mixture relative flow velocity

H_{Mat} = Material hardness

ρ_s = Solids density

f = A function of the materials of the component and sand

H_s = Solids hardness

ΔL = Length of pipe

In the book, this has then been combined with test data to produce an expression for wear based on the analytical formula, empirical data and experience (e.g. expert judgements). It is the same for this formula as the analytical one, and the uncertainty is high as it is based on an already uncertain foundation. There are some limitations as well for this formula based on the variables the parameters can be assigned. For this thesis, the bounds of these parameters will be met. Formula 6.2 shows the combined analytical and empirical formula used to quantify the yearly hydro-abrasive wear.

$$\frac{E_{R,a}}{E_{R,Ref}} = \frac{F_{Form}F_{Mat}F_{KG}F_{Form}F_{KF}F_{Hs}}{1+\frac{c_s}{\rho_s}}\left(\frac{c_{s,eq}}{c_{s,Ref}}\right)\left(\frac{w_{mix}}{w_{mix,Ref}}\right)^3 \tag{6.2}$$

As seen in formula 6.2 most parameters are close to linear, and the dominating influence of the wear is from the fluid velocity.

The following parameters are represented in the combined analytical and empirical formula 6.2, and here all the F's are different empirical parameters or form factors based on the parameters presented earlier:

$E_{R,Ref}$ - 1mm/year (to make numbers have the same unit)

F_{Form} - Form factor from geometry

F_{Mat} - Form factor from material

F_{KG} - Grain size factor

F_{KF} - Grain shape factor

F_{Hs} - Grain hardness factor

c_s - Solids concentration in oil

ρ_s - Solids (Sand) density

$c_{s,eq}$ - Equivalent solids concentration

$c_{s,Ref}$ - 1kg/m^3 (to make numbers have the same unit)

w_{mix} - Mixture (oil) speed (mixture relative flow velocity)

w_{Ref} - 10m/s (to make numbers have the same unit)

6.3 Model Input

In this section, all the numbers used in the simulation tool are presented. These are the numbers related to cost, operational data for the hydro-abrasive wear and failure data for lifetime modelling.

6.3.1 Cost Input

There are several costs related to the maintenance of subsea pumps, and these can mainly be divided into cost of maintenance, repair and cost due to loss of production.

1. **Intervention cost:** is the cost related to the planning, retrieval and transport of the failed pump, and as the transport and installation of the new pump. This cost contains among others, renting of a specialized crew and specialized vessels for retrieval and deployment of the old and new pump. These costs are approximated to between 5 and 10 million NOKs, and a mean is used, 7.5 mNOK.

2. **Corrective maintenance cost:** is the repair of a pump that had an unexpected failure. This cost is approximated to between 30 and 50 million NOKs, and a mean is used, 40 mNOK.

3. **Preventive maintenance cost:** is the repair of a pump that is repaired after a preventive intervention, either through the five year renewal time or by sufficient degradation of some components. This cost is approximated to between 20 and 30 million NOKs, and a mean is used, 25 mNOK.

4. **Production loss cost:** in terms of costs the normal amount of barrels of oil equivalents (boe) produced with a subsea system using a subsea pump is 25 000 for smaller pumps and 75 000 for larger pumps. The price of a barrel of oil this spring have been around 70USD, but a lower amount is often used when analyzing the profitability of fields. With a price of oil being around 70USD (= 605NOK), the daily costs due to loss of production is,
Small pump: $25,000 boe \cdot 605 NOK \approx 15 mill NOK$, and
Big pump: $75,000 boe \cdot 605 NOK \approx 45 mill NOK$. The big pump is evaluated in this thesis.

5. **Production loss:** It is assumed that the pump is in ultra-deep waters, which makes it critical for production, at least 2000m depth. A failure of the pump gives loss of all production.

The repair time for these pumps are usually 6-9 months, but as they are changed with a spare, this is not that relevant. The operator commonly only have one spare, so if two unexpected failures occur within six months, the system could be out of all production for some time. This is highly unlikely as the MTTF of components are usually a lot higher than the repair time, and is therefore neglected in this analysis. If it were to occur, it would lead to a massive loss for the operator.

6.3.2 Hydro-abrasive Wear Parameter Input

There is maximum wear each component can withstand before it is considered to fail. It will not necessarily fail, but instead not function well enough to have a profitable operation still. This is especially relevant for the impeller blades. The numbers of these are presented in table A.2 and are based on expert judgement and discussion.

Deterministic Input

$E_{R,Ref}$ - 1mm/year (to make numbers have the same unit)

F_{Form} - Is different for each component prone to hydro-abrasive wear. It is decided by the surface and form of the component.

F_{Mat} - Is decided by the hardness and how well the material of each component can withstand the wear. It is very low for components that can be coated by a hardening tungsten carbide coating.

F_{KF} - The shape of each sand grain will be different for all, but is assumed to be equal as there is no logical way to quantify a stochastic value.

F_{Hs} - The hardness of the sand is often sat to the hardest sand material that can be found in the field. This is often quartz, and its hardness factor is therefore used.

ρ_s - This will be the same as for the hardness, the density of quartz is used.

$c_{s,eq}$ - Is a number calculated based on the concentration of sand and what type of sand is in the fluid. All sand is assumed to be quarts and it is calculated by this formula $c_{s,eq} = c_s \cdot \frac{1100}{1150}$.

$c_{s,Ref}$ - 1kg/m^3 (to make numbers have the same unit)

w_{Ref} - 10m/s (to make numbers have the same unit)

Stochastic Input

c_s - The sand concentration will vary based on the field's life and the location inside the pump. It is, therefore, a stochastic variable with a normal distribution.

F_{KG} - The size of each sand grain will be different for all and is therefore randomized for all components. Hence, it is presented as a stochastic variable with a normal distribution.

w_{mix} - The velocity of the fluid moving through the pump will be different for every component, and it will also vary with time for all components. It is therefore presented as a stochastic variable with a normal distribution.

6.3.3 Life-time Modelling Input

To find failure dates for the components that are not prone to hydro-abrasive wear OREDA data (200, 2009) is used. This is then used to simulate the lifetime of these components. The flow chart in figure C.2 shows this procedure.

The MTTFs are mostly collected from the top side part of OREDA as there are no data for subsea pumps. This data is not as good as it could be as components made for subsea equipment often have higher reliability than those used for topside. It is a fair assumption to say that the reliability of a real subsea pump would be better for these components, as they are commonly manufactured with higher requirements.

The pressure volume regulators (PVR) are the only sub-units not presented in OREDA. The number for these are assumed based on input from experts. As it is a redundant part with a waiting stand-by unit, it should not impact the failures of the system considerably.

Table A.3 shows the MTTFs, and where they are collected, used as input for the analysis.

6.4 Modelling Assumptions and Limitations

There are several assumptions and limitations in the modelling tool developed, and they are listed below.

- All components in the pump system are assumed to be independent of each other.
- The modelling is based on simulated and OREDA data.
- The hydro-abrasive wear model used has a high uncertainty in its results, around 50%.
- Condition monitoring of components are assumed to be perfect. this means that the current state of a condition monitored component can always be found with a 100% accuracy.

- The alarm bounds found are based on a 5% confidence of being correct. This is then neglected in the simulation tool.
- The pump is assumed to be critical for production. if the pump fails there is no production.
- The daily production of the pump system is assumed to be 75 000 BOE.
- The repair time of a failed pump is neglected and is assumed to be 0.

6.5 Reliability of Pump System

To understand how well the system performs with the given parameters, the reliability of the components and for the whole system can be discussed. Based on the numbers in Table A.3 the reliability and expected MTTF for the system can be calculated based on the formulae D.9 and D.10. Table 6.1 shows the calculated numbers.

Table 6.1: Pump system, reliability

	MTTF [year]	$\lambda[year^{-1}]$	Reliability ($T = 5$)
Pump system	10.737	0.093136	0.627710

The MTTF for the system is found to be 10.74 years without including the degraded components, the pump systems MTTF is, therefore, lower than this. The total reliability if the system for five years is considered to be low for a system that is engineered for a long runtime without intervention.

6.6 Interface

A user-friendly interface for the code has been developed to make it possible to use without any knowledge about MATLAB. This was made with GUI MATLAB and is simple, but functional. It can be utilized by engineers who do not have deep knowledge of maintenance optimization and who are only given the numbers for the parameters. The code behind the GUI, which is used for the simulations in this thesis runs slowly, n = 1 000 simulations takes around 10 minutes (6300s), this is linear by increasing n. Having a high enough n to get reliable results leads to a slow program. Figure 6.1 shows the created interface for the simulation tool.

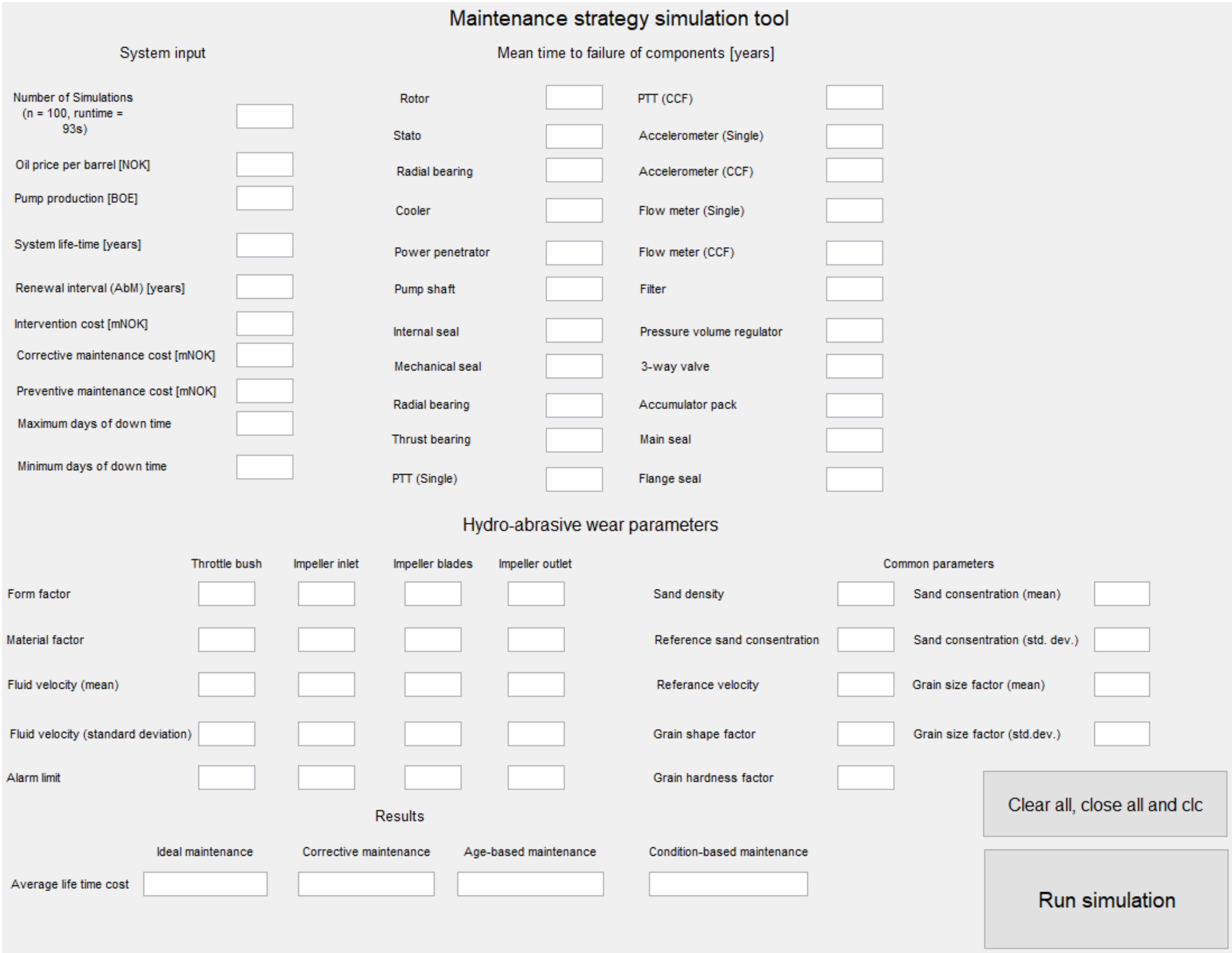


Figure 6.1: Interface for the simulation tool

6.7 Simulation of Alarm Bounds

The codes in Appendix B, do the simulations of the alarm bounds for the pump throttle bush, impeller inlet, impeller blades and impeller outlet and is more tangibly described by the flow chart C.1, Appendix C.

The simulations find an expected value for the wear for 30 days, as this is the number of days required to plan and perform the maintenance within the minimal downtime of 2 days. This is then decided by a percentage of possible error, sat with 95% confidence, of the distribution made by the simulation. The alarm limit is then found by $E_{Alarm} = E_{Fail} - E_{Limit}$.

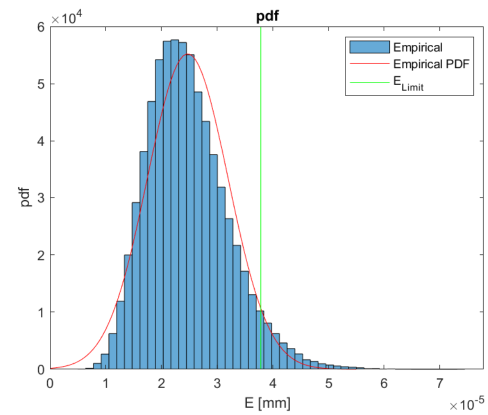
For each component this is done based on the numbers in figure A.2, Appendix A and the degradation level before a failure presented in table 6.2. Table shows the results 6.4 and figure 6.2 shows their distributions.

Table 6.2: Hydro-abrasive wear, failure level

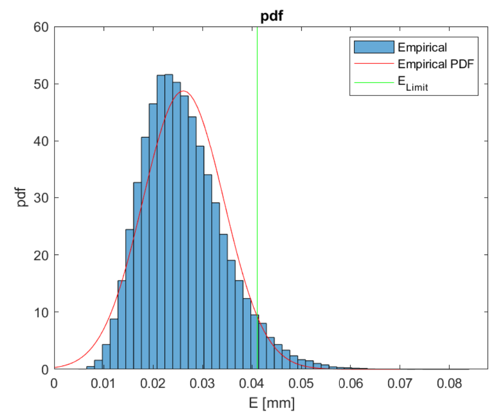
Parameter	Throttle bush	Impeller inlet	Impeller blades	Impeller outlet
E_{fail}	0.5700mm*	20.000mm	3.600mm**	4.000mm

*) Calculated from throttle bush clearance (C_{TB}) which can be tripled before it fails, $E_{fail} = 3 \cdot C_{TB}$

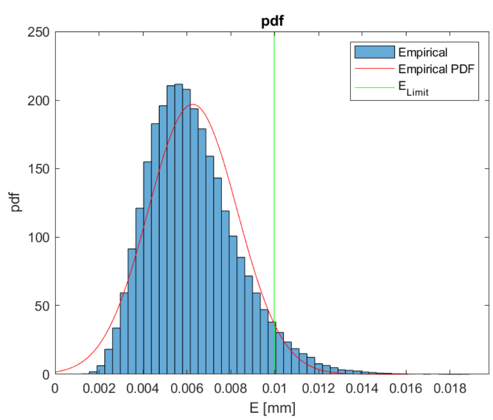
**) Calculated from the thickness of the blades, it can be reduced by 40% before they are considered failed. The thickness of each blade is 6.000mm and can be reduced by 2.400mm.



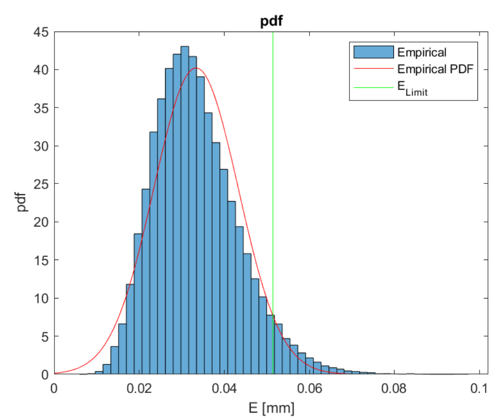
(a) Throttle bush



(b) Impeller inlet



(c) Impeller blades



(d) Impeller outlet

Figure 6.2: Probability density functions of monthly hydro-abrasive wear

Table 6.3: Hydro-abrasive wear, erosion limits

Parameter	Throttle bush	Impeller inlet	Impeller blades	Impeller outlet
E_{Limit}	3.78E-05mm	0.0411mm	0.0100mm	0.0514mm

Table 6.4: Hydro-abrasive wear, alarm bounds

Parameter	Throttle bush	Impeller inlet	Impeller blades	Impeller outlet
E_{Alarm}	0.5700mm	19.9589mm	3.5900mm	3.9486mm

In the code, an expected number of years before failure is also calculated to be able to compare it directly with the components of the lifetime model. It is, therefore, possible to see how long the components prone to hydro-abrasive wear are expected to last. Table 6.5 shows these numbers.

Table 6.5: Hydro-abrasive wear, failure year

Parameter	Throttle bush	Impeller inlet	Impeller blades	Impeller outlet
FD_{HaW}	1897.20 years	62.79 years	47.10 years	9.73 years

Table 6.5 shows that the degraded component most likely to cause a system failure is the impeller outlet. By comparing it to the impeller inlet, they have the same numbers for all parameters except variation in the stochastic variables, fluid velocity and the degradation before they are considered failed. As the impeller outlet has a higher expected fluid velocity and can withstand less hydro-abrasive wear, as it has a lower threshold for wear, it is the degradable component most likely to lead to a system failure. The impeller blades can withstand sufficiently more hydro-abrasive wear because there are several blades which leads to a lower form factor than those of the inlet and outlet. The throttle bush has almost no yearly degradation, which makes it very unlikely to cause a system failure.

The results from these simulations are used as the decision rule for when to perform preventive maintenance in the simulation tool for the maintenance strategy optimization. It is not incorporated into the code for the optimization but is done before this, and the numbers are entered in the same way as other parameters.

6.7.1 Remarks and Discussion

The simulations for the alarm bounds of the components prone to hydro-abrasive wear by sand is performed to get an expected level of degradation before a failure. The simulations are run 100 000 times, as testing of a lower number of simulations gave inconsistent results.

The alarm bounds are sat at 95% of the erosion distribution because the highest 5% leads to unlikely low degradation levels before a failure for all the components.

Expected yearly wear for some components are minimal compared to the E_{Alarm}, so in practice, these have no impact on the degradation of the system. The pump throttle bush has an average yearly degradation of 4.599E-04mm, which in practice means it is not that prone to the hydro abrasive wear. This is mainly due to the material factor of the component, which is very low (0.002). This is because the component is coated with a tungsten carbide alloy and without it the pump throttle bush would have the same material factor as the other components (2.3385) and due to the high fluid velocity over throttle bush (41.2m/s, almost twice as high as over the other components) it would be the fastest degraded component in the system.

The impeller outlet is the component most prone to degradation by hydro-abrasive wear as its expected failure date is after approximately ten years. The impeller blades and inlet have a higher expected lifetime of around 50 and 60 years. The impeller outlet will, therefore, be the component most likely to cause a system failure of these components. The impeller outlet has a high form factor of 20 and a higher flow velocity than the blades and inlet. It also have a low limit of degradation threshold before a failure, 4.00mm, the Impeller blades also have a low threshold for degradation, but is less degraded due to its form factor of 6. The form factor of the impeller blades is small because eight impellers share the load of the hydro-abrasive wear. The impeller inlet is the least degradable of the three because it has a high threshold value of degradation before it fails, 20.00mm.

6.8 Maintenance Strategy Optimization

To find the optimal maintenance strategy for the generic subsea pump system a simulation tool is developed in MATLAB, and it is presented in Appendix B and figure C.2 shows a a flow chart of it (where some sub-units are described in greater detail in figure C.3), Appendix C. This code is used to compare four maintenance strategies, ideal, corrective, age-based and a combination of condition-based and corrective maintenance (CCbMCrM). The code produces failure dates for each component in the system and then compares these to decide which component has the lowest failure date and cause a system failure. Based on the type of failure, either from a degraded component or a lifetime modelled component, a cost for the combined CbM and CrM is calculated. The other three maintenance strategies are only dependent on the failure date and their pre-set parameters and are calculated by these. The cost for a runtime or lifetime of the system is then calculated based on which type of maintenance is performed, corrective or preventive. This is run for several lifetimes of the system and an average lifetime cost for each strategy is calculated. This is then plotted together with the cost of each simulated lifetime. For the first run a system life of 30 years and a renewal interval for AbM of 5 years is used as this is a commonly used renewal interval in the industry. Figure 6.3 shows the plotted results of a simulation run of 100 000 simulations.

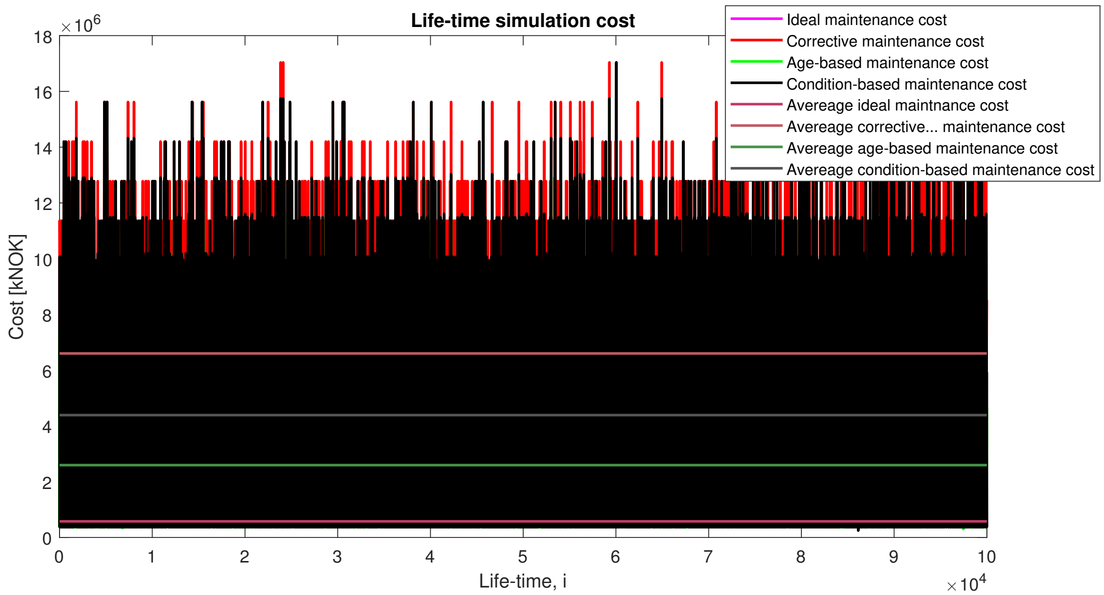


Figure 6.3: Simulation run 1

There are a lot of lifetimes simulated, which leads to a chaotic plot. The same numbers are simulated only 100 times and plotted in figure 6.4 to get a better view of the results.

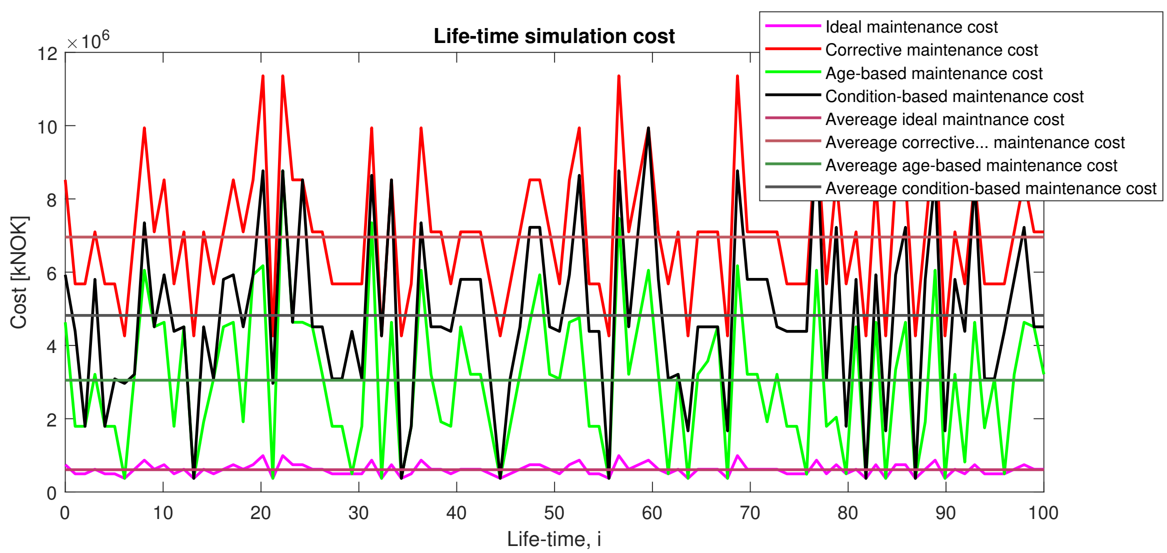


Figure 6.4: Simulation run 2, n = 100

Here it can be seen that the CrM always is the greatest for all simulations and ideal is the lowest for all, but AbM and CbM are also equal to the ideal for some lifetimes.

CbM is consistently higher than AbM, except when they are both close to or equal to ideal maintenance. What occurs each simulation is not that relevant as the results of a complete simulation run and the resulting averages are what is discussed.

Table 6.6: Average life-time cost of maintenance strategy, simulation run 1

	Ideal	Corrective	Age-based	Condition-based
Average life-time cost	0.579 bNOK	6.737 bNOK	2.632 bNOK	4.389 bNOK

Table 6.6 present the average lifetime cost of each maintenance strategy as a result of the 100 000 times simulation. These are also shown as the horizontal lines in figure 6.3. The table shows that the ideal maintenance has the lowest average lifetime cost. This is because it is always assumed to have the minimal, and it is included to see how all the strategies perform compared to the base-line of ideal maintenance.

The corrective maintenance has the highest average yearly cost, and it is included because it is a maintenance strategy that is utilized to some degree in the industry or at least has been. It is also used to see how the other strategies perform compared to the least effort maintenance strategy.

The age-based maintenance average yearly cost is lower than the CCbMCrM strategy, based on the discussions on CbM earlier in the thesis this is not logical, as the CbM should be closer to the ideal maintenance rather than higher than the AbM. The parameters of the hydro-abrasive wear can explain this. This is because this CbM strategy is a combination of CbM and CrM, as not all components can be condition monitored; it goes into corrective maintenance for all components that are not subject to hydro-abrasive wear. The most relevant components that are prone to hydro-abrasive wear have an average failure date of around 10-60 years, as shown in table 6.5, this makes it so every time the CCbMCrM failures are ideally maintained the AbM strategy have already replaced the system at a lower cost, as its renewal interval is 5 years. There should exist a better maintenance strategy where CbM and AbM are combined, that will result in lower average yearly costs for the CbM strategy.

6.8.1 Introducing a New Maintenance Strategy

Because of the discussion in the previous section, the new maintenance strategy with a combination of CbM and AbM (CCbMAbM) is further investigated in this section.

A simulation is run by substituting the previous code for the CbM with a new one, and the change set the CbM cost equal to the AbM cost or the ideal maintenance cost based on what component has caused a system failure. Figure 6.5 shows the flow chart of the new sub-unit for the CbM strategy. Figure 6.6 shows the plotted results, and table 6.7 shows the average life-time costs.

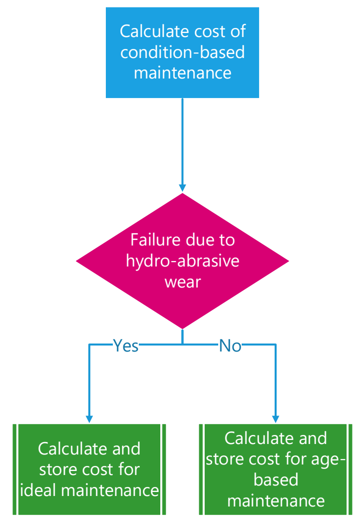


Figure 6.5: Flow chart of the CbM and AbM combined strategy

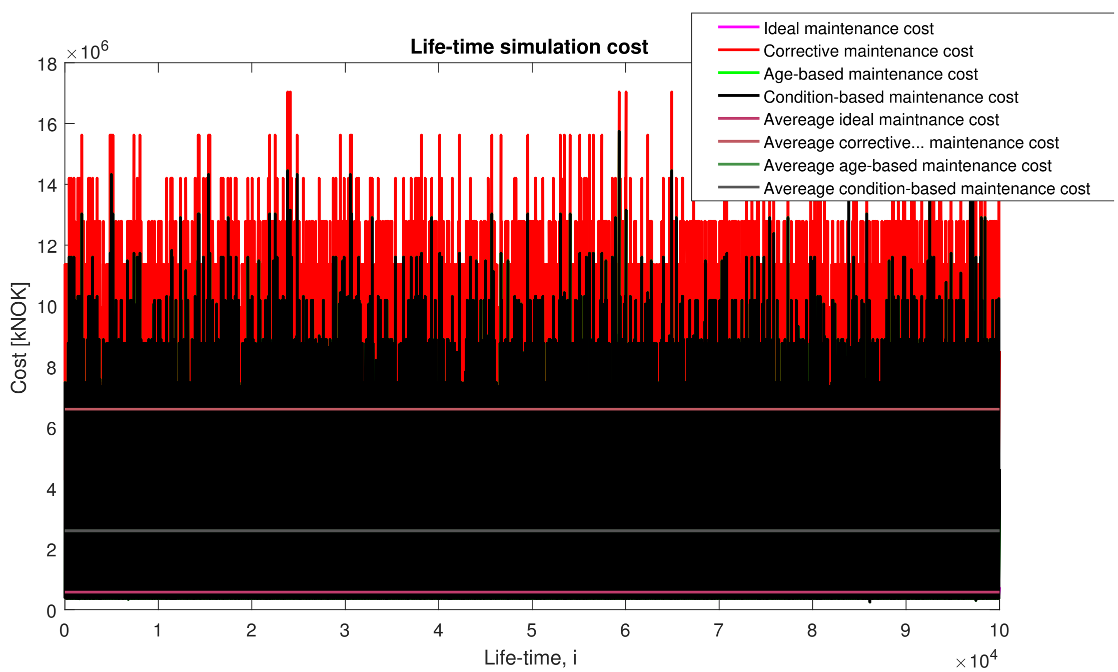


Figure 6.6: Simulation 3, CCbMAbM, n = 100 000

As for the previous simulation with n = 100 000, it is not easily seen how the different strategies perform for each simulation. A smaller sample set is therefore made and figure 6.7 shows the plotted results of this simulation.

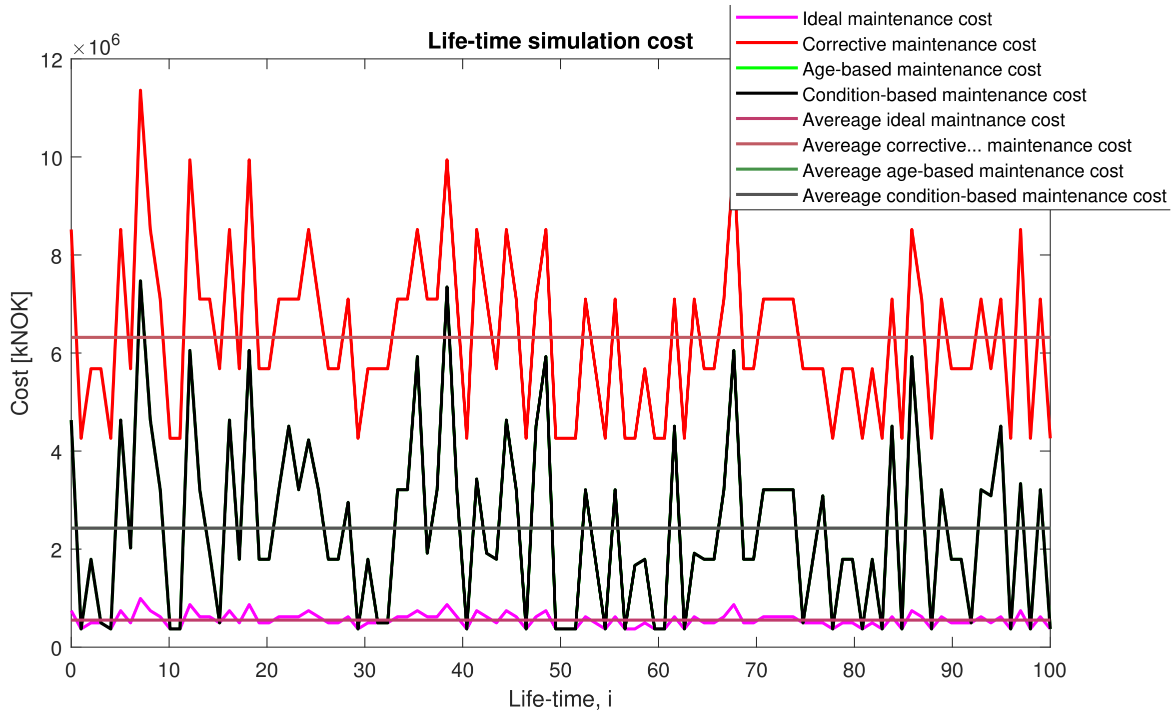


Figure 6.7: Simulation 4, CCbMAbM, n = 100

Table 6.7: Average life-time cost of maintenance strategy, simulation run 3

	Ideal	Corrective	Age-based	Condition-based
Average life-time cost	0.579 bNOK	6.737 bNOK	2.632 bNOK	2.632 bNOK

The dark green line in figure 6.7 shows that the CCbMAbM and AbM strategy has the same result for every lifetime simulated for the system, and from this their average lifetime costs are also the same, as shown in table 6.7. This is due to the average failure dates of the hydro-abrasive degraded components are higher than the renewal interval, as mentioned earlier and shown by table 6.5. This leads to the situation where every time the system fails due to a degraded component, the incorporated AbM strategy has already maintained it.

It can, therefore, be interesting to investigate a higher renewal interval to try and reduce the maintenance costs. The simulations are therefor ran again with a renewal interval of 10 years, $t_a = 10$, and n = 100 000.

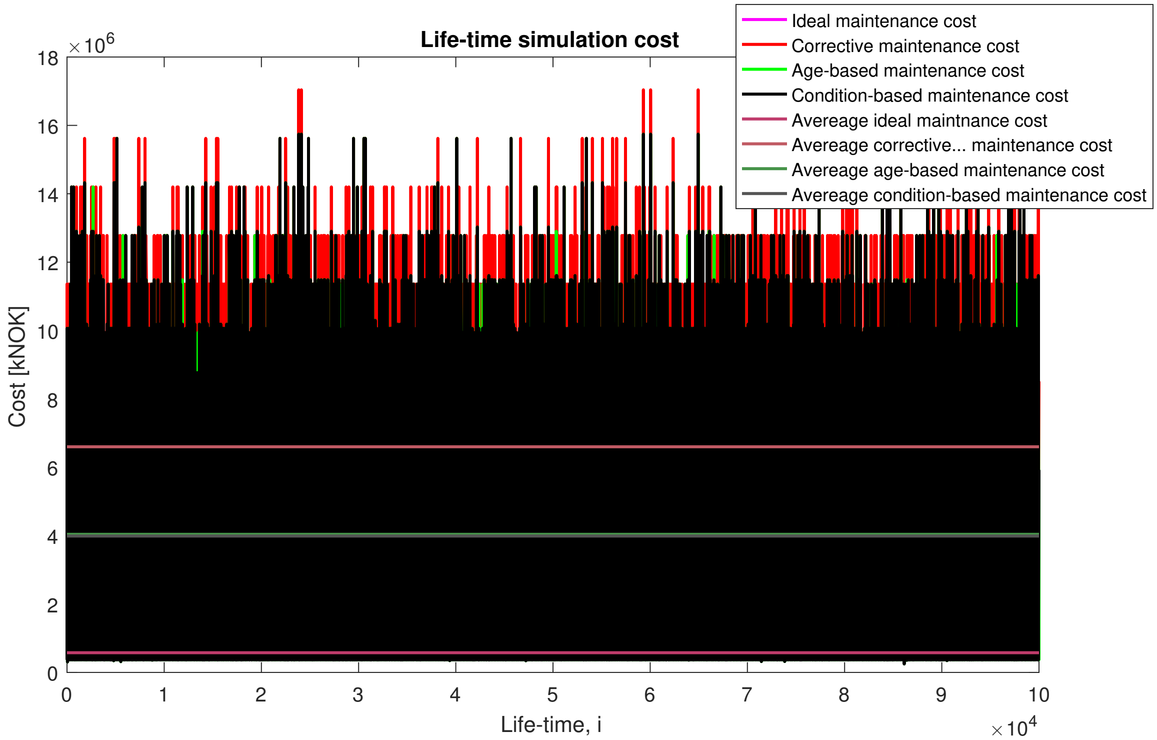


Figure 6.8: Simulation 5, CCbMAbM, n = 100 000, $t_a = 10$

As the results are difficult to see from this plot, a new simulation is done with n = 100, and figure 6.9 shows the created plot.

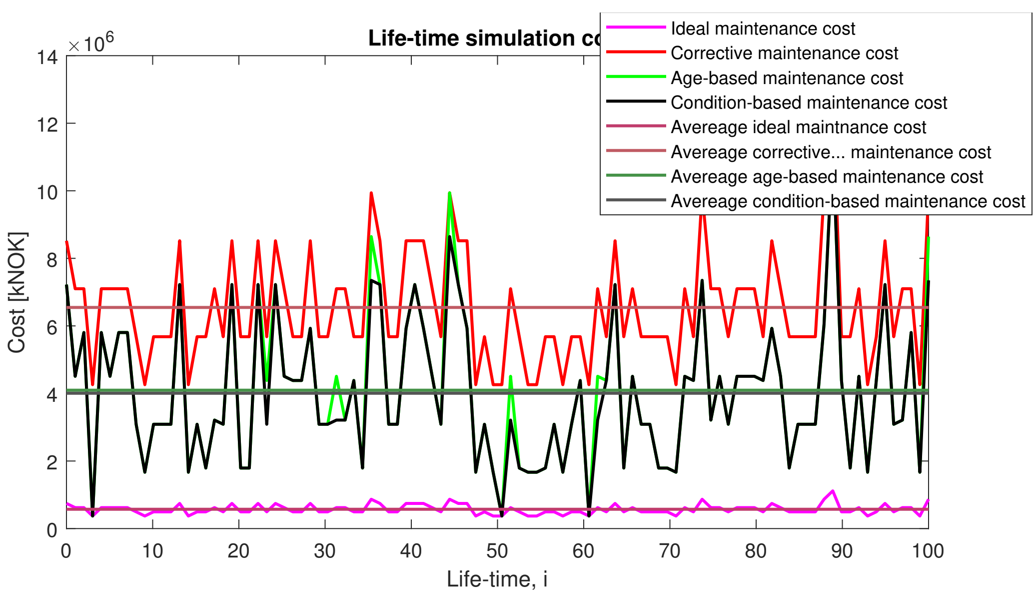


Figure 6.9: Simulation 6, CCbMAbM, n = 100, $t_a = 10$

Table 6.8: Average life-time cost of maintenance strategy, simulation run 5

	Ideal	Corrective	Age-based	Condition-based
Average life-time cost	0.579 bNOK	6.737 bNOK	3.917 bNOK	3.833 bNOK

Figure 6.8 and table 6.8 shows that the CCbMAbM strategy has a lower cost than the AbM strategy, the strategy still has a higher cost than that of AbM with a five year renewal time, which makes it a less profitable strategy. The spikes of green in the plot, figure 6.9, shows this better.

6.8.2 Increased Lifetime

The code can evaluate an increase in the lifetime of the system, as previously discussed many pump systems are expected to be implemented for more than 30 years, lifetime of 50 years can therefore also be analyzed.

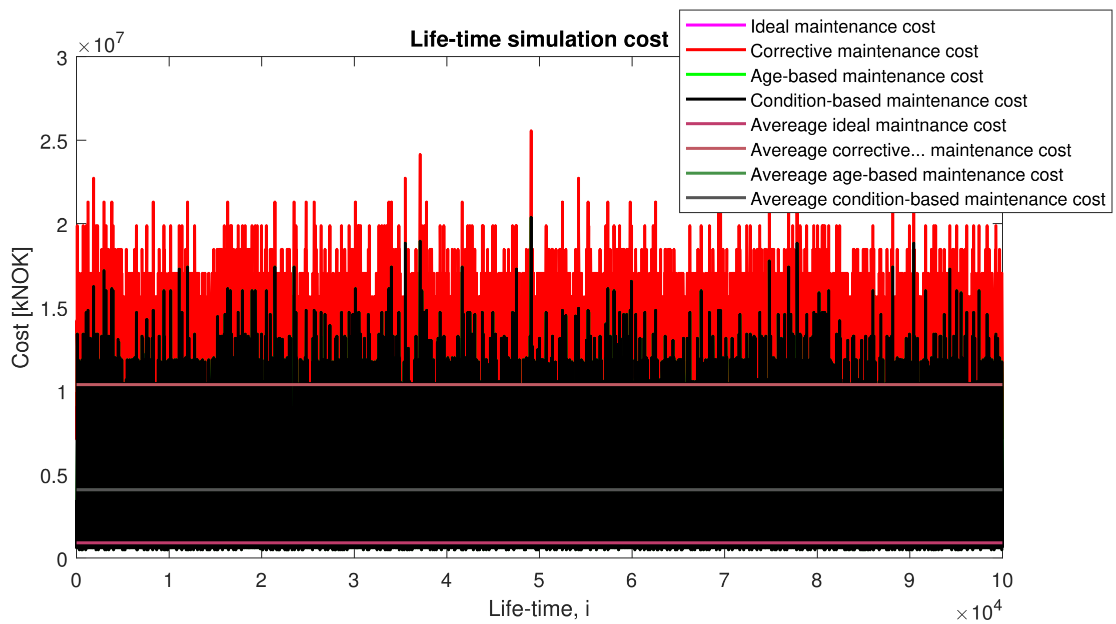


Figure 6.10: Simulation 7, CCbMAbM, n = 100 000, ta = t_a = 5, rt = 50

Table 6.9: Average life-time cost of maintenance strategy, simulation run 7

	Ideal	Corrective	Age-based	Condition-based
Average life-time cost	0.905bNOK	10.364bNOK	4.080bNOK	4.080bNOK

These results can be compared to a lifetime of 30-years to investigate the expected costs. This can be done by using the already found expected yearly cost of the two different lifetimes. It is only the age-based maintenance that is of interest in this case as it is shown to be the most profitable. Table 6.10 shows the results of these calculations.

Table 6.10: Comparing cost of life-time of 30 and 50 years

t_a	30	50
Average life-time cost	2.632bNOK	4.080bNOK
Average yearly cost	0.088bNOK	0.082bNOK

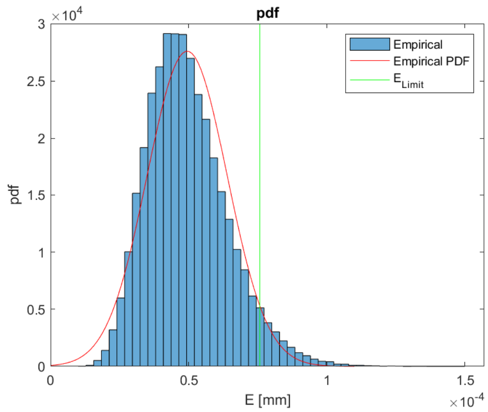
The difference in yearly costs for the two different life-time lengths are small, and only a difference of 4 million NOK a year.

6.8.3 Increased Hydro-abrasive Wear

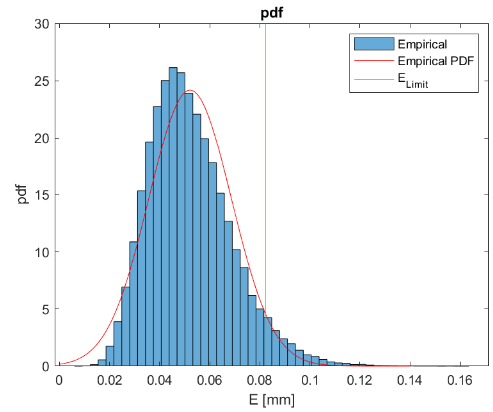
To investigate how the hydro-abrasive wear affects the profitability of the different maintenance strategies evaluation of increased sand concentration in the fluid through the pump is performed. By doubling the sand load to a mean of $0.0278 kg/m^3$ and a standard deviation of $0.004 kg/m^3$ one more simulation is run. First new alarm bounds must be analyzed before a new simulation with updated parameters can be performed.

Alarm bounds

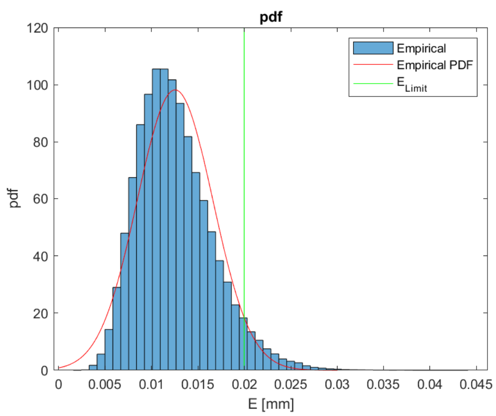
The approach is identical to that performed earlier in the chapter, but with other numbers for the sand concentration and the calculated alarm bounds. Figure 6.11 shows the erosion limits and the PDF of the expected monthly hydro-abrasive wear. Table 6.11 and 6.12 shows the alarm bounds and the expected failure year of each component as a result of the simulation of alarm bounds.



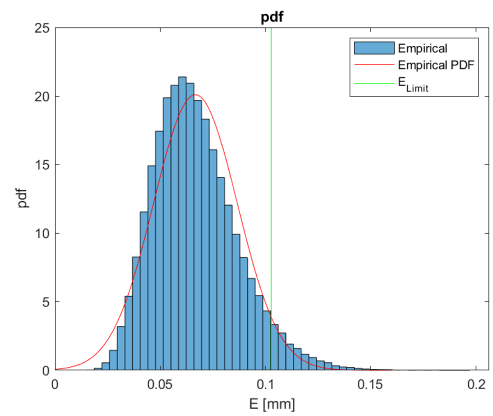
(a) Throttle bush



(b) Impeller inlet



(c) Impeller blades



(d) Impeller outlet

Figure 6.11: Probability density functions of monthly hydro-abrasive wear, doubled sand concentration

Table 6.11: Hydro-abrasive wear, alarm bounds, doubled sand concentration

Parameter	Throttle bush	Impeller inlet	Impeller blades	Impeller outlet
E_{Alarm}	0.5699mm	19.9177mm	3.5800mm	3.8973mm

Table 6.12: Hydro-abrasive wear, failure year, doubled sand concentration

Parameter	Throttle bush	Impeller inlet	Impeller blades	Impeller outlet
FD_{HaW}	948.13 years	31.3871 years	23.46 years	4.80 years

The results show that the expected life of the components is halved if compared to the numbers in table 6.5. As a result, the E_{Limit}'s are doubled, and the new alarm bounds are found and represented in table 6.11

Optimal Maintenance Strategy

Based on the results of the alarm bound simulation and the same parameters as before a new simulation run is performed, and the results are figure 6.12 and table 6.13 shows the results.

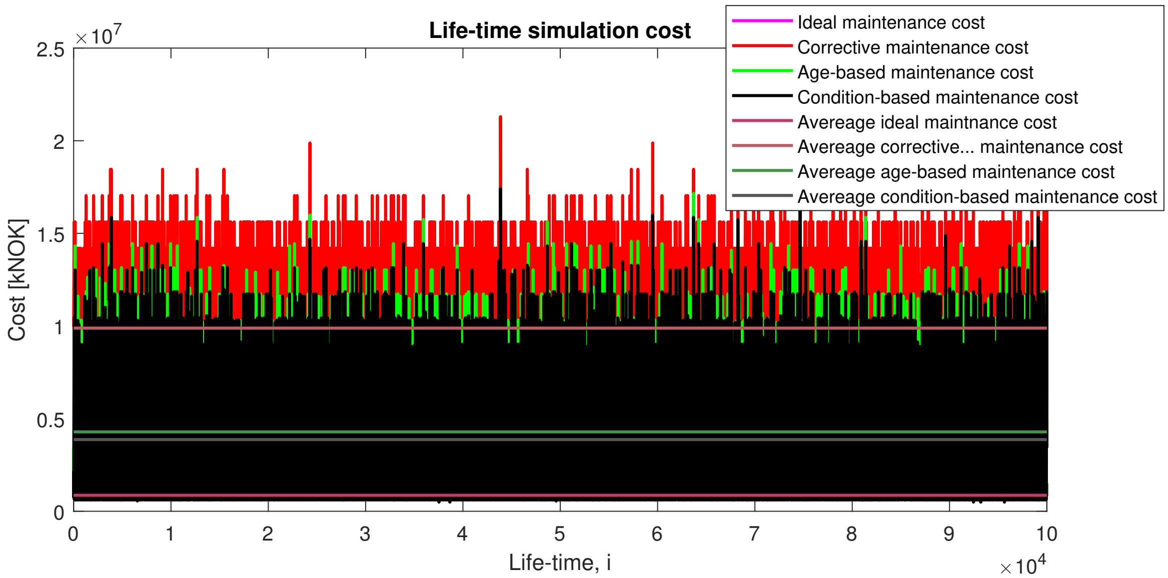


Figure 6.12: Simulation 8, CCbMAbM, doubled sand concentration

Table 6.13: Average life-time cost with doubled sand concentration

	Ideal	Corrective	Age-based	Condition-based
Average life-time cost	0.863bNOK	9.887bNOK	4.286bNOK	3.869bNOK

Now the CbM strategy is consistently cheaper than AbM for all lifetimes except when they are equal, and this leads to a lower average lifetime cost for the CbM strategy.

6.8.4 Remarks and Discussion

The number of simulations done was sat at 100 000 to get consistent results of the average life-time costs. Lower numbers were tested as the code ran slow, but to get consistent results with three decimals (per bNOK) 100 000 simulations were required. The code runs slowly due to all the loops it has to run through for every simulation. This could probably be improved by implementing more matrix analysis, but due to time being an issue, it was not expanded further.

As the reliability of the system is low for five years, $R(5) = 0.6277$, the system often fails before the renewal interval of the AbM. This leads to high costs and no need for the CbM strategy, as these components fail after ten years. The components that are not under condition monitoring are the problem of the system, and this can be solved by implementing CM for these components. The low redundancy of the system is also a result of almost every component being in a series structure. Because of this the reliability of the system will always be lower than the reliability of that of the weakest components in the system.

A new CbM strategy was implemented by combining it with AbM rather than CrM. This lead to results where AbM and CbM had an equal cost for all lifetimes. This was due to the expected life of the degradable components, and these were higher than ten years, which lead to the system being repaired before the occurrence of such failures. This lead to testing an increase in the AbM renewal period to ten years, up from five years, but the resulting average lifetime costs were higher than the previously tested AbM strategy. As the reliability of the system is low, this new maintenance strategy did not improve the profitability of the system.

When increasing the lifetime of the system from 30 years to 50 years, a small decrease in the yearly average cost of AbM was found. It is difficult to draw any conclusion from this as the difference is marginal and due to the uncertainties in the numbers and modelling.

By doubling the sand load of the system, the CbM strategy is shown to be more profitable than the AbM strategy. This is due to the new expected failure time of the impeller outlet, as it is now 4.80 years. This is lower than the renewal interval of the AbM strategy and every time this component fail before the renewal interval, and the CbM strategy has a lower cost than the AbM strategy. This increased the overall cost of maintenance for the system as the environment of the system changed.

Chapter 7

Conclusion

7.1 Summary and Conclusion

This thesis aims to investigate the maintenance strategies commonly implemented in the oil and gas industry today for subsea pump systems, and to investigate possible improvements of these. This is done by developing a simulation tool in MATLAB that can compare different strategies based on an optimization criterion of costs. Some of the most significant concerns for energy companies when operating subsea is downtime in production as this leads to loss of revenue and intervention to re-establish production is costly.

Maintenance planning is therefore done in advance to lower both the probability of downtime and the length of this downtime. Several maintenance strategies could be implemented for a subsea pump system, and the most commonly used strategy in the industry today are condition-based maintenance combined with a run-to-fail policy for the components that cannot be monitored. The second strategy usually implemented is an age-based maintenance strategy where the intervention decision is based on the run-time of the system. A renewal interval is decided based on the reliability of the system and commonly sat at five years in the industry.

Predictive and condition-based maintenance is defined together where PrM is an example of a CbM strategy where the time of intervention is based on a prediction of the future health of the system or a component under study. This is then used to estimate a future system failure based on the systems current condition and an expected degradation behaviour calculated from historical operational data.

Modularization of components to increase the maintainability is an essential aspect of subsea maintenance, but the pump system under study is retrieved and replaced by a spare upon system failure. Modularization also allows for opportunistic maintenance as components that have not failed are recovered and can be maintained before a failure.

Inspection and smaller interventions are performed by ROVs, which require specialized vessels and operators and is considered to be expensive. As the technology of sensors and condition monitoring is evolving continuous monitoring of the health of a component is increasing and can be implemented for more components in the future.

Availability of reliable operational data is a challenge when performing RAM analysis on subsea pumps as energy companies commonly do not share operational data, and they perform their studies. The RAM studies, therefore, have a theoretical approach rather than a practical approach. Infant mortality or failures due to sudden shocks are common problems that are challenging to model and are often neglected in RAM studies. Implementation of new technology can cause problems if not implemented in the design phase. Latest technology will be available during a lifetime of 30 years and it is essential to investigate how it can be implemented, as the retrieval of subsea equipment is costly and time-consuming.

The simulation tool developed is developed with a user-friendly interface so that engineers without deep knowledge in maintenance optimization or computer science can utilize it. The tool is developed based on a generic subsea pump system which has been developed in collaboration with Aker Solutions pump expert. The tool is based on a scenario-based maintenance modelling method by Monte Carlo simulations. Other methods were discussed, such as a state-transition approach by a Markovian process, but as the number of components and complexity in the system is high, the Monte Carlo simulations are argued as the best alternative.

The simulation tool was made to be used for quick comparing of maintenance strategies. The problem that arises is how slow the program runs, as this was made to be a program for quick use it runs too slow. It can still be used to get an understanding of how the different maintenance strategies will perform, but do not create confident enough results to be used for decision making.

In the simulation tool, a failure date for each component is simulated and compared to find which component caused a system failure. This failure date is found either by lifetime modelling of components based on OREDA data or by a degradation model. The components prone to degradation that can be modelled were the pump throttle bush and the impeller. The impeller is divided into three sub-components, inlet, blades and outlet as the degradation were individual for each of them. The degradation model used is an analytical and empirical model presented by Gülich (2010). This was used as Aker Solutions commonly use it for such an analysis. An alarm bound for these components were calculated based on simulating an expected remaining useful life time of 30 days, as this is the time required to plan an intervention with a minimal down time of operations of 2 days. Based on these calculations the impeller outlet was found to be the component with the lowest expected failure date, 9.7 years, and is, therefore, the component most likely to cause a system failure of the degraded components. This is due to its high material and form factor and its low threshold of degradation before considered to be failed. This expected degradation was sat based on simulating expected yearly wear and calculating the predicted deterioration of 30 days with a 5% uncertainty. The alarm bounds were then implemented when simulating the average lifetime costs of the four different maintenance strategies.

The maintenance strategies compared in the simulation tool were ideal, corrective, age-based and condition-based maintenance. From several simulations, the AbM strategy proved the most profitable one when both altering the renewal time and the lifetime of the system. This is due to the low reliability of the part of the system that is not modelled with degradation, and as the lowest expected failure date of the CbM strategy is higher than the renewal time of the AbM. This makes it so every time one of these components cause system failure, the system has already been repaired at a lower cost by the AbM strategy. A new maintenance strategy was therefore investigated by combining the CbM with the AbM strategy. This resulted in the AbM and the CbM strategy being equal for all lifetimes by the same argument as before, the degraded components fail after retrieval by the AbM strategy. To investigate if the CbM strategy could improve profitability, it was tested with a higher sand load. This resulted in an expected failure date of 4.80 years for the impeller inlet. This lead to the impeller outlet being blamed for some of the system failures and the CbM strategy proved more profitable than the AbM.

When the system was tested for a longer lifetime of 50 years, the AbM strategy proved to be more profitable based on the yearly expected cost, than a lifetime of 30 years. The difference was marginal, and it is difficult to claim any difference in the two lifetime lengths due to the uncertainties in the modelling.

The uncertainty in the models and numbers used is also an essential aspect of these results. As there was no operational data available, the uncertainty in the results are high, but as they are the same for all maintenance strategies being compared the results show some pattern in what is the best maintenance strategy for a subsea pump system.

7.2 Discussion

The two most decisive limiting factors of the analysis performed in this thesis are the data used and the uncertainties in the model. The data used is based on topside components, which leads to lower reliability of the system than that of a real subsea pump system. This affects the results of the analysis as the system fails earlier than that of a real system. The maintenance strategy found to be the optimal one is the age-based maintenance strategy with a five year renewal interval. This strategy is good as it renew the system regularly and avoid long down times due to unforeseen failures.

The uncertainty in the degradation model is also significant (50%), which leads to considerable uncertainty in the prediction of the hydro-abrasive wear of some components. As the system is also generic with assumptions on independencies and some components being excluded the model itself also leads to uncertainties in the results.

There are some strengths in the results as they are logical based on the numbers used. This means that the simulation tool can give some insight of what is to be expected from a more sophisticated maintenance analysis of a subsea pump system. It should not be used as a decision maker for the optimal strategy implemented but can be used to test several approaches and operational environments and compare their results.

With access to real data and a real system, a similar program could be built and used for decision making and this thesis presents the framework and approach to achieve this. It also serves as an introduction to maintenance optimization for subsea equipment by discussing and presenting relevant literature on the subject.

The pump is assumed to be critical for production, meaning that if it fails there is no production. This assumption is not realistic as a production field commonly would have at least 50% of its production after a pump failure. This was considered challenging to model as there would be some days with no production due to shutdown of the system and some with reduced production due to the pump failure.

The interface made is simple and makes it understandable for anyone to alter the parameters and test how a different sand-environment would affect the reliability of a subsea pump system.

7.3 Recommendations for Further Work

Several things can be implemented to expand the use of the simulation tool made in this thesis. By altering the RBD to a real system and providing real operational data would give results that can be used by the industry.

By implementing other or several degradation models based on condition monitoring data, a more reliable prognostics could be made. The analysis could be based on condition monitoring of all components, and better degradation models for these, which would lead to less uncertainty in the results.

The code made in this thesis runs slowly and could be improved. By improving it the program could be more frequently used to what was originally planned, which is to perform fast and reliable analysis of maintenance strategies.

The code could also be expanded by adding other features for more utility, and examples of these are:

- A blame-counter, to track which component caused a system failure, this can then be shown graphically.
- Build a visual interface to change the system structure.
- Connect the code with a database of failure data to increase accessibility of data.

The code could also be altered to test other subsea systems, such as the compressor system or other production equipment.

Other maintenance modelling approaches could be applied to the same system, for instance, a Markovian process could be tested to verify the results from this thesis and to get more accurate results possibly.

A more realistic modelling of production due to pump failures could also be investigated as the assumption of no production without a pump is not considered realistic.

Bibliography

(2009). OREDA : offshore reliability data handbook : Vol. 1 : Topside equipment.

AKSO (2018). Who we are.

Akula, A., Goel, S., and Ghosh, R. (2017). Condition monitoring saves money and prevents failures. *Chemical Engineering Progress*, 113(8):58–62. Copyright - Copyright American Institute of Chemical Engineers Aug 2017; Last updated - 2018-04-23.

Alrabghi, A. and Tiwari, A. (2016). A novel approach for modelling complex maintenance systems using discrete event simulation. *Reliability Engineering & System Safety*, 154:160–170.

Aspen, E. H. (2018). *Maintenance Assessment of Subsea Pump Systems*. Norwegian University of Science and Technology.

Barros, A. (2018). *Data Driven Prognostic and Predictive Maintenance - Course compendium TPK4450*. NTNU, MTP.

Byington, C. S., Roemer, M. J., and Galie, T. (2002). Prognostic enhancements to diagnostic systems for improved condition-based maintenance [military aircraft]. In *Proceedings, IEEE Aerospace Conference*, volume 6, page 6.

Cui, L. (2008). Maintenance Models and Optimization. In *Handbook of Performability Engineering*, pages 789–805. Springer London, London.

Dhillon, B. (2002). *Engineering Maintenance: A Modern Approach*. CRC Press.

Eriksson, K. and Antonakopoulos, K. (2014). Subsea Processing Systems: Optimising the Maintenance, Maximising the Production. In *Offshore Technology Conference-Asia*. Offshore Technology Conference.

Eriksson, K. G. (2010). Control System And Condition Monitoring For a Subsea Gas Compressor Pilot.

Friedemann, J. D., Varma, A., Bonissone, P., and Iyer, N. (2008). Subsea Condition Monitoring: A Path To Increased Availability And Increased Recovery. In *Intelligent Energy Conference and Exhibition*. Society of Petroleum Engineers.

Gülich, J. F. (2010). *Centrifugal Pumps*. Berlin, Heidelberg, 2nd ed. edition.

Heng, A., Zhang, S., Tan, A. C., and Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical Systems and Signal Processing*, 23(3):724–739.

Hernæs, S. and Aas, T. (2015). An Alternative Approach to 50 Years Design Life. In *Offshore Technology Conference*. Offshore Technology Conference.

IEC 60050-192 (2015). *International electrotechnical vocabulary - Part 192: Dependability*.

ISO 13372 (2012). *Condition monitoring and diagnostics of machines — Vocabulary*.

ISO 17359 (2018). *Condition monitoring and diagnostics of machines — General guidelines*.

Johnson, S. B., Gormley, T. J., Kessler, S. S., Mott, C. D., Patterson-Hine, A., Reichard, K. M., and Scandura Jr., P. A. (2011). *System Health Management: With Aerospace Applications*. John Wiley & Sons, Ltd.

Kaboli, S. O. and Hashem (2016). *Reliability in power electronics and electrical machines : industrial applications and performance models*. IGI Global.

Lei, Y. and Huang, A. Q. (2017). Data center power distribution system reliability analysis tool based on Monte Carlo next event simulation method. In *2017 IEEE Energy Conversion Congress and Exposition (ECCE)*, pages 2031–2035.

Levitt, J. (2011). *Complete Guide to Predictive and Preventive Maintenance (2. ed)*. Industrial Press, Inc.

Lima, F. S., Storstenvik, A., and Nyborg, K. (2011). Subsea Compression: A Game Changer. In *OTC Brasil*. Offshore Technology Conference.

Mai, C., Pedersen, S., Hansen, L., Jepsen, K., and Yang, Z. (2017). Modeling and Control of Industrial ROV's for Semi-Autonomous Subsea Maintenance Services. *IFAC-PapersOnLine*, 50(1):13686–13691.

Markeset, T., Moreno-Trejo, J., and Kumar, R. (2013). Maintenance of subsea petroleum production systems: a case study. *Journal of Quality in Maintenance Engineering*, 19(2):128–143.

Moreno-Trejo, J. and Markeset, T. (2012). Identifying Challenges in the Maintenance of Subsea Petroleum Production Systems. pages 251–259. Springer, Berlin, Heidelberg.

NS-EN13306 (2018). *Maintenance - Maintenance terminology*.

Oria (2019). Academic library.

Pham, H. and Wang, H. (1996). Imperfect maintenance. *European Journal of Operational Research*, 94(3):425–438.

Rausand, M. and Høyland, A. (2004). *System Reliability Theory: Models, Statistical Methods, and Applications*. Wiley, Hoboken, NJ, 2nd edition.

Rubinstein, R. Y. and Kroese, D. P. (2016). *Simulation and the Monte Carlo method*. Wiley.

Schjølberg, I., Gjersvik, T. B., Transeth, A. A., and Utne, I. B. (2016). Next Generation Subsea Inspection, Maintenance and Repair Operations. *IFAC-PapersOnLine*, 49(23):434–439.

Schjølberg, I. and Utne, I. B. (2015). Towards autonomy in ROV operations. *IFAC-PapersOnLine*, 48(2):183–188.

Schmidt, B. and Wang, L. (2018). Cloud-enhanced predictive maintenance. *The International Journal of Advanced Manufacturing Technology*, 99(1-4):5–13.

Selcuk, S. (2017). Predictive maintenance, its implementation and latest trends. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 231(9):1670–1679.

Serene, C. Y. and Chze, L. P. (2015). Subsea Condition Monitoring: Does Effective Diagnosis Increase Availability? *Journal of Petroleum Technology*, 67(12):52–55.

Skytte af Sätra, U., Christensen, R., Tanase, A., Koppervik, I., and Rokke, E. (2011). Proactive Maintenance in the Context of Integrated Operations Generation 2. *SPE Economics & Management*, 3(02):102–108.

Soosaipillai, C., Roald, P. K., Alfstad, D., Aas, T., Smith, G., and Bressand, J.-Y. (2013). Condition Performance Monitoring for Subsea: Experience and Value documentation From the Gjoa Field. In *Offshore Technology Conference*. Offshore Technology Conference.

SPE-International (2019). Oil and gas separators.

Vachtsevanos, G., Lewis, F., Roemer, M., Hess, A., and Wu, B. (2007). *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*. John Wiley & Sons, Inc., Hoboken, NJ, USA.

Vaidya, P. (2010). Prognosis-subsea oil and gas industry. Technical report.

Van Horenbeek, A., Pintelon, L., and Muchiri, P. (2010). Maintenance optimization models and criteria. *International Journal of System Assurance Engineering and Management*, 1(3):189–200.

Winge Rudh, M. G., Fritz Jahnsen, O., and Hasan, Z. (2016). Subsea Cooling; Passive, Active or Sea Current Controlled? In *SPE Asia Pacific Oil & Gas Conference and Exhibition*. Society of Petroleum Engineers.

Zhu, Q., Peng, H., and van Houtum, G.-J. (2015). A condition-based maintenance policy for multi-component systems with a high maintenance setup cost. *OR Spectrum*, 37(4):1007–1035.

Zio, E. and Compare, M. (2012). A snapshot on maintenance modeling and applications. *Marine Technology and Engineering*, 2.

Appendix A

Input for Analysis

This appendix presents all the input parameters used in the simulations tool that are not directly described in the thesis.

A.1 Cost Input

Table A.1: Costs related to maintenance

	Cost [mNOK]
Intervention cost	7.5
Corrective maintenance cost	40
Preventive maintenance cost	25
Daily production loss cost	45.75

A.2 Hydro-abrasive Wear Input

Table A.2: Hydro-abrasive wear parameters

Parameter	Throttle bush	Impeller inlet	Impeller blades	Impeller outlet
E_{Ref}	1mm/year	1mm/year	1mm/year	1mm/year
F_{Form}	5	20	6	20
F_{Mat}	0.002	2.3385	2.3385	2.3385
F_{KF}	0.8	0.8	0.8	0.8
F_{Hs}	1	1	1	1
ρ_s	2660kg/m^3	2660kg/m^3	2660kg/m^3	2660kg/m^3
$c_{s,Ref}$	1kg/m^3	1kg/m^3	1kg/m^3	1kg/m^3
w_{Ref}	10m/s	10m/s	10m/s	10m/s
c_s	$\mathcal{N}(0.0139, 0.002)$	$\mathcal{N}(0.0139, 0.002)$	$\mathcal{N}(0.0139, 0.002)$	$\mathcal{N}(0.0139, 0.002)$
$c_{s,eq}$	$c_s \cdot \frac{1100}{1150}$	$c_s \cdot \frac{1100}{1150}$	$c_s \cdot \frac{1100}{1150}$	$c_s \cdot \frac{1100}{1150}$
F_{KG}	$\mathcal{N}(0.04, 0.005)$	$\mathcal{N}(0.04, 0.005)$	$\mathcal{N}(0.04, 0.005)$	$\mathcal{N}(0.04, 0.005)$
w_{mix}	$\mathcal{N}(41.1, 3)$	$\mathcal{N}(23.2, 2)$	$\mathcal{N}(23.2, 2)$	$\mathcal{N}(25.2, 2)$

A.3 Life-time Model Input

Table A.3: Data for life-time modeled components

Component	**MTTF[Y]**	**Data source**
Rotor	508	OREDA Topside
Stator	128	OREDA Topside
Radial bearing	421	OREDA Topside
Cooler	256	OREDA Subsea
Power penetrator	342	OREDA Subsea
Pump shaft	249	OREDA Topside
Internal seal	109	OREDA Topside
Mechanical seal	54	OREDA Topside
Radial bearings	421	OREDA Topside
Thrust bearing	152	OREDA Topside
PTT single failure	132	OREDA Subsea
PTT CCF	365	OREDA Subsea
Accelerometer single	80.5	OREDA Topside
Accelerometer CCF	228	OREDA Topside
Flow meter single	170	OREDA Subsea
Flow meter CCF	480	OREDA Subsea
Filter	4660	OREDA Subsea
PVR	55	Expert judgement
3-way valve	290	OREDA Subsea
Accumulator pack	2693	OREDA Subsea
Main seal	265	OREDA Topside
Flange seal	265	OREDA Topside

Appendix B

MATLAB code

In this appendix shows the the code used in the simulation tool. To save space only two are presented and some variables may be altered to performed all the simulations of this thesis.

B.1 Alarm Bounds - Pump Throttle Bush

The code is the same for all components, but there are some variables that are different and these are presented in table A.2.

Listing B.1: Alarm bounds - Pump throttle bush

```
% Alarm bound for the pump throttle bush
close all
clear all
clc

% Constants
FForm = 5;              % Form factor based on the geometry of component
FMat = 0.002;           % Material factor of component
FKF = 0.8;              % Grain shape factor
FHs = 1;                % Grain hardness factor
F = FForm * FMat * FKF * FHs;

ps = 2660;              % sand density kg/m^3

csRef = 1;              % reference consentration
wRef = 10;              % Refereance speed
```

```
% Fatigue at failure
cTB = 0.19;            % [mm] TB clearance, failure ate 3times this value
E_Fail = cTB*3;

% Simulations
n = 100000;

E_sim = [];

% Variables
for q = 1:n                          % Run for each simulation
    % Random variables
    cs = normrnd(0.0139 , 0.002); % Solid content in oil
    csEq = cs*(1100/1150); % Equivalent solids consentration
    FKG = normrnd(0.04, 0.005); % Grain size factor.
    wmix = normrnd(41.1, 3);      % Fluid velocity
    E_monthly = ((csEq/csRef)*(wmix/wRef).^3) * ((F*FKG)/(1+(cs/ps))) *...
        (30/365); % 30/365 per 30th day.
    E_sim(q) = E_monthly;
end

E_avg = mean(E_sim);

%------------------------------------------------------------------------
% Fit a distribution to the empirical data set
createFit(E_sim);         % Used app "Distribution Fitter" in Matlab
%------------------------------------------------------------------------

%------------------------------------------------------------------------
% Alarm bound at 5%
max = 95;       % alarm at 5%
x = linspace(0, 0.000055);              % x-value for the empirical dist.
E_Limit = prctile(E_sim, max);          % 30 day degradation limit
% ---------------------------------------------------------

E_Alarm = E_Fail - E_Limit;       % Alarm bound found
```

```
FD_TB = (E_Alarm/E_avg)*(30/365);
% Empirical PDF
Emp_dist = normpdf(x, ans.mu, ans.sigma);

% PLOT1 - EMpirical histogram of E_sim
figure(2);
histogram(E_sim,50,'Normalization','pdf');    %Empirical prob distribution
hold on;
xlim = get(gca,'xlim');                       %Get limits to use in theoretical
ylim = get(gca,'ylim');                       %Get limits to use in theoretical

plot(x, Emp_dist, 'r');
plot([E_Limit, E_Limit], ylim, 'g');

legend('Empirical','Empirical PDF','E_L_i_m_i_t')
title('pdf')
xlabel('E')
ylabel('pdf')
```

B.2 Simulation Tool (With CCbMAbM)

This is the code used for the simulation tool, and it is changed for the CbM-part based on what simulation is performed.

Listing B.2: Simulation tool - CCbMAbM

```
% Simulations tool for comparing maintenance strategies
close all
clear all
clc

oilp = 610/1000;      % 70USD per barrel around 610NOK,
Pr_Pump = 75000;      % barrels produces each day for a big subsea pump
n = 100000;               % Number of simulations
ta = 5;               % Renewal interval AbM
rt = 30;              % Run-time, how long is the desired life-time

% Costs
```

```
c_intervention = 7500;                    % Intervention cost
cost_C = 40000 + c_intervention;          % CrM cost  + intervention
cost_I = 25000 + c_intervention;          % Ideal M cost + intervention
cost_A = 25000 + c_intervention;          % AbM cost + intervention
dt_cost = oilp * Pr_Pump;           % Down time cost pr day
%Downtime
max_dt = 30;     % maximum down time [days]
min_dt = 2;      % minimum down time [days]

% Ideal
sim_tot_cost_ideal = [];
sim_tot_years_ideal = [];
sim_tot_dt_ideal = [];
% Corrective
sim_tot_cost_CorM = [];
sim_tot_years_CorM = [];
sim_tot_dt_CorM = [];
% Age-based
sim_tot_cost_AbM = [];
sim_tot_years_AbM = [];
sim_tot_dt_AbM = [];
% CbM
sim_tot_cost_CbM = [];
sim_tot_years_CbM = [];
sim_tot_dt_CbM = [];

% Register what failure causes system failure
Failure_Errosion = 0;
Failure_Life = 0;
%Register all failure dates
FD_sim = [];

% MTTFs and failure rates for life-time modeled components
MTTF_Rotor = 508;
lambda_Rotor = 1/MTTF_Rotor;

MTTF_Stator = 128;
```

```
lambda_Stator = 1/MTTF_Stator;

MTTF_RadBear = 421;
lambda_RadBear = 1/MTTF_RadBear;

MTTF_Cooler = 256;
lambda_Cooler = 1/MTTF_Cooler;

MTTF_PowPen = 342;
lambda_PowPen = 1/MTTF_PowPen;

MTTF_Shaft = 249;
lambda_Shaft = 1/MTTF_Shaft;

MTTF_IntSeal = 109;
lambda_IntSeal = 1/MTTF_IntSeal;

MTTF_MechSeal = 54;
lambda_MechSeal = 1/MTTF_MechSeal;

MTTF_RadBear2 = 421;
lambda_RadBear2 = 1/MTTF_RadBear2;

MTTF_ThrustBear = 152;
lambda_ThrustBear = 1/MTTF_ThrustBear;

MTTF_PTT = 132;
MTTF_PTT_CCF = 365;
lambda_PTT = 1/MTTF_PTT;
lambda_PTT_CCF = 1/MTTF_PTT_CCF;

MTTF_Acc = 80.5;
MTTF_Acc_CCF = 228;
lambda_Acc = 1/MTTF_Acc;
lambda_Acc_CCF = 1/MTTF_Acc_CCF;

MTTF_FlowM = 170;
```

```
MTTF_FlowM_CCF = 480;
lambda_FlowM = 1/MTTF_FlowM;
lambda_FlowM_CCF = 1/MTTF_FlowM_CCF;

MTTF_Filter = 4660;
lambda_Filter = 1/MTTF_Filter;

MTTF_PVR = 55;
lambda_PVR = 1/MTTF_PVR;

MTTF3Way = 290;
lambda3Way = 1/MTTF3Way;

MTTF_AccPack = 2693;
lambda_AccPack = 1/MTTF_AccPack;

MTTF_MainSeal = 265;
lambda_MainSeal = 1/MTTF_MainSeal;

MTTF_FlangeSeal = 265;
lambda_FlangeSeal = 1/MTTF_FlangeSeal;

% Parameters for hydro-abrasive wear
ps = 2660;                % sand density kg/m^3
csRef = 1;                % reference consentration
wRef = 10;                % Refereance speed
FKF = 0.8;                % Grain shape factor
FHs = 1;                  % Grain hardness factor
cs_mean = 0.0139;
cs_dev = 0.002;
FKG_mean = 0.04;
FKG_dev = 0.005;

%Throttle bush
FForm_TB = 5; % Form factor of the geometry of the component
FMat_TB = 0.002;              % Material factor of component
F_TB = FForm_TB * FMat_TB * FKF * FHs;
```

```
wmix_mean_TB = 41.1;
wmix_dev_TB = 3;
E_Alarm_TB = 0.5700;

%Impeller inlet
FForm_Imp_Inl = 20; % Form factor of the geometry of the component
FMat_Imp_Inl = 2.3385;          % Material factor of component
F_Imp_Inl = FForm_Imp_Inl * FMat_Imp_Inl * FKF * FHs;
wmix_mean_Imp_Inl = 23.2;
wmix_dev_Imp_Inl = 2;
E_Alarm_Imp_Inl = 19.9589;      % Alarm bound found by MCS


% Impeller blades
FForm_Imp_Blade = 6; % Form factor of the geometry of the component eroded
FMat_Imp_Blade = 2.3385;          % Material factor of component
F_Imp_Blade = FForm_Imp_Blade * FMat_Imp_Blade * FKF * FHs;
E_Alarm_Imp_Blade = 3.5900;       % Alarm bound found by MCS
wmix_mean_Imp_Blade = 23.2;
wmix_dev_Imp_Blade = 2;



% Impeller outlet
FForm_Imp_Outl = 20; % Form factor based on the geometry
%of the component
FMat_Imp_Outl = 2.3385;          % Material factor of component
F_Imp_Outl = FForm_Imp_Outl * FMat_Imp_Outl * FKF * FHs;
wmix_mean_Imp_Outl = 25.2;
wmix_dev_Imp_Outl = 2;
E_Alarm_Imp_Outl = 3.9486;       % Alarm bound found by MCS


for k = 1:n          % the simulation loop
    % Ideal
    tot_cost_ideal = 0;
    tot_dt_ideal = 0;
    % Corrective
```

```
    tot_cost_CorM = 0;
    tot_dt_CorM = 0;
    % Age-based
    tot_cost_AbM = 0;
    tot_dt_AbM = 0;
    % CbM
    tot_cost_CbM = 0;
    tot_dt_CbM = 0;

    years = 0;
    counter = 1;            % determine row, next renewal phase (FD_sim)
    while years < rt
% Life-time exponential (No degradation)
    %Motor module
        %component 1 - Rotor
        T_Rotor = rand;
        FD_Rotor = (log(1-T_Rotor))/(-lambda_Rotor);  % Fialure date based
        %on T

        %component 2 - Stator
        T_Stator = rand;
        FD_Stator = (log(1-T_Stator))/(-lambda_Stator);  % Fialure date
        %based on T

        %component 3 - Radial bearing
        T_RadBear = rand;
        FD_RadBear = (log(1-T_RadBear))/(-lambda_RadBear);  % Fialure date
        %based on T

        %component 4 - Cooler
        T_Cooler = rand;
        FD_Cooler = (log(1-T_Cooler))/(-lambda_Cooler);  % Fialure date
        %based on T

        %component 5 - Power Penetrator
        T_PowPen = rand;
        FD_PowPen = (log(1-T_PowPen))/(-lambda_PowPen);  % Fialure date
```

```
        %based on T

    % Pump module

        %component 6 - Shaft
        T_Shaft = rand;
        FD_Shaft = (log(1-T_Shaft))/(-lambda_Shaft);  % Fialure date based
        %on T

        %component 7 - Internal seals
        T_IntSeal = rand;
        FD_IntSeal = (log(1-T_IntSeal))/(-lambda_IntSeal);  % Fialure date
        %based on T

        %component 8 - Mechanical seal
        T_MeachSeal = rand;
        FD_MeachSeal = (log(1-T_MeachSeal))/(-lambda_MechSeal);  % Fialure
        %date based on T

        %component 9 - Radial Bearings
        T_RadBear2 = rand;
        FD_RadBear2 = (log(1-T_RadBear2))/(-lambda_RadBear2);  % Fialure
        %date based on T

        %component 10 - Thrust bearing
        T_ThrustBear = rand;
        FD_ThrustBear = (log(1-T_ThrustBear))/(-lambda_ThrustBear);
        % Fialure date based on T

        %component 12 - PTT1 and 2 (Run simuntaneously, so fail when the
        %last one fails) or because of CCF
        T_PTT_1 = rand;
        T_PTT_2 = rand;
        T_PTT_CCF = rand;
        FD_PTT_1 = (log(1-T_PTT_1))/(-lambda_PTT);  % Fialure date based
        %on T
        FD_PTT_2 = (log(1-T_PTT_2))/(-lambda_PTT);  % Fialure date based
```

```
        %n T
        FD_PTT_CCF = (log(1-T_PTT_CCF))/(-lambda_PTT_CCF);
        FD_PTT = min([FD_PTT_CCF max([FD_PTT_1 FD_PTT_2])]); % check what
        %failures come first of CCF or one of the other components

        %component 13 - accelerometer1 and 2 (Run simuntaneously, so fail
        %when the last one fails) or when they fail due to a CCF
        T_Acc_1 = rand;
        T_Acc_2 = rand;
        T_Acc_CCF = rand;
        FD_Acc_1 = (log(1-T_Acc_1))/(-lambda_Acc);  % Fialure date based
        %on T
        FD_Acc_2 = (log(1-T_Acc_2))/(-lambda_Acc);  % Fialure date based
        %on T
        FD_Acc_CCF = (log(1-T_Acc_CCF))/(-lambda_Acc_CCF);
        FD_Acc = min([FD_Acc_CCF max([FD_Acc_1 FD_Acc_2])]); % check what
        %failures come first of CCF or one of the other components

        %component 14 - Flow meter
        T_FlowM_1 = rand;
        T_FlowM_2 = rand;
        T_FlowM_CCF = rand;
        FD_FlowM_1 = (log(1-T_FlowM_1))/(-lambda_FlowM);  % Fialure date
        %based on T
        FD_FlowM_2 = (log(1-T_FlowM_2))/(-lambda_FlowM);  % Fialure date
        %based on T
        FD_FlowM_CCF = (log(1-T_FlowM_CCF))/(-lambda_FlowM_CCF); % ---||---
        FD_FlowM = min([FD_FlowM_CCF max([FD_FlowM_1 FD_FlowM_2])]);

    % Barrier fluid system
        %component 15 - Filter
        T_Filter = rand;
        FD_Filter = (log(1-T_Filter))/(-lambda_Filter);  % Fialure date
        %based on T

        %component PVR Paralell (FD = FD1+FD2, as one of them are on
        %standby until the first one fails)
```

```
        T_PVR_1 = rand;
        T_PVR_2 = rand;
        FD_PVR_1 = (log(1-T_PVR_1))/(-lambda_PVR);  % Fialure date based
        %on T
        FD_PVR_2 = (log(1-T_PVR_2))/(-lambda_PVR);  % Fialure date based
        %on T
        FD_PVR = FD_PVR_1 + FD_PVR_2;     % Look at when the paralell
        %strcture fail, where one component is in stand-by

        %component 17 - 3-way valve
        T3Way = rand;
        FD3Way = (log(1-T3Way))/(-lambda3Way);  % Fialure date based on T

        %component 18 - Accumulator pack
        T_AccPack = rand;
        FD_AccPack = (log(1-T_AccPack))/(-lambda_AccPack);  % Fialure date
        %based on T

        %component 19 - Main seal
        T_MainSeal = rand;
        FD_MainSeal = (log(1-T_MainSeal))/(-lambda_MainSeal);  % Fialure
        %date based on T

        %component 20 - Flange seals
        T_FlangeSeal = rand;
        FD_FlangeSeal = (log(1-T_FlangeSeal))/(-lambda_FlangeSeal);
        % Fialure date based on T

        %Find failure date of life-time system
        FD_Life = min([FD_Rotor FD_Stator FD_RadBear FD_Cooler FD_PowPen...
            FD_Shaft FD_IntSeal FD_MeachSeal FD_RadBear2 FD_ThrustBear...
            FD_PTT FD_Acc FD_FlowM FD_Filter FD_PVR FD3Way FD_AccPack...
            FD_MainSeal FD_FlangeSeal]);

    % Degradated components
        % Erossion Throttle bush
        E_tot_TB = 0;
```

```
year_TB = 0;
while E_tot_TB < E_Alarm_TB                      % Run every year
    cs_TB = normrnd(cs_mean , cs_dev); % Solid content in oil
    csEq_TB = (cs_TB)*(1100/1150); % Equiv. solids consentration
    FKG_TB = normrnd(FKG_mean, FKG_dev); % Grain size factor.
    wmix_TB = normrnd(wmix_mean_TB, wmix_dev_TB);  % Fluid velocity
    E_TB = ((csEq_TB/csRef)*(wmix_TB/wRef).^3) *...
        ((F_TB*FKG_TB)/(1+(cs_TB/ps)));
    E_tot_TB = E_tot_TB + E_TB;
    year_TB = year_TB + 1;
end
% Failure date of the Throttle bush / Alarm bound being reached
FD_TB = year_TB - 1 + (E_tot_TB - E_Alarm_TB);

% Erossion Impeller Inlet
E_tot_Imp_Inl = 0;                  % Erosion total when alarmbound
%is reached
year_Imp_Inl = 0;                  % Year of alarm bound being reached
while E_tot_Imp_Inl < E_Alarm_Imp_Inl
    cs_Imp_Inl = normrnd(cs_mean , cs_dev); % Solid content in oil
    csEq_Imp_Inl = (cs_Imp_Inl)*(1100/1150); % Equivalent solids
    %consentration
    FKG_Imp_Inl = normrnd(FKG_mean, FKG_dev); % Grain size factor
    wmix_Imp_Inl = normrnd(wmix_mean_Imp_Inl, wmix_dev_Imp_Inl);
    % Fluid velocity
    E_Imp_Inl = ((csEq_Imp_Inl/csRef)*(wmix_Imp_Inl/...
        wRef).^3) * ((F_Imp_Inl*FKG_Imp_Inl)/...
        (1+(cs_Imp_Inl/ps)));
    E_tot_Imp_Inl = E_tot_Imp_Inl + E_Imp_Inl;
    year_Imp_Inl = year_Imp_Inl + 1;
end
FD_Imp_Inl = year_Imp_Inl - 1 + (E_tot_Imp_Inl - E_Alarm_Imp_Inl);

% Erossion Impeller Blade
E_tot_Imp_Blade = 0;   % Errosion total when alarmbound is reached
year_Imp_Blade = 0;              % YEar of alarm bound being reached
```

```
while E_tot_Imp_Blade < E_Alarm_Imp_Blade
    cs_Imp_Blade = normrnd(cs_mean , cs_dev); %Solid content in oil
    csEq_Imp_Blade = (cs_Imp_Blade)*(1100/1150); % Equivalent
    %solids consentration
    FKG_Imp_Blade = normrnd(FKG_mean, FKG_dev); % Grain size factor
    wmix_Imp_Blade = normrnd(wmix_mean_Imp_Blade,...
        wmix_dev_Imp_Blade);    % Fluid velocity
    E_Imp_Blade = ((csEq_Imp_Blade/csRef)*...
        (wmix_Imp_Blade/wRef).^3) *...
        ((F_Imp_Blade*FKG_Imp_Blade)/(1+(cs_Imp_Blade/ps)));
    E_tot_Imp_Blade = E_tot_Imp_Blade + E_Imp_Blade;
    year_Imp_Blade = year_Imp_Blade + 1;
end
FD_Imp_Blade = year_Imp_Blade - 1 + (E_tot_Imp_Blade -...
    E_Alarm_Imp_Blade); % Date of alarm bound being reached

% Erossion Impeller Outlet
E_tot_Imp_Outl = 0; % Errosion total when alarmbound is reached
year_Imp_Outl = 0;        % YEar of alarm bound being reached

while E_tot_Imp_Outl < E_Alarm_Imp_Outl
    cs_Imp_Outl = normrnd(cs_mean , cs_dev); % Solid content in oil
    csEq_Imp_Outl = (cs_Imp_Outl)*(1100/1150); %Equivalent
    %solids consentration
    FKG_Imp_Outl = normrnd(FKG_mean, FKG_dev); % Grain size factor
    wmix_Imp_Outl = normrnd(wmix_mean_Imp_Outl, wmix_dev_Imp_Outl);
    % Fluid velocity
    E_Imp_Outl = ((csEq_Imp_Outl/csRef)*...
        (wmix_Imp_Outl/wRef).^3) * ((F_Imp_Outl*...
        FKG_Imp_Outl)/(1+(cs_Imp_Outl/ps)));
    E_tot_Imp_Outl = E_tot_Imp_Outl + E_Imp_Outl;
    year_Imp_Outl = year_Imp_Outl + 1;
end
FD_Imp_Outl = year_Imp_Outl - 1 + (E_tot_Imp_Outl -...
    E_Alarm_Imp_Outl); % Date of alarm bound being reached

% Find sand eroded components FD
```

```
    FD_Ero = min([FD_TB FD_Imp_Inl FD_Imp_Blade FD_Imp_Outl]);

    % Store number of times system fails due to errosion or
    %life model component
    if FD_Ero < FD_Life
        Failure_Errosion = Failure_Errosion + 1;
    else
        Failure_Life = Failure_Life + 1;
    end
    % Find system failure date
    FD = min([FD_Life FD_Ero]);
    FD_sim(k,counter) = FD;        % Put the FD into storer
    counter = counter + 1; % move to next row-space in the
    %cycle (coloumn)

% Maintenance strategy
    %Ideal
    cost_ideal = cost_I + (min_dt * dt_cost);
    tot_cost_ideal =  tot_cost_ideal + cost_ideal;
    tot_dt_ideal = tot_dt_ideal + min_dt;

    % Corrective
    cost_CorM = cost_C + (max_dt * dt_cost);
    tot_cost_CorM =  tot_cost_CorM + cost_CorM;
    tot_dt_CorM = tot_dt_CorM + max_dt;

    % Age-based
    if FD < ta
        %  Calculate cost based on failure day
        if ta-FD > max_dt/365  % Max number of days out of operations
            dt_AbM = max_dt;
            cost_AbM = cost_C + (dt_AbM * dt_cost);
            % It failed and costs are same as for CorM
        else                             % If the FD is lower than 30 days
            %the maintenance is already under planning, and will
            %be performed at the planned time
            dt_AbM = (ta-FD) * 365;
```

```
            cost_AbM = cost_C + (dt_AbM * dt_cost);
        end
    else            % If no failure before the renewal occurs
        FD_AbM = 5;                     % FD would be 5 years
        dt_AbM = 2;                     % dt would be 1 day, or 0
        cost_AbM = cost_A + (dt_AbM * dt_cost);
        % Only cost would be that of a planned downtime
    end
    % Collect the cost of this life-time
    tot_cost_AbM =  tot_cost_AbM + cost_AbM;
    tot_dt_AbM = tot_dt_AbM + dt_AbM;

    % Condition-based Maintenance with AbM
    if FD_Ero < FD_Life
        dt_CbM = min_dt;
        cost_CbM = cost_ideal;
        tot_cost_CbM =  tot_cost_CbM + cost_CbM;
    else                            % Everything equal to AbM
        dt_CbM = dt_AbM;
        cost_CbM = cost_AbM;
        tot_cost_CbM =  tot_cost_CbM + cost_CbM;
    end

    years = years + FD;
end
% Ideal
sim_tot_cost_ideal(k) = tot_cost_ideal;  % Collect the cost of
%all simulations life-time
sim_tot_years_ideal(k) = years;
sim_tot_dt_ideal(k) = tot_dt_ideal;

% Corrective
sim_tot_cost_CorM(k) = tot_cost_CorM;   % Collect the cost of all
%simulations life-time
sim_tot_years_CorM(k) = years;
sim_tot_dt_CorM(k) = tot_dt_CorM;
```

```
    % Age-based
    sim_tot_cost_AbM(k) = tot_cost_AbM;          % Collect the cost of all
    %simulations life-time
    sim_tot_years_AbM(k) = years;
    sim_tot_dt_AbM(k) = tot_dt_AbM;

    % CbM
    sim_tot_cost_CbM(k) = tot_cost_CbM;          % Collect the cost of all
    %simulations life-time
    sim_tot_years_CbM(k) = years;
    sim_tot_dt_CbM(k) = tot_dt_CbM;
end

% Averages of all simulations

% Ideal
avg_life_cost_ideal = mean(sim_tot_cost_ideal); % Calculate average cost
%of all life-times
avg_life_ideal = mean(sim_tot_years_ideal);
avg_dt_ideal = mean(tot_dt_ideal);
avg_availability_ideal = 1 - (avg_dt_ideal/(365*avg_life_ideal));

% Corrective
avg_life_cost_CorM = mean(sim_tot_cost_CorM);
avg_life_CorM = mean(sim_tot_years_CorM);
avg_dt_CorM = mean(tot_dt_CorM);
avg_availability_CorM = 1 - (avg_dt_CorM/(365*avg_life_CorM));

% Age-based
avg_life_cost_AbM = mean(sim_tot_cost_AbM);
avg_life_AbM = mean(sim_tot_years_AbM);
avg_dt_AbM = mean(tot_dt_AbM);
avg_availability_AbM = 1 - (avg_dt_AbM/(365*avg_life_AbM));

% CbM
avg_life_cost_CbM = mean(sim_tot_cost_CbM);
avg_life_CbM = mean(sim_tot_years_CbM);
```

```
avg_dt_CbM = mean(tot_dt_CbM);
avg_availability_CbM = 1 - (avg_dt_AbM/(365*avg_life_CbM));

% Line graph
figure(1);
x1 = linspace(0,n,n);
plot(x1, sim_tot_cost_ideal, 'm','linewidth',1.5);
hold on;
plot(x1, sim_tot_cost_CorM, 'r','linewidth',1.5);
plot(x1, sim_tot_cost_AbM, 'g','linewidth',1.5);
plot(x1, sim_tot_cost_CbM, 'k','linewidth',1.5);
% Plot averages
xlim = get(gca,'xlim');                    %Get limits to use on averages
ylim = get(gca,'ylim');                    %Get limits to use on averages
plot(xlim, [avg_life_cost_ideal, avg_life_cost_ideal],'Color',...
    [193/256 60/256 108/256],'linewidth',1.5);
plot(xlim, [avg_life_cost_CorM,avg_life_cost_CorM],'Color',...
    [193/256 90/256 99/256],'linewidth',1.5);
plot(xlim, [avg_life_cost_AbM, avg_life_cost_AbM],'Color',...
    [70/256 148/256 73/256],'linewidth',1.5);
plot(xlim, [avg_life_cost_CbM, avg_life_cost_CbM],'Color',...
    [85/256 85/256 85/256],'linewidth',1.5);
% Name graphs
legend('Ideal maintenance cost', 'Corrective maintenance cost',...
    'Age-based maintenance cost', 'Condition-based maintenance cost',...
    'Avereage ideal maintnance cost',...
    'Avereage corrective... maintenance cost',...
    'Avereage age-based maintenance cost',...
    'Avereage condition-based maintenance cost');
title('Life-time simulation cost');
xlabel('Life-time, i');
ylabel('Cost [kNOK]');
```

Appendix C

Flow Charts of MATLAB Code

This appendix gives a more tangible understanding of the code made for the simulation tool by presenting flow-charts for the code.

C.1 Simulation of Alarm Bound of Degradation

Figure C.1 show the simulations performed to find the alarm bounds for the four hydro-abrasive prone components.

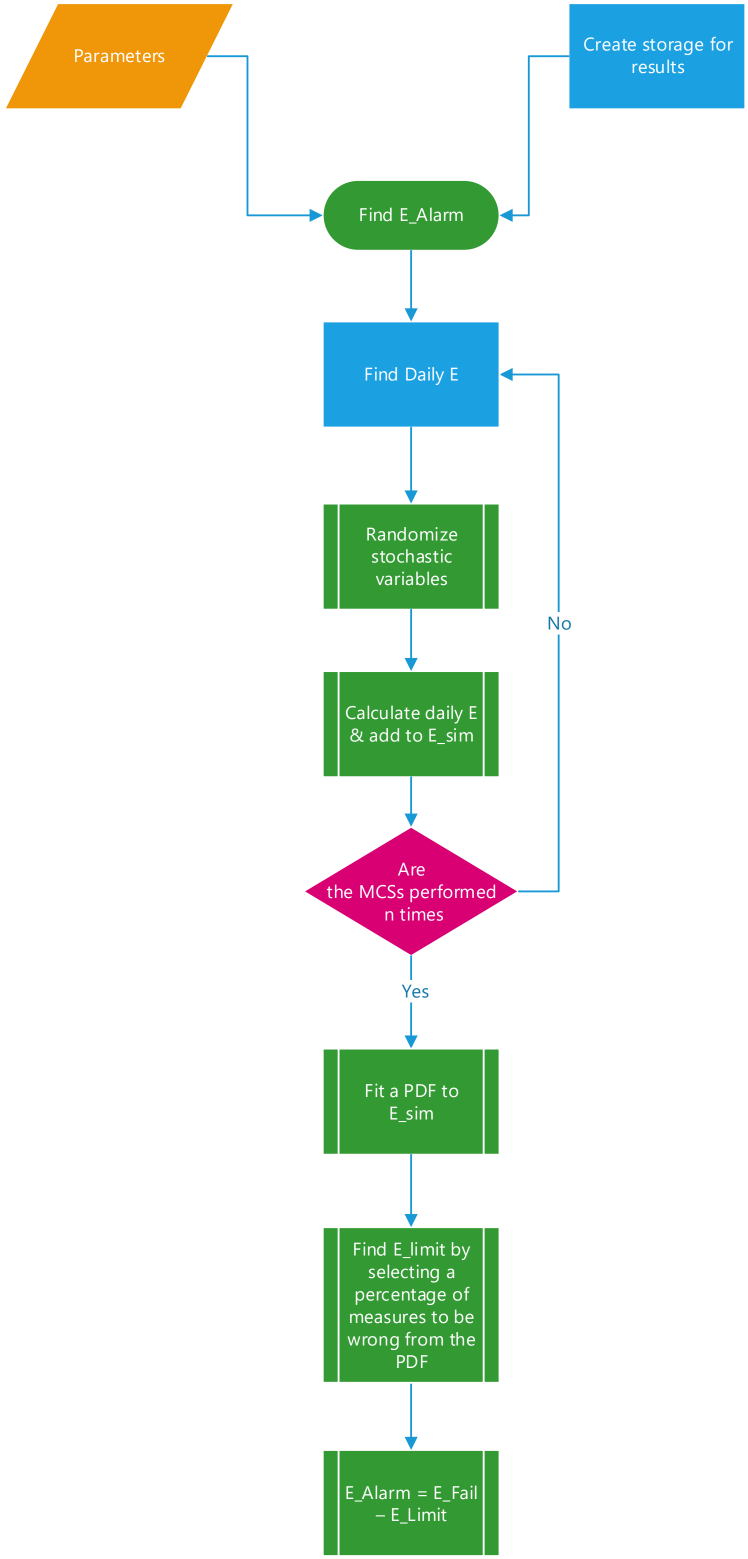


Figure C.1: Flow chart: Alarm bound simulation

C.2 Simulation Tool of Optimal Maintenance Strategy

Figure C.2 show the simulation tool to find the optimum maintenance strategy based on cost.

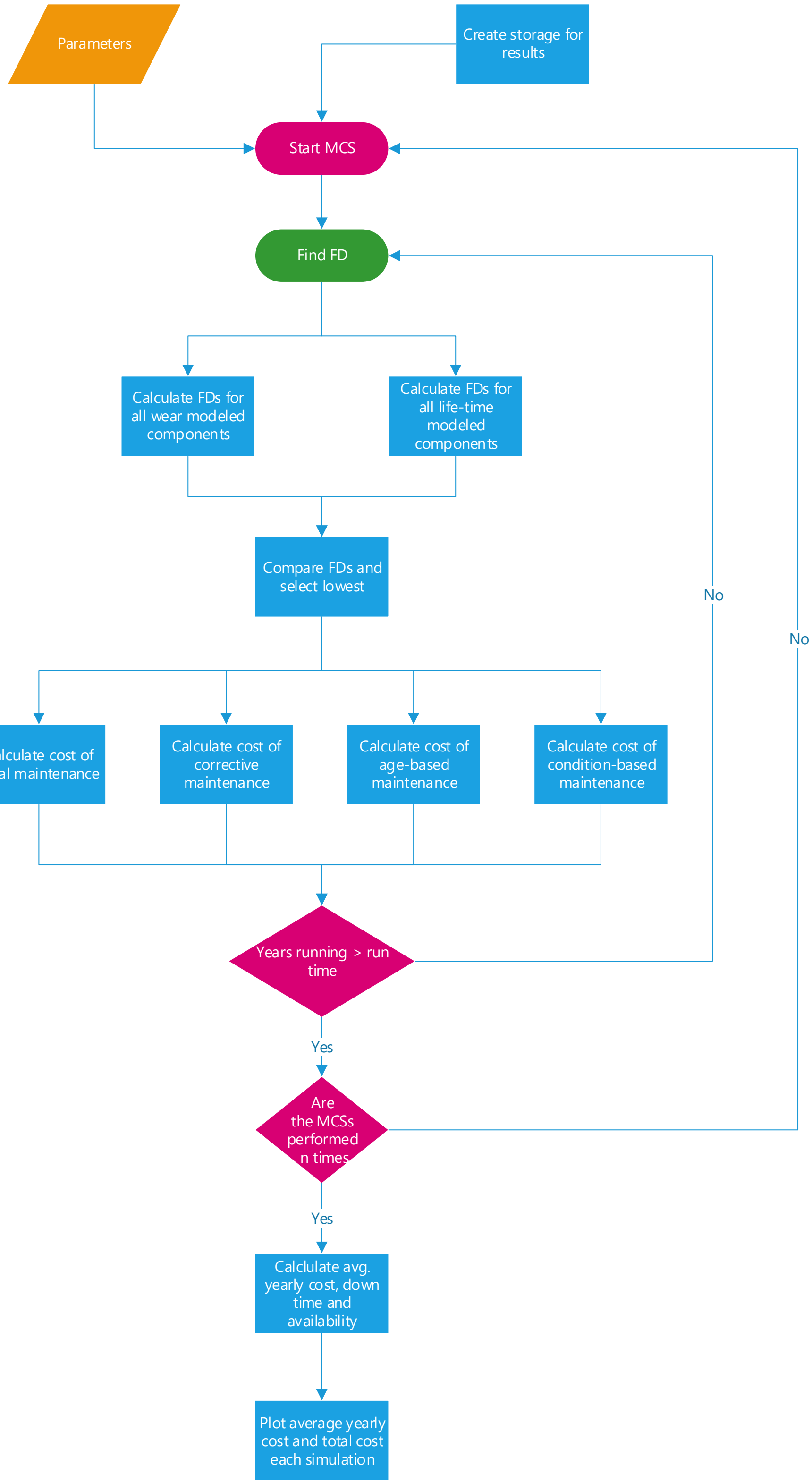


Figure C.2: Flow chart of the maintenance optimization tool

C.3 Sub-units of Optimal Maintenance Strategy Simulation

Figure C.3: Show the sub-units of some parts of the flow chart in Figure C.2

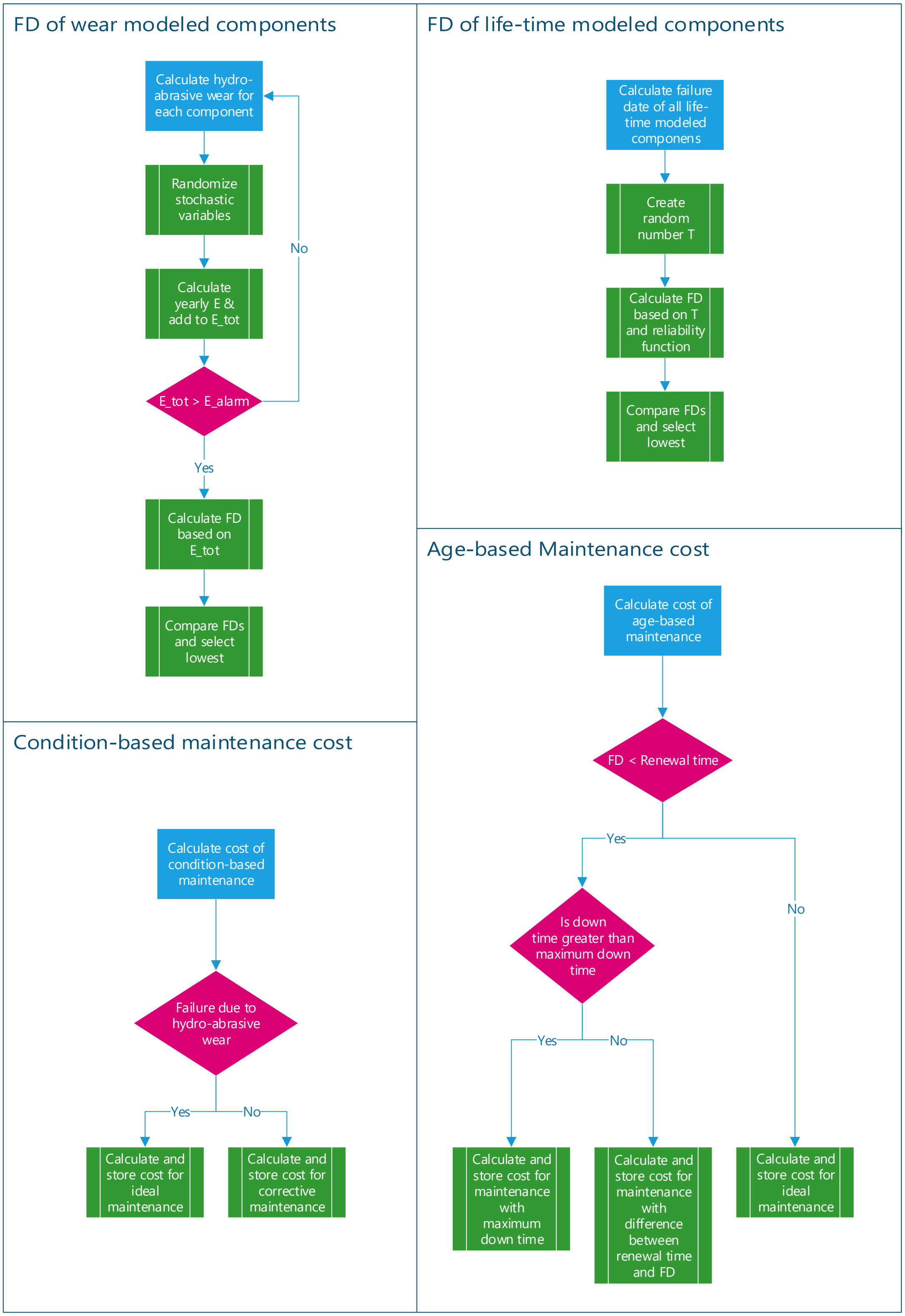


Figure C.3: Flow chart of sub-units in the maintenance optimization tool

C.4 Combined Condition-based and Age-based Maintennce Strategy

Figure C.4: Show the new proposed maintenance strategy based on the results of the first simulations

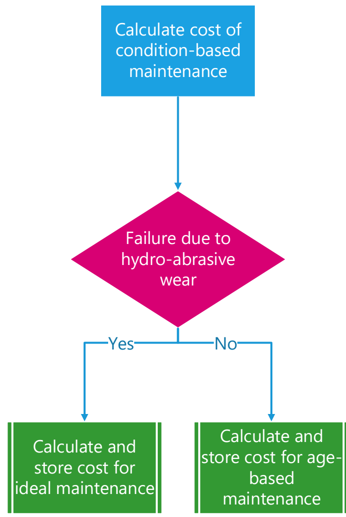


Figure C.4: Flow chart of the new maintenance strategy tested

Appendix D

Mathematical Formulas and Definitions

This appendix presents the distributions used in this thesis and the mathematical foundation of reliability.

D.1 Statistical Distributions

D.1.1 Normal Distribution

The normal distribution (Gaussion distribution) is the most common continuous probability distribution in statistics (Rausand and Høyland, 2004). A random variable T is said to be normally distributed with mean μ and variance σ_2, formulated as $T \sim \mathcal{N}(\mu, \sigma_2)$. The probability density of T is then:

$$f(t) = \frac{1}{\sqrt{2\pi} \cdot \sigma} e^{\frac{-(t-\mu)^2}{2\sigma^2}} \tag{D.1}$$

This can be simplified as the *standard normal distribution*, then N(0,1), this is often denoted $\Phi(\cdot)$. The standard normal probability density function is:

$$\phi(t) = \frac{1}{\sqrt{2\pi}} e^{\frac{-t^2}{2}} \tag{D.2}$$

A graphical representation of the same probability density is illustrated in fig ***

INSERT DISTRIBUTION GRAPH/ILLUSTRATION

D.1.2 Exponential Distribution

The exponential distribution is common in reliability engineering. It is used when considering a component put into operation at $t = 0$ and is often written as $T \sim \exp(\lambda)$. The time to failure T

of the component have the probability density function:

$$f(t) = \begin{cases} \lambda e^{-\lambda t} & \text{for } t > 0, \lambda > 0 \\ 0 & \text{otherwise} \end{cases} \tag{D.3}$$

The reliability function or survivor function of the component is:

$$R(t) = \Pr(T > t) = \int_t^\infty f(u)du = e^{-\lambda t}, \text{ for } t > 0 \tag{D.4}$$

The mean time to failure is:

$$\text{MTTF} = \int_t^\infty R(t) = \int_t^\infty e^{-\lambda t} = \frac{1}{\lambda} \tag{D.5}$$

The variance of T is:

$$\text{var}(T) = \frac{1}{\lambda^2} \tag{D.6}$$

The relability function can be used to calculate the probability that the component will survive it's mean time to failure:

$$R(\text{MTTF}) = R(\frac{1}{\lambda}) = e^{-1} \approx 0.3679 = 36.79\% \tag{D.7}$$

The failure rate function is:

$$z(t) = \frac{f(t)}{R(t)} = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}} = \lambda \tag{D.8}$$

According to the failure rate function of a component with en exponential life distribution is constant, which means its independent of time. From this it is common to OMTALE the exponential distribution as one without memory. To elaborate on this a new component put into operation and an old component that is still functioning and have been functioning in operation for some time will have the same probability to survive a given time interval.

This is a realistic distribution in the useful life period of the component. This is also what makes it easy to in reliability engineering. Therefor it also requires some assumptions (Rausand and Høyland, 2004):

- An old component is assume stochastically as good as new, so there is no need to replace a functioning component.
- The age of the item is not of interest, so it is sufficient to estimate the reliability function solely based on hours in operation and number of failures in this time interval.

D.2 System Reliability

The reliability of a component with a constant failure rate is often modeled by an exponential distribution. The reliability for a component in series and parallel can then be calculated based on formula D.9 and D.10.

$$R_S(t) = \prod_{i=1}^{n} R_i(t) \tag{D.9}$$

$$R_S(t) = 1 - \prod_{i=1}^{n} (1 - R_i(t)) \tag{D.10}$$