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Predictive Maintenance for an Industrial Application

Contribution to Maintenance Modelling
Utilizing Petri Nets with Predicates

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Abstract

In the current industrial scenario, maintenance activities are recognized as a strategic issue. With the increasing demands of the maintenance organizations, maintenance policies have to ensure that physical assets will continue to fulfill their intended function with a minimal expenditure of resources. This issue has led to a growing interest in new maintenance paradigms, such as Condition-Based Maintenance and Predictive Maintenance. These maintenance policies intend to operate systems in a dynamic way. Where failures are avoided through preventive actions, which are planned on-line, given the current and the predicted future condition of the system. This is a new paradigm that completely changes the problem statement for the operational decision rules.

This thesis aim was to investigate the aspects of Predictive Maintenance and maintenance modelling, in association with a study case provided by Equinor. With the objective to establish maintenance models of a gas compressor station, for analysis and optimizing of maintenance actions. Moreover, to highlight the possibilities and challenges within the field of Predictive Maintenance and maintenance modelling.

Maintenance modelling can be used for multiple objectives, within performance assessment and maintenance optimization. In general, the aim is to establish a model in which describes the behavior of the system, with associated organizational actions as maintenance policy. Further to implement the obtained optimal policy on the real-life system. In this study, Petri Nets with Predicates were utilized for modelling the system. The methods modelling capabilities make it suitable for modelling complex systems, where advanced maintenance policies are applied. The predicates allow implementation of conditional aspects needed to realize a realistic behavior of the model.

Two maintenance models were established for two different maintenance policies: Condition-Based Maintenance and Time-Based Maintenance. The models consisted of two compressor drive systems, for each system an electrical motor and compressor were included. For the Time-Based Maintenance model, a two-parameter Weibull distribution was utilized to model the failure characteristics of the respective components. Based on the mean time to failure, and different selected standard deviation, i.e. 10%-, 20%-, and 100% of the mean time to failure. For the Condition-Based Maintenance model, a prognosis based degradation model from previous studies on the study case was applied on the electrical motor. In addition, a degradation model was established for the compressor.

The problem statement was to optimize maintenance actions to enhance system availability. Due to seasonal variations in the production demand, a reduced number of compressor drive systems is needed in certain time periods. Thus, it is possible to maintain the compressor drive system preventively in these periods, without causing downtime on the gas compressor station. Hence, the maintenance problem at hand is; ”when should preventive maintenance actions be conducted, to make as little as possible impact on system availability?”.

The maintenance model proposed where based on a variety of assumptions, simplifications, and limited data. A definite conclusion is therefore not given based on the results

from the optimization and analysis of the maintenance models. Although, the results highlight interesting aspects of the system characteristics. It was recognized that the Condition-Based Maintenance policy achieve a high system availability, with a significant reduction in maintenance actions compared to the Time-Based Maintenance policy. Moreover, the standard deviation on the failure characteristics proved to have an insignificant impact on the performance of the policy, due to its dynamic nature. For low standard deviation, the Time-Based Maintenance policy achieve an even higher system availability. However, when increased the negative impact on the performance was substantial. Besides, the policy relayed on a large number of preventive maintenance actions, which is acknowledged as excessive.

The study highlights what is needed to build an adequate maintenance model. The model proposes a starting point for further work, where many aspects can be improved and implemented to enhance the accuracy of the model behavior. Through improvement, one can reach the case study's initial goal; a simulator that aids optimal maintenance decisions.

Sammendrag

I dagens industri er vedlikeholdsaktiviteter anerkjent som en strategisk utfordring. Grunnet de strenge kravene til vedlikeholdsorganisasjonen, må vedlikeholdstrategier utvikles for å sikre at maskineri vil fortsette å oppfylle sin tiltenkte funksjon med et minimalt ressursforbruk. Dette har ført til økende interesse for nye vedlikeholdsparadigmer, som tilstandsbasert- og prediktiv vedlikehold. Disse vedlikeholdsstrategiene har som mål å operere systemer på en dynamisk måte. Hvor feil unngås gjennom forebyggende tiltak, som er planlagt fortløpende på bakgrunn av dagens og den predikerte fremtidige tilstanden av systemet. Dette er et nytt paradigme som endrer problemstillingen for operasjonelle beslutninger.

Målet med denne avhandlingen var å undersøke aspekter ved prediktiv vedlikehold og vedlikeholdsmodellering, i tilknytning til et casestudie levert av Equinor. Med sikte på å etablere vedlikeholdsmodeller av en gasskompressor stasjon, for å analysere og optimere vedlikeholdsaksjoner. Samt belyse mulighetene og utfordringene innen vedlikeholdsmodellering og prediktiv vedlikehold.

Vedlikeholdsmodellering kan benyttes til flere formål innen ytelsesvurdering og vedlikeholdsoptimalisering. Generelt er målet å etablere en modell som beskriver systemets oppførsel, med tilhørende organisatoriske tiltak som vedlikeholdsstrategi. For videre å implementere den oppnådde optimale strategien eller løsningen på det virkelige systemet. I denne studien ble Petri Nets med predikater benyttet for modellering. Grunnet metodens modelleringsevner er den egnet til modellering av komplekse systemer, hvor avanserte vedlikeholdsstrategier benyttes. Predikatene tillater implementering av betingede aspekter vedrørende det respektive systemet, som er nyttig for å oppnå en realistisk oppførsel av modellen.

To vedlikeholdsmodeller ble etablert for to forskjellige vedlikeholdsstrategier, tilstandsbasert vedlikehold og tidsbasert vedlikehold. Modellene besto av to Compressor Drive System, for hvert system ble en elektrisk motor og en kompressor inkludert. For tidsbaserte vedlikehold ble en to-parameter Weibull distribusjon benyttet for å modellere levetiden til de respektive komponentene. Basert på gjennomsnittlig tid til feil, og tre valgte standardavvik; 10%, 20% og 100% av den gjennomsnittlig tid til feil. For tilstandsbasert vedlikeholdsmodell ble det utnyttet en prognosebasert degraderingsmodell for den elektriske motoren, etablert i et tidligere studier på samme case. I tillegg ble det etablert en degraderingsmodell for kompressoren.

Problemstillingen var å optimalisere vedlikeholdsaksjonene for å forbedre systemets tilgjengelighet. Grunnet sesongvariasjoner i produksjons etterspørselen, er antallet Compressor Drive System nødvendig redusert i visse tidsrom. Det er således mulig å gjennomføre forebyggende vedlikehold på et Compressor Drive System uten å forårsake nedetid på gasskompressor stasjonen. Derfor er vedlikeholdsproblemet som følger: "Når bør det gjennomføres forebyggende vedlikehold, for å forårsake minimal innvirkningen på systemets tilgjengelighet?"

Vedlikeholdsmodellene som ble foreslått var basert på en rekke antagelser, foren-

klinger og begrensede data. En bestemt konklusjon er derfor ikke gitt på bagrunn av resultatene fra optimalisering og analysen av vedlikeholdsmodellene. Likevell fremhever resultatene interessante aspekter av system egenskapene. Det ble anerkjent at den tilstandsbaserte vedlikeholdsstrategien oppnådde høy tilgjengelighet. Med en betydelig reduksjon i vedlikeholdsaksjoner, i forhold til den tidsbaserte vedlikeholdsstrategien. Videre viste standardavviket på levetiddistrubisjonene å ha ubetydelig innvirkning på strategiens ytelse, grunnet sin dynamiske natur. For lave standardavvik oppnådde den tidsbaserte vedlikeholdsstrategien en enda høyere systemtilgjengelighet, men ved stort standardavvik ble ytelsen betydelig svekket. Dessuten er strategien avhengig av et stort antall forebyggende vedlikeholdsaksjoner, som ble anerkjent som unødvendig.

Studien fremhever hva som trengs for å bygge en tilstrekkelig vedlikeholdsmodell. Modellen fremstår som et utgangspunkt for videre arbeid, hvor mange aspekter kan forbedres og implementeres for å forbedre nøyaktigheten av modellens oppførsel. Gjennom forbedring kan man nå casestudiens initielle mål: en simulator som bistår vedlikeholdsorganisasjonen til å oppnå optimale vedlikeholdsbeslutninger.

Preface

This thesis was conducted as a partial requirement in the 2-year Master of Science program, Subsea Technology, for the Department of Mechanical and Industrial Engineering (MTP) at Norwegian University of Science and Technology (NTNU). The study was conducted during the spring semester of 2018, based on a pre-study undertaken during the autumn semester of 2017.

This thesis investigates a topic within the scope of maintenance modelling and optimization, in a case study provided by Equinor. The case has been subjected to study through several prior master's projects. Thus, the thesis is a continuation of these studies, addressing new aspects of the case study. To gain knowledge from the thesis, the reader should have basic insight in the field of Reliability, Availability, Maintainability, and Safety (RAMS).

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J.N.S.

Table of Contents

List of Tables

List of Figures

Abbreviations

CDS	=	Compressor Drive System
CBM	=	Condition-Based Maintenance
CM	=	Corrective Maintenance
CDF	=	Cumulative Distribution Function
DC	=	Deming Cycle
MTP	=	Department of Mechanical and Industrial Engineering
DES	=	Discrete-Event Simulation
FBM	=	Failure-Based Maintenance
FMECA	=	Failure Mode, Effect & Criticality Analysis
IPPD	=	Integrated Product and Process Design
KPI	=	Key Performance Indicator
MA	=	Maintenance Action
MCS	=	Monte Carlo Simulation
MTBF	=	Mean Time Between Failures
MTTF	=	Mean Time to Failure
NTNU	=	Norwegian University of Science and Technology
PD	=	Partial Discharge
RAMS	=	Reliability, Availability, Maintainability, and Safety
PN	=	Petri Net with Predicates
PrM	=	Predictive Maintenance
PHA	=	Preliminary Hazard Analysis
PM	=	Preventive Maintenance
PDF	=	Probability Density Function
PHM	=	Prognosis & Health Management
RBD	=	Reliability Block Diagram
RUL	=	Remaining Useful Lifetime
SD	=	Standard Deviation
TBM	=	Time-Based Maintenance
VDS	=	Variable Speed Drive
WPP	=	Weibull Probability Plot

Chapter 1

Introduction

This chapter provides a presentation of the background, problem description, and the specific objectives which are targeted. Further, the scope and limitation associated with the study are presented, along with an overview of the approach chosen. Finally, the chapter provides a structural blueprint of the report.

1.1 Background

In the last decades maintenance activities have gained a broad recognition as a strategic issue in the industrial scenario. The development which contributed to this change is increasing requirements and the drive for cost reduction. With the increasing demands of the maintenance organizations, maintenance programs have to be developed to ensure that physical assets will continue to fulfill their intended function with a minimal consumption of resources, and to eliminate activities which do not contribute to preserving or restoring the intended functions of the assets (Tsang, 1995).

These issues have led to a growing interest in new maintenance paradigms, such as Condition-Based Maintenance (CBM) and Predictive Maintenance (PrM). These maintenance policies intend to operate systems in a more preventive and dynamic way, where failures are avoided by preventive actions which are planned consequently, given the current and the predicted future condition of the system (Zio and Compare, 2013). These policies are dependent on methods that enables diagnosis and prognosis of the system condition. This is a new paradigm that completely changes the problem statement for the operational decision rules.

As a response to the interest, extensive research have guided the way in the framework of Prognostic & Health Management (PHM) and PrM. Several international scientific societies are devoted to this topic, and many companies invest in projects dedicated to it. NTNU is also supporting and contributing to these projects to meet the emerging needs in the industry (Barros, 2017b).

Equinor (former Statoil) has provided a case study regarding a gas compressor station at Kollsnes processing plant, northwest of Bergen, where Equinor is the technical service provider. The processing facility is a center for treatment of gas from several gas fields on the Norwegian Continental Shelf. From Kollsnes, the gas is exported to the European market as dry gas (Gassco and Statoil, 2009). A gas compressor station is one of the key systems in such networks. Its role is to transport the dry gas to the final customers or other intermediate gas stations. A failure of such a system may lead to substantial production losses. Besides, the operational cost for a large-scale compressor station outweighs the capital cost of the purchase of the system in the long run. These facts are the reason for the industry (in this case Equinor) to focus on efficient operation and maintenance policies (Xenos et al., 2016). Hence, by considering the health condition of the compressor station, one can achieve these goals.

CBM and PrM are often considered as a concept or target, rather than a mature methodology ready for implementation. Hence, reduction of the gap between scientific research and industrial implementation is needed (Vachtsevanos et al., 2006). The case provided by Equinor has been a subject of previous studies, where three master thesis were written within the scope of prognosis and maintenance optimization. However, many challenges are still to address to aid optimal maintenance decision.

1.2 Problem Description

This master's project aims to investigate the aspects within the field of PrM and maintenance modelling, in association with a study case provided by Equinor, and to establish a maintenance model for analysis and optimization of system performance. The model has to take into account the operational-, failure- and repair characteristics of the system.

The main outcome should be an overview of the possibilities and challenges of PrM and maintenance modelling, and to obtain a maintenance model that can aid optimal maintenance decisions.

1.3 Objectives

The main objective of this study is the establish maintenance models for two different maintenance policies, Time-Based Maintenance (TBM) and CBM, taking into consideration the operational-, maintenance- and failure characteristics of the system. With the aim optimize maintenance actions and analyze the effects from the standard deviation (SD) on failure prediction, with respect to system availability.

To achieve the main objective the report shall address the following:

- Give an overview of the gas compressor station, both on operational and component level.
- Present main aspects of PrM including; management and the scheme of PHM, with a review of challenges and opportunities. For further present and discuss the previous studies regarding prognostic modelling on the case study.
- Present the main aspects of maintenance modelling, including framework, modelling methods, and approaches.

- Establish different maintenance models of the Kollsnes gas compressor station. Furthermore, analyze, optimize and discuss the results of the proposed maintenance models for the respective maintenance policies.

The case provided from Equinor may be subjected to further studies, where many aspects of establishing PrM is still underexplored, thus this study has the overall objective to provide knowledge to bring this process a step further in the scope of maintenance modelling.

1.4 Scope and Limitations

The scope of the study is limited to maintenance modelling, with additional focus on the scheme of PrM and PHM to get the full picture of the complexity of the case study. Thus, the framework of PrM, approaches for prognostics, and previous studies on the case are presented.

The different features in the framework of PrM have not been considered (e.g. Failure Mode Effects and Criticality Analysis, Trade Studies), due to limited available information and time. Thus the maintenance model is based on restricted information, where assumptions and simplifications are made by the author in collaboration with supervisor Anne Barros, to be able to model the system. Therefore, the study provides a more general view on maintenance modelling for similar maintenance problems.

1.5 Approach

The main building blocks for the thesis is a literature review and a qualitative approach for investigating the respective maintenance problem.

A literature review is conducted on the different aspects regarding both PrM and maintenance modelling. The literature is obtained from various journal databases subscribed by NTNU. Furthermore, the quantitative analysis utilizes GRIF Petri Module for maintenance modelling and simulation, the software is provided by SATODEV - Safety Tools Development (2018). In addition, MATLAB is used for computations regarding statistical distributions and graphs.

1.6 Structure of Report

The chapters of the report are structured as follows. Chapter 2 provides an overview of the gas compressor station at Kollsnes, including the study case, and the operational- and system characteristics. Chapter 3 presents the different aspects of PrM, and discusses the challenges and opportunities within the strategy. Chapter 4 provides a review and discussion of two previous master's thesis written on the case. Chapter 5 provides a literature review on maintenance modelling, including framework, techniques, and approaches. Chapter 6 gives the process of establishing the maintenance models for the respective case. Chapter 7 provides the optimization of the models and presents the results with a discussing of the interpretation. Finally, chapter 8 summarizes and concludes the study, with additional recommendations for further research.

Chapter 2

System- & Study Case Overview

This chapter presents the gas compressor station at Kollsnes, with an overview of both operational and system characteristics; a short description of the different components in the system will be provided. Furthermore, with a presentation of the study case, with associated questions of interest.

2.1 Operational Overview

Norway supplies over 20% of the European gas demand. The Kollsnes facility is responsible for close to 40% of the total gas exported from Norway, meaning that the facility supplies around 8% of the European gas demand.

Rich gas from the offshore installations; Visund, Troll, and Kvitebjørn in the North Sea are transported to Kollsnes. The facility is a center for gas treatment and export. From Kollsnes, the gas is exported to the United Kingdom and the European mainland as dry gas through the pipelines; Zeepipe II A and –II B, via the offshore installations Draupner E and Sleipner (Gassco and Statoil, 2009).

A compressor station is one of the key systems of such a network. Hence downtime of the system will cause substantial production losses if the system is not able to fulfill the production demand. Which is the basis of Equinor's interest in efficient operations and maintenance policies (Xenos et al., 2016).

Figure 2.1 illustrates the topology of the gas compressor station at Kollsnes. The facility consists of six compressor drive system's (CDS), with a nominal power range from 34 to 37 MW. Five of the six compressors have same characteristics, and one compressor with higher production capacity. All CDS can deliver gas to both headers, however, not simultaneously.

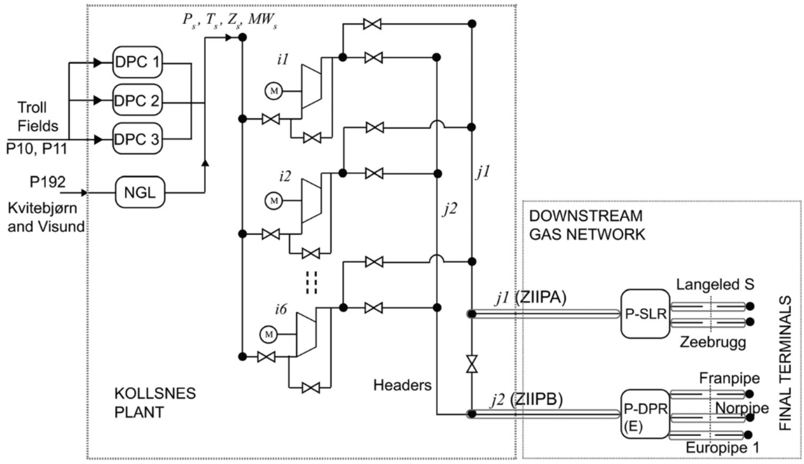


Figure 2.1: Topology of an export gas station and its downstream gas network (Xenos et al., 2016)

The gas demand is fluctuating, hence the operational constraint of the system is fluctuating (Xenos et al., 2016). It is therefore critical to ensure that the CDS is in a functional state upon demand. An example of a typical production profile is illustrated in figure 2.2, which displays that the system is under high demand from October to the end of March. Furthermore, the demand from April to the end of September is significantly lower. Thus, these months may be used for preventive maintenance (PM) activities without causing production losses.

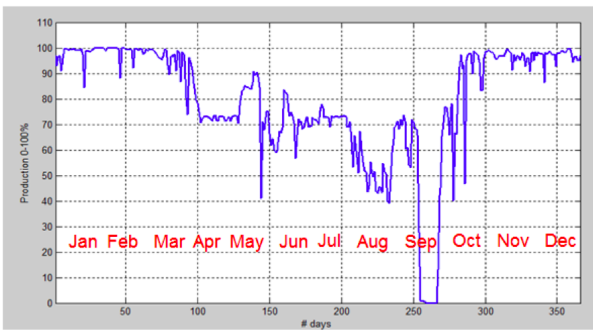


Figure 2.2: Typical production profile

2.2 System Overview

Each CDS consist of: a variable speed drive (VSD), an electrical motor, a gearbox and a multistage centrifugal compressor; as illustrated in figure 2.3. All the four units need to be functioning for the CDS to be in an acceptable state. Thus the units are considered to be in a series structure.

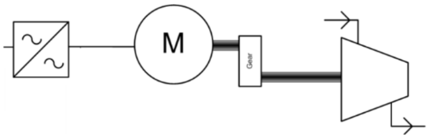


Figure 2.3: CDS

2.2.1 Multistage Centrifugal Compressor

A compressor is machinery used for transportation of gas, by changing the pressure in the gas from a lower to a higher pressure level (Lorentzen, 2017).

In a multistage centrifugal compressor, energy is transferred from multiple rotating impellers to the gas. The gas is drawn into the center of rotating impellers with radial blades, pushed by the centrifugal force, increasing the pressure for each stage. Figure 2.4 illustrates a typical multistage barrel centrifugal compressor, used for natural gas applications, both onshore and offshore. Where the compressors is subjected to medium/large flow and high-pressure (SPE International, 2015).

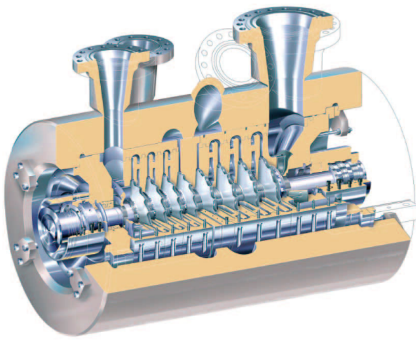


Figure 2.4: Multistage barrel centrifugal compressor (Direct Industry, 2017).

2.2.2 Synchronous Electrical Motor

A motor can be defined as a machine converting electrical- or hydraulic force into mechanical force. In this case, the CDS consists of a synchronous electric motor delivering mechanical force to the compressor. A synchronous electric motor uses AC power supply and utilizes the laws of electromagnetism to produce mechanical force. The mechanical output force is generated from current carrying conductors, which are placed in a magnetic field (Hughes and Drury, 2013). Figure 2.5 illustrates an electrical motor, with its key components.

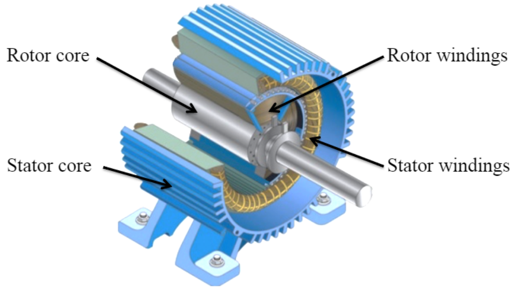


Figure 2.5: Synchronous electrical motor (Bitlanders, 2014)

2.2.3 Variable Speed Drive

A VSD is used to control the output force of the electrical motor, by regulating the speed and torque. Hence, match the speed and torque to the process requirement. Some electrical motors cannot run without a VSD, however, in general a VSD provides reduced energy consumption and improved efficiency (ABB, 2008).

2.2.4 Gearbox

A gearbox provides power transmission from a unit to another unit; in this case from the electrical motor to the compressor. It consist of an inbound axel, gears and an outbound axel. Due to different size of the gears, the number of revolutions is changed from the inbound to the outbound axel, in order customize the torque and revelations to the actuation unit (Toldnes, 2017).

2.3 Study Case Overview

Given the operational- and system characteristics of the gas compressor station, the interest from Equinor lies in predicting the future evolution of the condition of the system, and how it will affect the availability of the system. With the objective to optimize PM actions during summer when only some of the CDS's are needed to fulfill the production demand. Typical questions of interest are therefore;

- What is the remaining useful lifetime (RUL) at a given time t, and the probability of having 100% capacity during the next 6 months?
- How can the RUL be used to optimize maintenance decisions given a certain delay before maintenance intervention, and what are the effects of utilizing such estimate?

To answer such complex questions, a variety of topics has to be addressed and investigated. Due to the challenges presented are including aspects concerning operations-, maintenance- and replacement strategies, and can only be answered through extensive research within the scheme of PrM, including PHM and maintenance modelling.

Chapter 3

Predictive Maintenance

This chapter will present the concept of PrM with the most important aspects, including management, framework, and PHM. With the objective to establish an overall understanding regarding the opportunities and challenges within the PrM scheme. Furthermore, the chapter is used as a background for previous studies on the topic of prognosis, which is presented in the next chapter, and for discussion with relation to maintenance modelling.

3.1 Introduction to PrM

PrM, also referred to as CBM, is based on the fact that the majority of failures do not happen instantaneously, rather develop over a period of time from faulty to functional failure, and the existence of symptoms of deterioration during the time interval (Wang et al., 2010). The strategy aims to recommend optimal maintenance actions, by using machinery health data to determine its condition and future health condition. The data is used to schedule maintenance prior to breakdown (Vachtsevanos et al., 2006).

When the condition of a system can be monitored continuously or by inspections, a PrM strategy can be implemented. This enables the decision of maintaining the system to be taken dynamically based on the condition (Marseguerra et al., 2002).

Prediction of the present and the future condition can be obtained through a broad specter of techniques, including condition monitoring, fault diagnosis, reliability estimation, and life prediction (Wang et al., 2010). To establish an efficient PrM strategy, it is essential to develop an adequate prediction model describing the future evolution of the system degradation and the relevant health indicator. Besides, be able to evaluate different maintenance strategies within the optimization scheme, aiming at optimizing the objectives of interest, typically profit and availability (Marseguerra et al., 2002).

A PrM strategy aims to reduce maintenance cost by reducing the number of maintenance actions, enhance the useful life of the equipment, and find the midway between excessive and deficient maintenance. These positive aspects of PrM can only be achieved if adequately established and effectively implemented, with a solid framework and precise prediction models (Wang et al., 2010).

3.2 Framework and Management

The following sections will provide a presentation of some of the most important aspects comprehending management and framework in PrM, which is regarded as essential for an effective PrM strategy.

3.2.1 System Approach to PrM

Firstly, one has to gather information of the respective system; this can be done by various analysis methodologies. The approach presented here is targeting a PrM policy. However, these methods are widely used as a foundation for other policies and areas within maintenance- and reliability engineering. Based on Vachtsevanos et al. (2006) presentation of system approach to PrM, the main building blocks are presented as follows.

Trade Studies

The objective of a trade study is to arrive at the most balanced or best solution. In the formal framework for trade studies, following the integrated product and process design (IPPD) methodology. The IPPD attempts to: establish the need, define the problem, establish objective with associated key performance indicators (KPI), generate sufficient and feasible alternatives, and make decisions.

For a PrM strategy, other aspects are included to consider the diagnosis and prognosis of critical components failure modes. With the objective to arrive at an optimal PrM strategy. These objectives include:

- Support the decision needs of the system engineering process.
- Evaluate alternatives (requirements, functions, configurations).
- Integrate and balance all considerations.
- Recommend optimal solution.
- Develop and refine a system concept.
- Determine if additional analysis, synthesis, or trade-off studies are required to make a selection.

Failure Mode, Effects and Criticality Analysis

Understanding the behavior of the system with regards to the physics of failure mechanisms is the cornerstone of PrM. Failure Mode, Effects and Criticality Analysis (FMECA) are aiming to provide such information. The study provides procedures and tools, leading to a systematic and thorough framework for design.

An FMECA study attempts to find the relationship between failure events to their respective root cause. This is done by identifying failure modes, and rank them according to these characteristics; severity, the frequency of occurrence, and testability.

Severity comprehends the failure modes ultimate consequence, and are categorized into different severity levels, for example:

- Category 1: Catastrophic, a failure that results in death, significant injury, or total loss of equipment.

- Category 2: Critical, a failure that may cause severe injury, equipment damage or termination.

- Category 3: Marginal, a failure that may cause minor injury, equipment damage, or degradation of system performance.

- Category 4: Minor, a failure that does not cause injury or equipment damage. However, may lead to equipment failure if left unattended, downtime, or unscheduled maintenance.

The frequency of occurrence is distinguished based on the mean time between failures (MTBF), and are classified by the probability of an occurrence of a failure. A possible classification can be: likely, probable, occasional and unlikely, each class with a given probability interval in a given time span.

Testability implies the ability to identify symptoms or indicators of a particular failure modes condition, based on periodic- or continuous monitoring. Thus, the tasks of the FMECA identifies the failure modes that cannot be measured and which failure modes where monitoring is possible.

The information obtained in the FMECA is then utilized to nurture other studies, for further to establish where to employ actions that provide the most substantial impact on the respective KPIs.

Performance Assessment

A PrM system aims to meet multiple objectives, providing useful information to various end-users, including maintenance personnel, system operators, process managers, and system designers.

For the maintenance personnel, a PrM system assists in decision-making to determine the optimum time to perform maintenance actions, given the organizational constraints (e.g., spare parts, personnel availability, etc.). In addition, it provides the process manager and operator with information regarding confidence bounds on the availability of critical processes to fulfill the production demand. While the system designer may be assisted in improving the operational capabilities of the system, by the findings of the PrM practices, to obtain a more robust and reliable system.

The reason for conducting a performance assessment is to evaluate the technical and economic feasibility of implementing a PrM strategy, including various diagnostic and prognostic technologies. However, sufficient performance data are not available before implementation. Thus the analysis is based on an estimate of future performance.

The objective of the performance assessment is to estimate the return of investment of the PrM strategy. Hence, what is the performance if the PrM practices are followed in comparison with the current maintenance practices? Such cost-benefit analysis may proceed as follows:

- Establish the baseline for the comparison, by estimating the cost of current maintenance practices, including their impact on operations (e.g., downtime for maintenance, the frequency of maintenance, cost of maintenance, etc.). Personnel may also provide qualitative estimates of operation impact.
- Estimate system performance obtained with PrM, including reduction of CM, PM and system downtime, with the associated cost for the respective quantities.
- Estimate the intangible benefits of PrM, by interviewing personnel.
- Estimate the cost of implementing PrM. That is, cost of investment in computing, instrumentation, installation, and maintenance of equipment and personnel training.

By combining the technical and economic measures and information just detailed, one obtains an estimate of the life-cycle cost and benefits. Thus, giving a good foundation to evaluate the technical and economic feasibility of implementing a PrM strategy.

Verification and Validation

Verification and validation (V&V) is an important task before the implementation of PrM technologies, such as: monitoring systems, failure prediction models, and decision support systems. V&V serves to ensure that the system design requirements are equal to the delivered capabilities of the system. In the process of V&V the following questions are answered:

- Verification: Is the system build right? (i.e. does the system built meet the performance specifications given?).
- Validation: Is the right system build? (i.e. is the system model close enough to the real-life system, and are the performance specifications and system constraints correct?).

The system performance calculations provide the foundation for V&V. However, few universally accepted methodologies exist. Thus when the question; ”Do I trust that the system will meet the system performance criteria, within the stated system constraints?”, is given an affirmative answered the V&V process is considered completed.

3.2.2 Improvement Model

In maintenance management, continuous improvement models play an essential part in enhancing the quality of service and optimizing the operating cost. This is also important in CBM and PrM strategies with the utilization of new technologies arriving on the market.

Different types of maintenance strategies have been widely subjected to cost-effectiveness studies. However, it usually is difficult to measure the impact of these new tools in the PrM strategy. To overcome the gap, Gilabert et al. (2017) has developed an improvement model for PrM, with the objective to exhibit how PrM can assist in improving cost-effectiveness.

The model is based on the Deming Cycle (DC), which is a well-established model for continuous improvement. A basic DC consists of four steps (Johnson, 2002);

1. **Plan**: Recognize the improvement opportunity, and plan the change.
2. **Do**: Test the change.
3. **Check**: Test, analyze the result of the change, and identify what has been learned.
4. **Act**: Take actions on the results and what has been learned from the change. If successfully, implement the changes in a wider order, if not, redo the cycle.

The cycle draws its structure from the understanding that constant evaluation of management practices and processes is pivotal for a successful organization (Johnson, 2002). The new model proposed by Gilabert et al. (2017), see figure 3.1, is an evolution of the DC based on the same understanding. Developed to reach the full potential of the PrM strategy, unlocking the possibilities for increasing cost-effectiveness. The model is based on different existing tools, e.g. Trade Studies, FMECA, Preliminary Hazard Analysis, Performance Assessment, etc. The innovation of the model is the inclusion aspects related to PrM technologies, and therefore the improvement process obtains a more advanced nature where these aspects are taken into consideration.

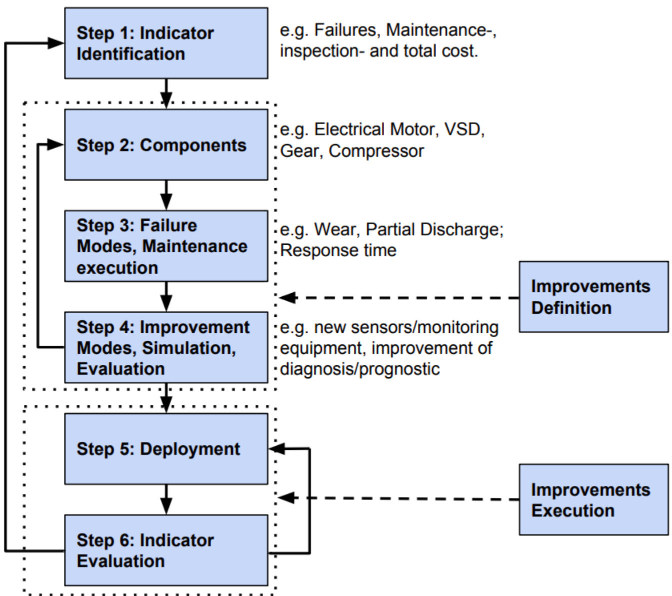


Figure 3.1: Adopted DC for PrM application (Gilabert et al., 2017).

Step 1: Indicator Identification

The first step is regarding the selection of the primary objectives. It is pivotal to take into the account the situation of the organization to identify the areas of improvement and accordingly align the strategies, objectives, and indicators. This step refers to the trade study in the system approach to PrM, where KPI should be established in association with the different objectives.

Step 2: Identification of important components

In step 2, the identification of processes where the improvements would give the most impact with regards to the selected KPIs. These types of processes include; machinery systems (e.g., CDS), machinery subsystems (e.g., electrical motor) or target sectors (e.g., production demand). By identifying and ranking the different processes with regards to impact, one can select a process for further analysis in the following steps.

Step 3: Analysis of the selected components

By carrying out an extensive analysis of the selected processes, one obtains a clear idea of the different aspects of the process, with their respective importance. The utilization of various tools, e.g., FMECA, provides the information of critically and impact on the process. This is useful to identify where to make improvements to achieve the previously established objectives.

Step 4: Identification of improvements for each critical component

In step 4, analysis and assessment of various improvements for the selected components or processes are conducted. The performance assessment objective is to evaluate the improvements to ensure that the objectives are met before implementation.

Simulation plays a big part of the cost assessment, by establishing a simulation model one can evaluate the improvements. The key issue for simulation models is to have valid information to obtain a realistic and relevant result of the characteristics and behavior of the component or process. It may be favorable to make assumptions and approximations if necessary, hence the importance of understanding the behavior of the process and the model, and validation of the simulation outcomes to ensure realistic results for further evaluation (Gilabert et al., 2017). If the evaluation of the improvements shows that the objectives are not achieved, the model suggests that the improvement process cycle back to step 2, for further instigation of the component or process.

Step 5 and 6: Implementation and Indicator Evaluation

Step 5 and 6 are repeatedly done in a sub-cycle, as illustrated in figure 3.1. Hence, to compare the result from the simulation in the previous step to the actual result obtained after implementation of the improvements.

The selected improvement/strategy is implemented in small-scale, to evaluate the results. The new concept, with procedures and/or hardware and software technologies, are then implemented and tested, using the initial KPIs for evaluation. The process then cycles in the sub-cycle of step 5 and 6, until the initial objectives have been fulfilled. When the objectives are fulfilled, the model advocates the return to step 1, for the establishment of new objectives and start the cycle over to ensure continuous improvement.

Improvement of Information

The improvement cycle proposed does not only focusing on optimizing the maintenance processes. It also takes into account the related process of information acquisition and identification of indicators to discover and evaluate deficiencies in the system. As mentioned in the previous section, information is one of the ground pillars in a PrM policy, thus more important to acquisition and store information in an adequate manner than in other maintenance policies.

In the first steps in the cycle is very much related to the improvement of information. Usually, one notices a single indicator as machinery availability or reliability as an initial KPI. During the development of the project, new indicators are discovered with an additional need of information to evaluate the indicators. Gilabert et al. (2017) advocates that the search for information while running the improvement cycle, should be conducted within the company as it is much more rewarding than a global search of all available information. Thus, the initial assessment with reduced feedback will identify the shortcomings of information source in the company.

An insufficient information source may be a result of the way failure data is managed. This can be improved by erasing vaguely defined work orders, to achieve a reduction of the amount incidences not linked with a type of failure. A consolidated FMECA shared between both engineering and maintenance areas, and clear procedures regarding failure, cause and action can improve the source of information. This type of improvement can be addressed in the initial DC, as the problem does not necessarily include PrM technologies.

3.3 Methods for Failures Prediction

Failure prediction is an important element of PrM, where the modelling methods are moving from traditional reliability approach towards advanced prognosis approaches. With the increasing interest of PrM, the field has been subjected to a extensive research over the years, in which has resulted in a broad specter of techniques and approaches. However, traditional reliability models still widely used for failure prediction. Heng et al. (2009) classifies failure prediction of machinery into three main categories:

- Reliability approaches; event data based prediction.
- Prognostic approaches; condition data based prediction.
- Integrated approaches; prediction based on both event and condition data.

The traditional reliability approach is well established in the discipline of reliability engineering with numerous of published books and articles on the subject. These approaches are based on historical time-to-failure data to estimate the reliability of the unit. The approach enables a general long-range forecast of a population of units, and does not require any condition monitoring. However, the approach does not give accurate short-term predictions or predictions for individual units (Heng et al., 2009), in which is one of the driving factors for the gained interest in the scheme of PHM.

3.3.1 Prognosis & Health Management

PHM refers specifically to phases involving fault diagnostics and prognostics within PrM, in which the objective is to predict the current and future condition of the system. PHM is a broad discipline with many different aspects, including; diagnostic, prognostic. However, this thesis will only present and evaluate the prognostic aspects of PHM, in which is regarded as an essential aspect of an effective PrM, thus considered as its Achilles' heel (Vachtsevanos et al., 2006).

Prognosis aims to predict the Remaining Useful Lifetime (RUL) of a degrading component or subsystem. The interest lies in the ongoing reliability of the unit, i.e., the actual health of the unit and the development of the health. By utilizing non-intrusive degradation measurements, one obtains a rich source of valuable condition monitoring data on the evaluation of the health of the unit. As a consequence of this opportunity, researchers have developed prognostic models that estimate the RUL based on the acquired data (Heng et al., 2009).

Remaining Useful Lifetime

Generally, RUL may be defined as: *"The remaining lifetime of a unit at time t, given that it is running at time t, and that all information available related to the unit at time t is given"*. However, the definition may vary depending on the approach used for estimating the RUL and the information available (Le Son et al., 2013).

Barros (2017a) presents a formalization of RUL, where RUL is presented as a stochastic process. $RUL(t)$ is a random variable corresponding to the RUL at time t, the process can then be defined as;

$$RUL(t) = inf\{h : Y(t+h) \in S_L | Y(t), Y(t) \notin S_L\} \tag{3.1}$$

Where; inf denotes the greatest lower bound of a set, $Y(t)$ the current condition, S_L the set of failed or unacceptable states, t the current time, h the time after t, and $Y(t+h)$ the future condition at any time after t, hence prognosis.

$RUL(t)$ is therefore the time from current time t to time h, where the unit is failed or in an unacceptable state. It is also important to notice that $Y(t)$ can be dependent on the past and future usage profile.

3.3.2 Approaches for Prognosis

Vachtsevanos et al. (2006) gives a detailed description of approaches for prognosis, the book categorizes the approaches into: model-based, data-driven and probability-based approaches. Moreover, Si et al. (2011) gives a review on statistical data driven approaches within the prognosis scheme. Figure 3.2 is based on the literature's presentations of the different approaches prognosis and related methods.

Data-Driven- and Probability-Based approach rely on available data. Wang and Christer (2000) divides condition monitoring data into two classifications, direct condition monitoring data and indirect condition monitoring data. The direct condition monitoring data classification emphasizes data which describe the underlying state of the system directly, meaning that the prediction of the RUL is the prediction of the condition monitoring data to reach the predetermined threshold (e.g., undesirable state, failure). Crack size and wear monitoring are typical examples of direct condition monitoring data. On the other hand, indirect condition monitoring data classification emphasizes data which indirect or partial indicate the underlying state of the system. Hence, additional failure event data may be needed to use the data for RUL estimation purposes. Vibration monitoring is an example of monitoring that obtains indirect condition monitoring data.

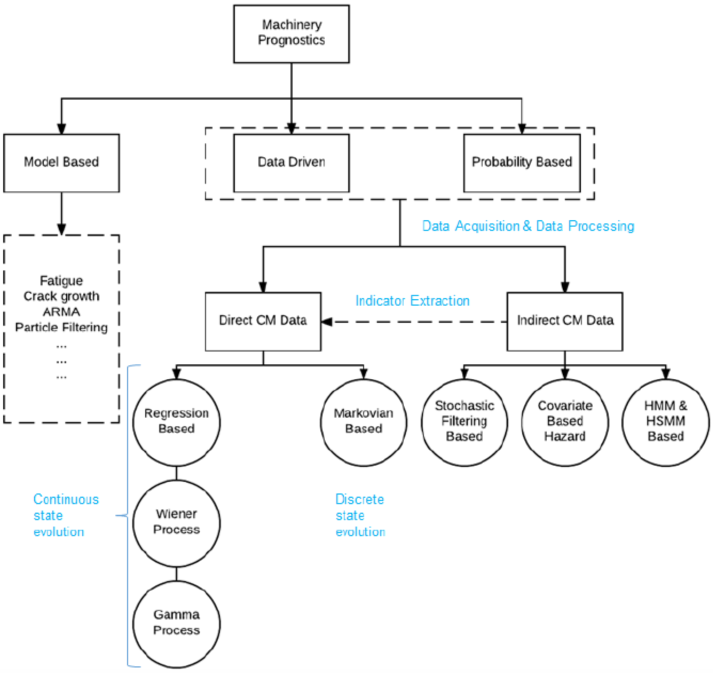


Figure 3.2: Approaches for machinery prognosis (Islam, 2017)

Model-Based Approach

Approach based on mathematical models to describe the relation between physical characteristics of the system and failure mode progression. A physics-based model provides a way to calculate the damage impact to components, as a function of operation conditions and the cumulative effects of the physical usage in the component life (Vachtsevanos et al., 2006).

A model-based approach is only used for pure physical models and has a very specific application area, as crack propagation modeling. For these particular application areas, the approach can provide a knowledge-rich prognosis output by combining system-specific mechanistic knowledge, degradation evolution formulas and condition monitoring data (Heng et al., 2009).

Data-Driven Approach

Approach based on deriving models from routinely collected condition monitoring data directly, by utilizing for example projection and regression models. The advantages of the approach lies in the simplicity of calculations. However, the prediction relies on the past degradation patterns, thus the accuracy is vulnerable if the future degradation deviates from the expected path. Commonly used techniques for data-driven approach includes; Artificial Neural Network, Bayesian-related methods and Hidden Markov Models. These methods are efficient for complex systems or when data is not adapted to probability-based approaches (Heng et al., 2009).

Probability-Based Approach

A statistical approach based on collected condition monitoring data and historical data, utilizing a combination of reliability and prognostic models. Thus, referred to as integrated approach by Heng et al. (2009). While condition monitoring data is a rich source of information to make prognostic models, does not mean that reliability data and analysis is unnecessary. Due to this fact, researchers have taken upon the integration of prognosis into reliability, vice versa, and has established several valuable models. By utilizing available information more fully, both condition and event data, increases the accuracy of regular reliability models.

If the data from the respective component takes a statistical form that can be transferred into a probability distribution, a probability-based approach can be utilized for prognosis. The approach provides confidence limits of the prediction of the RUL, that are useful while evaluating the accuracy of the predictions (Vachtsevanos et al., 2006).

Data-Driven- and Probability-Based approach is not clearly distinguished. Hence the classification of the approaches are complicated, and therefore a probability-based approach can be considered as in the scope of data-driven approach.

3.3.3 Opportunities and Challenges

Heng et al. (2009) and Vachtsevanos et al. (2006) addresses the opportunities and challenges within the prognosis and PrM scheme. The literature highlights the need for extensive research on the topic. However, the growing interest in the topic is now reducing the gap from theory to real-life practices.

Heng et al. (2009) emphasizes the importance of utilizing available data in a fully and accurately manner. Historical event data, such as time to failure, are required for establishing a prognostic model. However, in practice systems rarely runs to failure. Once a fault in a unit is detected, the unit is replaced or overhauled. Hence, the condition of the unit where it will cease to function is not recorded or known. This type of data is called censored or suspended data, and prognostic model based on these types of data may produce an underestimation of the time to failure.

Another challenge regards machines subjected to variable operating patterns, including operational parameters and repairs. If these characteristics are not considered, the accuracy of the prognosis output may be reduced.

As mention in previous sections, the primary objective of implementing PrM is to optimize maintenance actions. It is therefore favorable to extend the prognostics research, to also include the effects of maintenance actions on the units conditions, and estimating the change in unit reliability. A maintenance action does not always restore the unit to a ”good as new” condition and may affect the unit characteristic, i.e., increasing degradation rate. These effects should be accounted for when developing a prognostic model. By enhancing well-established reliability models that consider maintenance effects, the opportunity can be exploited.

The complexity of real-life machinery is regarded as a hinder for practical application of various prognostic models. Many models are designed to predict the time to failure of a specific failure mode, without considering the interaction of the health of other components or the operating environment. If the interaction effects between the components are not considered, the probability of system failure will be an underestimation.

Chapter 4

Review of Previous Studies

In the spring of 2017, three masters thesis were written related to gas compressor station at Kollsnes, on topics of prognostic modeling and maintenance optimization. This chapter will give a short review of the two studies that regarded prognostic modeling, with the objective to provide knowledge and discuss prior studies.

Both studies were based on establishing a degradation model for the electrical motor, i.e. unit level of the CDS, with the objectives to estimate the RUL to answer the questions presented in the study case overview; "What is the RUL at a given time t, and the probability of having 100% capacity during the next 6 months?"

Through a literature review different degradation mechanisms were presented, such as thermal-, ambient-, electrical- and mechanical- aging. It was noticed that aging processes influenced by multiple stresses acting in a synergistic manner, which makes degradation modeling difficult. Further, it recognized that regardless of which stresses acting most dominantly on the degradation process, the failure usually occurs due to electrical aging (Islam, 2017). Based on the literature study, the insulation was identified as the unit which has a significant impact on the lifetime of the unit. The reasons identified was lack of maintainability and its vulnerability to degradation mechanisms. Partial Discharge (PD) was considered to be closely linked with these mechanisms, and therefore chosen as the prognostic condition indicator for the health of the stator windings (Heimdal, 2017).

Figure 4.1 illustrates the insulation quality with respect to PD. The guideline is provided by Karsten Moholt AS, who is responsible company for the condition monitoring of the rotary machines at the Kollsnes process facility.

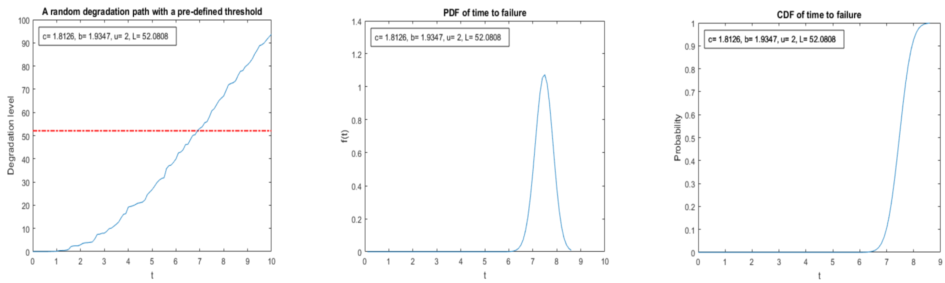
Insulation Quality	**PD (nC)**
Excellent	<2
Good	>2<4
Average	>4<10
Still acceptable	>10<15
Inspection recommended	>15<25
Unreliable	>25

Figure 4.1: PD Guideline provided by Karsten Moholt AS (Islam, 2017)

4.1 Degradation Modeling for Predictive Maintenance - An Application to High Voltage Rotary Machines

To estimate the RUL, Islam (2017) utilized a probability-based approach based on a non-homogeneous Gamma process for modeling of the degradation of PD. Important Gamma process properties were discussed, concerning rotary machine prognostics. The study claims that the Gamma process is a natural choice for degradation processes where the evolution of the health indicator is monotonic and unidirectional, with positive increments over time and continuous state evolution. The model established is based on condition monitoring data.

Figure 4.2 present the results of the analysis of the degradation model. Where figure 4.2a illustrates a random degradation path for the process, with a pre-defined threshold value, figure 4.2b present the Probability Density Function (PDF) of the time to failures for the system, and figure 4.2c present the Cumulative Distribution Function (CDF) of the time to failures for the system.



(a) Path **(b)** PDF **(c)** CDF

Figure 4.2: Analysis results (Islam, 2017)

Based on expert opinion provided by Equinor and literature review, the proposed approach appears to be the most appropriate for degradation modeling for this case. However, the proposed model requires validation based on field data. The model is full of possibilities to improve, hence make the transition from theoretical to practical application as more information becomes available (Islam, 2017).

4.2 Remaining Useful Lifetime Modeling of a Compressor Drive System

Heimdal (2017) utilized a probability-based approach for modeling the degradation of PD. Where Markov process is used for the degradation model, with estimated transition rates based on condition monitoring data that are associated with the PD guideline (figure 4.1). A Markov process has discrete state evolution in a finite state space and has to fulfill the Markov property, meaning that the process is based on exponential law; thus the future state evolution is independent of the past.

The model proposed utilizes increasing failure rates between the respective states to describe the behavior of the health indicator best. Figure 4.3 illustrates the state transition diagram for the Markov model, this presentation of the unit gives a good overview of the degrading process.

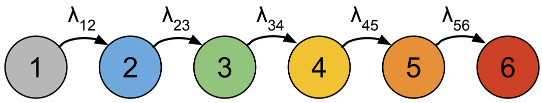
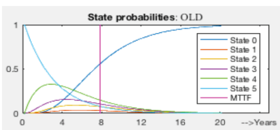
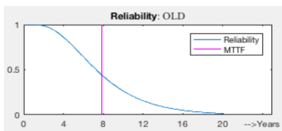


Figure 4.3: Markov state transition diagram of degradation model (Heimdal, 2017)

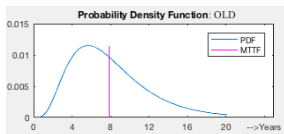
The analysis results are presented in several survival measures, such as reliability function, state probabilities, and probability density function. Figure 4.4 illustrates the results from the model obtained through the study. In figure 4.4a the probability of being in each state at time t is presented, figure 4.4b present the reliability function for the system, while figure 4.4c present the PDF for the system. The RUL of the motor was estimated to be 7,83 years, from new state. The result identified a significant uncertainty related to the estimate, as shown in figure 4.4c. With a confidential interval of 95%, the RUL varies from 1,10 to 55,59 years. Consequently, inspections should be carried out as often as possible, to reduce the probability of unexpected failures (Heimdal, 2017).



(a) PDF for each state



(b) Reliability function



(c) PDF for system

Figure 4.4: Analysis results (Heimdal, 2017)

4.3 Discussion of Previous Studies

Both studies investigate interesting aspects of its respective approaches for modeling the degradation of the stator windings with respect to PD. Where the two different methods have different qualities.

Heimdal (2017) provides a user-friendly model, that can be used in close relationship with the guideline provided by Karsten Moholt AS. With the discrete states the limits the threshold limits for activating maintenance actions are intuitive and easy to implement in a maintenance organization. However, the accuracy is questionable and with the limited opportunities for calibrating the behavior of the model is a considerable weakness. Islam (2017) provides a more advanced model, with the opportunity to better calibrate and fit the Gamma distribution to condition monitoring data. This gives the model clear advantages relative to the Markov model. As the study claims, the non-homogeneous Gamma process with its abilities seems like the best way of modeling the degradation of the stator windings.

Chapter 5

Maintenance Modelling

This chapter will present maintenance modelling through a literature review on the different aspects within the scheme, including framework, degradation modelling, optimization and modelling approaches. The objective is to present what has been done in the literature, which will provide the foundation of the maintenance model established in the case study in the following chapter.

In the scheme of PrM, maintenance modelling may be utilized for performance assessment to establish a baseline for comparison, estimate system performance obtained with PrM, estimate the benefits of PrM, and to estimate the cost. Hence, maintenance modelling can provide crucial insight of the behavior of the system, which aids to find the optimal policy with associated strategies for the respective system.

5.1 Introduction & Literature Review

Today, maintenance management is a key issue for companies with the drive for cost reduction. Companies seek more efficient and effective maintenance, which has emerged as one of the ground pillars to be successful in the modern industry. Maintenance modelling has therefore been subjected to research in a large volume of published studies, with the objective to enhance the performance of maintainable systems through modelling and optimization (Alrabghi and Tiwari, 2016).

There are a variety of modelling techniques and approaches for maintenance modelling. All techniques have different characteristics, and one needs to choose the technique best suited to solve the initial problem or achieve the objective of the model. In general, the most important choices for modelling techniques is whether the model should be continuous or discrete; dynamic or static; deterministic or probabilistic; constrained or unconstrained; and single- or multi-objective (Pintelon and Van Puyvelde, 2006).

For maintenance specific modelling, the choices are whether the model should be: component or system perspective, and have a finite or infinite time horizon. The most common optimization models choose the component perspective (Van Horenbeek et al., 2010). However, with growing research on the topic many articles have proposed new methods and approaches to develop the maintenance modelling scheme.

Alrabghi and Tiwari (2016) emphasizes the limitations of analytical modelling methods, due to the complex industrial challenges that have emerged. To counter this, the article proposes a modelling approach for simulation of complex system behaviors based on fewer assumptions. Moreover, Alaswad and Xiang (2017) provides a review of CBM optimization models for stochastically deteriorating systems. With an emphasis on mathematical modelling and optimization approaches and the associated essential aspects of CBM such as inspection frequency, maintenance effectiveness, optimization criteria, etc., for single- and multi-unit systems. With the objective to provide useful references for CBM management and researchers.

Many articles are published on maintenance policy optimization, where different policies are modeled and compared based on the optimization's criteria. In Van Horenbeek and Pintelon (2011), maintenance decision-making based on RUL predictions is explored, with the objective to optimally plan maintenance for multi-component systems considering the different component dependencies. The article utilizes Weibull law for the failure prediction and Discrete-Event Simulation (DES) as the modelling method. Furthermore, Gilabert et al. (2017) proposes a methodology for simulation of PrM strategies for cost-effectiveness analysis, utilizing Monte Carlo Simulation for simulating the performance of an asset with the associated cost.

Van Horenbeek et al. (2010) propose a general framework for maintenance modelling and optimization, where different criteria for obtaining a valuable maintenance model is discussed. Hence, the article is used as the basis for further presentation and discussion in this chapter, with a more elaborate presentation of the different articles presented. That will provide a clear picture of the possibilities and limitations of maintenance modelling, before modelling the gas compressor station at Kollsnes processing plant.

5.2 Maintenance Modelling Framework

There are a lot of ways to model a maintainable system, with both approaches and information that is taken into account for the model, where no standard maintenance models exist to fit different optimization problems. However, a methodology can be established on how to reach different maintenance optimization objectives. Van Horenbeek et al. (2010) proposes a methodology based on a maintenance optimization classification framework, that provides an overview of the aspects that can be taken into account for an optimization model, with associated methods and techniques. This framework makes it easier for companies and academics, to see what is possible with current techniques and which areas still in need of further research.

Figure 5.1 illustrates the maintenance modelling framework. The framework can be utilized as a starting point to chose methods and techniques best fitted to a specific problem. Building a business-specific model can start with the framework and the determination of important input parameters for the model, to be able to obtain an optimal solution to the maintenance problem. Thus, the first step to reach a decision support system.

The framework will be used as a reference for the following chapters, where a selection of aspects will be presented with associated literature.

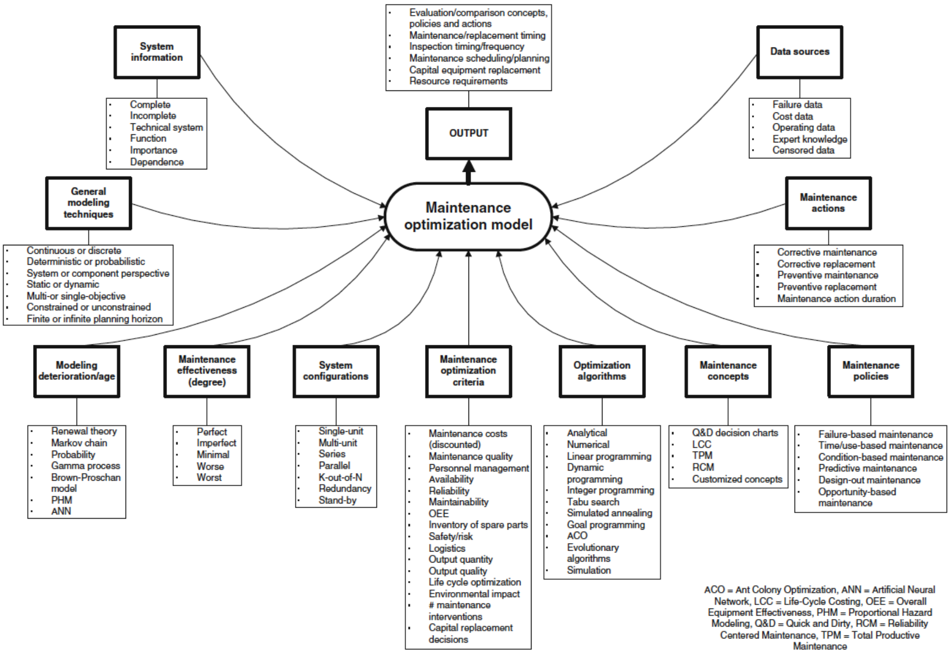


Figure 5.1: Maintenance modelling framework (Van Horenbeek et al., 2010)

5.2.1 System Information & Data Source

For maintenance modelling, it is essential to understand the working principle, criticality, system configuration, etc., for each unit in which shall be included in the model. By establishing a good understanding of the system information, one obtains knowledge on the underlying mechanisms of the system, which is pivotal before analyzing data, the unit or the system as a whole. Furthermore, the system information will reveal dependence characteristics between components. When no dependence is present, i.e. independent, the optimal maintenance decision is obtained for each unit. Thus, if the system units have dependency the maintenance decision has to take this into account to achieve the optimal decision. Three types of dependence exist; economic, failure and stochastic. In addition system configuration is also essential for modelling the system. For multi-component systems many different configurations are possible, including; series, parallel, K-out-of-N, standby.

Data is the foundation of a maintenance model, and as often looked upon as one of the most significant challenges regarding implementation of maintenance models in real-life study cases (Van Horenbeek et al., 2010).

Failure data are necessary to model the degradation of the respective components; the accuracy of the results depends on the accuracy of the failure prediction. As discussed in the PrM chapter, there are many ways for failure prediction, and which approach chosen reflects on the results. In some cases, long-term projections are the goal; thus conventional reliability approaches are sufficient. If one wants to evaluate the system performance in the short-term, more detailed condition and failure data are needed to increase the accuracy (Heng et al., 2009).

Maintenance data is also necessary to model the behavior of the organization, and the impact of the maintenance on the respective system. Gilabert et al. (2017) presents the data required to obtain a maintenance model for PrM strategy in table 5.1, where the information necessary is classified into general-, reliability-, CM- and PM information. This is similar to more basic strategies, however there is some additional information required to be able to model the behavior of condition monitoring, in regards to the probability of false positive and negative failure detection.

Table 5.1: Data for the simulation of PrM (Gilabert et al., 2017)

Type	Data	Description
General	Production hours	Total simulated time (e.g. the useful system/component)
	Useful life	Useful life of the system/component
	Replacement cost	Cost of replacement/refurbishment of the system/component at the end of useful life
Reliability	Location, scale and shape	Parameters describing the Weibull distribution
CM	Failure cost	Cost of unexpected failures requiring unscheduled maintenance
PM	Action cost	Cost of performing a failure detection analysis
	Action interval	Pre-defined time interval for performing failure detection analysis
	Repair cost	Cost of dealing with a failure detected by the failure detection analysis
	False positive probability	Probability of the failure detection analysis generating a false alarm
	False negative probability	Probability of the failure detection analysis missing an actual failure

It is essential to determine the data necessary for the specific case. A solid framework for maintenance modelling can assist in gathering the relevant data to reduce the uncertainty of the model, as well as avoid gathering of irrelevant data. If the system information and data is incomplete, expert judgment is needed to determine essential information regarding the system characteristic before a maintenance model can be adequately established (Van Horenbeek et al., 2010).

5.3 Maintenance Modelling & Optimization

Maintenance modelling refers to the modelling of a system or a group of units subjected to maintenance. This section will go through the some of the aspects of maintenance modelling and optimization.

5.3.1 Maintenance Optimization Criteria

Optimization refers to a process performed for maximizing or minimizing an objective function. With regards to maintenance modelling the objective functions is to optimize one or more specific quantities (e.g., availability, cost, reliability) of the respective system. According to Van Horenbeek et al. (2010) many maintenance optimization models only take into account one criteria, which is a well-studied field within maintenance optimization modelling. However, in real-life cases multi-objective optimization is often necessary to obtain the optimal solution.

Table 5.2 present different optimization criteria, with associated measurement to the KPI. The maintenance optimization criteria are the most important parameter for maintenance optimization. Hence, optimizing wrong objectives will lead to a sub-optimal solution.

Table 5.2: Generic list of optimization criteria (Van Horenbeek et al., 2010)

Key Performance Indicator	Measurement
Maintenance costs	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

5.3.2 Maintenance Policies

To evaluate the system behavior, the maintenance model should be as close as possible to the behavior of the real-life system; concerning both failure and repair characteristics. The modelling of maintenance policy plays a crucial part to achieve this goal.

The different maintenance policies can be classified as failure-based maintenance (FBM), TBM and CBM. The policies trigger maintenance actions when specific events occur. In regards to optimization, each respective policy has different parameters to be optimized.

For FBM, corrective maintenance (CM) action is triggered when a failure occurs. Thus the policy does not have any maintenance actions to optimize, nevertheless reliability and organizational aspects could be subject to optimization. While for TBM, a PM action is triggered by calendar and/or operation hours. Thus, the time interval parameter for PM actions is optimized to establish the best KPIs. For CBM, a PM action is triggered by if the condition of the unit exceeds a pre-defined maintenance threshold. Condition monitoring is therefore required for such maintenance policy, the monitoring can either be continuous or based on periodic inspections. The optimization is therefore based on determining the optimal maintenance threshold, and the inspection interval for periodic inspections.

Van Horenbeek et al. (2010) claims that in most maintenance models, the maintenance duration is assumed negligible. However, assumptions like this needs to be evaluated.

The maintenance duration may have a significant influence on the KPIs, which provides an unrealistic model which obtains sub-optimal solutions to the maintenance optimization problem. This advocates the evaluation of all assumptions regarding maintenance activities, against their impact on the respective KPIs.

5.3.3 Maintenance Effectiveness

The obtain a realistic maintenance model, the effectiveness of maintenance should be considered. In real-life systems, the units are maintained to various states, thus not always ”as good as new” state. Maintenance effectiveness comprehends the degree to which condition of the unit is restored to after a maintenance action is performed. The possible different degrees of restoration may be (Van Horenbeek et al., 2010):

- Perfect repair: the unit is restored to an ”as good as new” state, meaning that the degradation level and failure rate are equal to the initial level and value.
- Minimal repair: the failure rate is restored to the rate that the unit had before the maintenance action was performed, referred to ”as bad as old” state.
- Imperfect repair: the condition of the unit is restored to a state between ”as good as new” and ”as bad as old”.
- Worse repair: the units failure rate increases by performing a maintenance action, however the unit does not break down.
- Worst repair: the unit will suffer failure by performing a maintenance action.

Researchers recognize the importance of taking into account the maintenance effectiveness in maintenance models. However, only a limited amount of CBM models proposed in the literature consider the impact of imperfect repair (Alaswad and Xiang, 2017).

For the modelling of the gas compressor station, the following approaches for modelling maintenance degree are interesting. Huynh et al. (2012) proposed a model based on conducting minimal repair, where the unit is maintained to the previous stage of degradation. Hence, when the unit is repaired in stage k, the maintenance action returns the unit to state $k-1$. Furthermore, Wu et al. (2015) proposed a model where the imperfect maintenance action reduced the units degradation by a random amount.

5.3.4 Inspection Frequency & Quality

As mentioned, a CBM policy is based on the information obtained through inspections. Thus the choice of inspection strategy is important. The main types of inspection strategies in CBM are; continuous monitoring, periodic inspections, and non-periodic inspections. Each strategy provides benefits with associated disadvantages, moreover the implementation of such strategy is often dependent on what is possible on the respective system. Several papers are published with the objective to develop CBM models for different inspection- frequencies and qualities.

The benefits of continuous monitoring is that it offers real-time data on the units health condition. However, the monitoring strategy may imply high cost, and inaccurate diagnostic may cause unnecessary maintenance actions due to noise created by the vast amount of data flow (Liu et al., 2012). Besnard and Bertling (2010) propose a modelling approach for optimization of inspection frequency on wind turbines, where the study displays that a continuous monitoring strategy is optimal for high failure rate system. Hence, the strategy's application area lies mostly in monitoring critical systems. Thus continuous monitoring is often implemented in systems where a unit failure makes a significant impact on relevant KPIs (e.g., availability, safety, etc.)

For systems where continuous monitoring is not applicable or too expensive, a periodic inspection strategy can be utilized. The strategy is recognized as cost effective, however it may lead to a higher amount of unscheduled maintenance, and more documentation work for the maintenance organization. For periodic inspection, the interest for optimization lies in determining the optimal inspection interval, which has been extensively studied by researchers, for example Ferreira et al. (2009). Furthermore, in cases where it may not always be worth inspecting the unit at a given inspection interval, thus a non-periodic inspection strategy may be suitable. Where the next inspection is scheduled based on the condition of the unit obtained from the previous inspection, hence the inspection interval decreases as the condition of the unit degrades. This strategy is recognized as the most cost-efficient, however it will cause more documentation work, increase the probability of human error, and it may cause higher failure cost (Lam and Banjevic, 2015).

The quality of the inspection is also of interest. Generally, perfect inspection is assumed for CBM models, i.e. the inspection reveals the exact unit condition without any error. However, it may be more realistic to assume imperfect inspection (Alaswad and Xiang, 2017). By for example taking into account the probabilities of false-positive and false-negative in the failure detection, as presented in data source table (table 5.1) for modelling PrM policy (Gilabert et al., 2017). Alaswad and Xiang (2017) provides a review on different modelling approaches with respect of inspection quality, presented in the literature.

5.4 Modelling Methods

The choice of method should be evaluated up against the respective system one wants to model. The different methods all have different characteristics that are suitable for different problems or analyses.

In general, one can divide the modelling approaches into two categories, analytically and simulation methods. This study will review Markovian-, Discrete-Event Simulation- (DES) and Petri Nets with Predicates (PN) modelling method, to further to discuss and choose the most suitable modelling method for the case study.

5.4.1 Markovian Method

A Markov process is a type of stochastic process, with the ability to describe the characteristics of a system, by introducing states and the transitions between them.

Markov chain is divided into two different groups, discrete-time, and continuous-time. This report will only consider continuous-time Markov chain, referred to as Markov Process. A Markov process fulfills the Markov property, meaning that when the present state of the process is known, the future development is independent for the past and exponentially distributed. A more elaborate presentation of Markov property can be found in Rausand and Høyland (2004).

Transition Rate Matrix and State Equation

By considering a Markov process with continuous time and finite state space size N. The process is defined by the transition rates $A(i, j)$ from state i to state j. The transition rates are inserted into a matrix A.

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

The probability for the process to be in state j at time t, given that the process is in state i at time 0, is denoted $P_{ij}(t)$. For calculation, these probabilities are inserted into a matrix $P(t)$. The sum of each row equals to 1.

$$P(t) = \begin{bmatrix} P_0(t), & P_1(t), & \dots, & P_r(t) \end{bmatrix} \tag{5.2}$$

The formula to calculate the state probabilities is:

$$P(t) \times A = \dot{P}(t) \tag{5.3}$$

State Transition Diagram

A Markov process can be illustrated in a state transition diagram, also called Markov diagram. The diagram presents the different states as circles and the transitions between them with arrows. To establish a Markov model one has to list and describe all relevant system states. Identical states should be merged, to achieve that each remaining state is unique (Rausand and Høyland, 2004).

Steady-State Probabilities

For a repairable system, it can be interesting to look at the probabilities in the long-run, referred to as the steady-state probabilities, that is the value of $P_j(t)$ when $t \to \infty$. The steady-state probabilities are not dependent on the initial state of the system and is irreducible if all states have a transition out of the state.

The steady state probabilities $P = [P_0, P_1, \dots, P_r]$ has to satisfy the equation:

$$\begin{bmatrix} P_0(t), & P_1(t), & \dots, & P_r(t) \end{bmatrix} \times \begin{bmatrix} a_{00} & a_{01} & \vdots & a_{0r} \\ a_{10} & a_{11} & \vdots & a_{1r} \\ \vdots & \vdots & \ddots & \vdots \\ a_{r0} & a_{r1} & \vdots & a_{rr} \end{bmatrix} = \begin{bmatrix} 0, & 0, & \dots, & 0 \end{bmatrix} \tag{5.4}$$

Calculation of the steady state probabilities, we use r of the $r + 1$ linear algebraic equation from equation 5.4.

Multiphase Markov Process

The foundation of Markov process is valid for a Multiphase Markov process, however it has additional attributes that can take into account the seasonal operation changes and more advanced maintenance strategies.

A Multiphase Markov process is a Markovian system with parameters changes at different points in time. These points in time can be denote as $T_0 = 0, T_1, T_2, ..., T_n$. Between T_{i-1} and T_i, the systems evolves according to a regular homogeneous Markov process with the transition matrix A_i. One can calculate the probability law of the process at time t, by assuming that $T_i \leq t < T_{i+1}$. The probability law of the process at time T_1, can be calculated by following formula (Jin and Rausand, 2014):

$$\mu_{T_1} = \mu_0 e^{T_1 A_1} \tag{5.5}$$

At time T_1 the transition matrix changes to A_2, and between T_1 and T_2 matrix A_2 evolves with the initial law μ_{T_1}. The probability law of the process at time T_2 is therefor:

$$\mu_{T_2} = \mu_{T_1} e^{(T_2 - T_1)A_2} = \mu_0 e^{T_1 A_1} e^{(T_2 - T_1)A_2} \tag{5.6}$$

These characteristics make it possible to model more advanced maintenance strategies. For example, assuming two units a and b in a series structure, where the system is renewed every τ. We are able to model the system behavior with inspections in the interval [0, τ]. A failure of the units are supposed to be detected immediately, and the time to repair is taking a constant value. During inspections, the condition of the units are diagnosed. Furthermore, the degradation of the units is modeled in phase i, while the inspection and maintenance actions are modeled in phase j. The given inspection interval changes the phase of the model, where the units are diagnosed and different maintenance actions may be conducted dependent on the state of the units. The time in phase j is determined by the time to repair or inspection duration. Hence, the time to repair is often neglected in these kinds of models since it is not possible to model a conditional characteristic, e.g, repair if exceeding maintenance threshold.

A Multiphase Markov process can therefore be used to model more complex systems then a regular Markov process. For a system that changes characteristic at time t_i, as the CDS, a regular Markov process is not sufficient. By utilizing a Multiphase Markov, it is possible to model the change in seasonal constraints, inspection strategy, maintenance policies and configuration of the system.

5.4.2 Simulation Method

The use of simulations for modelling of system health and maintenance strategies is on the rise. Simulation techniques enables the modelling of more complex system behaviour and requires fewer assumptions then analytic modelling. The application for maintenance is still developing, although simulation is well-established in other areas, as in manufacturing processes (Alrabghi and Tiwari, 2016).

Discrete-Event Simulation

DES is based upon the foundation of Monte Carlo methods and is carried out by simulating lifetime scenarios of a system. In DES, one starts with a model of the system characteristics: random events (i.e. component failures), scheduled events (e.g. PM and inspection) and conditional events (i.e. events initiated by other events). The objective is to create a simulation that is as close to the real lifetime of the system as possible (Rausand and Høyland, 2004). Based on the system characteristics, DES creates a chronological sequence of events that affect the state of the respective system, then the simulation moves through these events and apply the predetermined changes on the system (Alrabghi and Tiwari, 2016).

When a lifetime scenario has been simulated by a DES, the output scenario can be treated as a real experiment, to calculate performance measures. However, for maintenance models with probabilistic measures it is more convenient to run the simulation n number of times, n depends on the system complexity and the reliability of the system components. From the simulations one can carry out calculation of the mean performance and survivor measures of all the simulated scenarios, i.e:

- The mean time to failure (MTTF).
- The mean availability of the system.
- The mean number of system failures.
- The mean number of failures for each component.
- The mean contribution to system unavailability for each component.
- Number of PM actions.
- Number of CM actions.
- RUL

When the system is simulated n number of time, one has also the opportunities to investigate the variance of the different simulations. Hence, a better understanding on system behavior. With the possibility to apply confidential intervals on the output data, reliable decision can be taken.

DES is a good modelling technique, due to its ability to take into account for any aspects and circumstances affecting an item or system (Rausand and Høyland, 2004).

Petri Nets with Predicates

Petri Nets can be categorized as both analytical and simulation method. The method is based on predetermined formulas that characterize analytical methods, however it is often necessary to simulate the model to solve the equations (Kawauchi and Rausand, 2002). Which means that it can be regarded as a hybrid between analytical and simulation methods.

The method combines graphical and mathematical modelling, in order to simulate systems, subjected to discrete events in a discrete state space. Petri Nets were introduced by Carl Adam Petri in 1962. Since then, the tool has been extended and adopted for applications in many different fields, including communications, automation, industrial production systems and computer science.

Figure 5.2 illustrates a Petri Net with Predicates (PN), with the main graphical elements, which is used for modelling the system behavior. Places, presented as circles, symbolize the state of the system/component. Transitions, presented as rectangles, present events occurring in the system in which lead to a change in the state of the system, meaning that the token change location from a place to another place. Tokes represent where the location of an resource or system state, and is symbolized by small full marks inside the places. The places and transitions is connected to each other by arcs, presented as arrows (Santos et al., 2015).

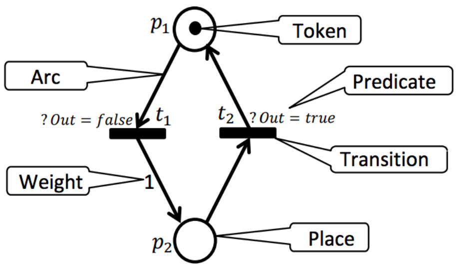


Figure 5.2: Main graphical elements in PN (Martínez, 2014)

PN allow properly modelling of the behavior of a system and its maintenance activities, by modelling the interactions and dependencies between the different components in a system. The integration of Monte Carlo Simulation in the original PN gives the possibility to produce stochastic performance outputs, and the ability to use predicates, which has proven to be powerful for modelling complex systems.

Transitions can be fired stochastically, deterministically and/or by predicates. There are two types of predicates, guards and assignments. A assignment is a post-condition message that update variables in the model, while a guard is a pre-condition that inhibit or enable the firing of transitions. Symbolized in the model around the respective transition with the notation; ! (assignment) and ? (guard) (Santos et al., 2015).

5.4.3 Modelling Method Discussion

All the different methods with different characteristics have suitable application areas in maintenance modelling, thus the decision on which one to chose to solve a maintenance optimization problem has to be taken on basis on the characteristics of the problem at hand.

Markov Process method is considered to be static, due to the limitations of the Markov property and the difficulties to model conditional constraints. Thus, it is not suitable for modelling for modelling complex systems with multiple components and variable operating patterns, such as the gas compressor station at Kollsnes.

Simulation methods like DES and PN, offer a dynamic modelling suitable to model complex systems in a adequate manner. These methods are not limited to exponential law, and it is possible to model complex maintenance strategies with associated constrains. The differentiation of the two methods lies in that a DES can have a discrete or continuous state space, while PN can only model discrete state space. Thus, the choice of modelling methods needs to taken on the basis system characteristics, e.g. failure prediction models, etc. For researches in maintenance modelling, simulation is looked upon as a powerful method, which is preferred for modelling of complex system.

5.5 Approach for Maintenance Modelling

Alrabghi and Tiwari (2016) presents a approach for maintenance modelling, for various of policies, based on simulation modelling method. In the following a modelling approach for TBM and CBM policies is presented. These approaches highlight the mindset behind modelling maintenance polices. However, the approaches does not consider the assets dependence to other assets.

Approach for Modelling TBM Policy

For a TBM policy, the asset is maintained at a given time interval to minimize unexpected failures. Figure 5.3 illustrates the modelling approach provided by Alrabghi and Tiwari (2016), for an asset i where TBM is applied.

The approach is divided into two steps:

1. **Develop the simulation model**:
   Both CM and PM are defined as possible maintenance actions, since the asset can still suffer failure. Variables related to the assets characteristics are then added, including reliability (e.g. lifetime distribution), CM (e.g. repair time, cost etc.) and PM (PM frequency, repair times, cost, etc.). As the simulation clock advances, the asset can be subjected to both maintenance actions.

2. **Manage the effects of maintenance actions on the same asset**:
   The simulation clock advances to the next event, and a maintenance actions is duo on asset i, either CM or PM. If the asset is failed, CM is conducted and the variables associated is sampled and updated. If the asset is functioning, PM will be conducted and variables will be sampled and updated. Meaning that the effects of maintenance

are included in the respective variables, e.g. lifetime distribution of the asset, taking the maintenance effectiveness into account. Then the process returns to simulating the next event, with the updated variables.

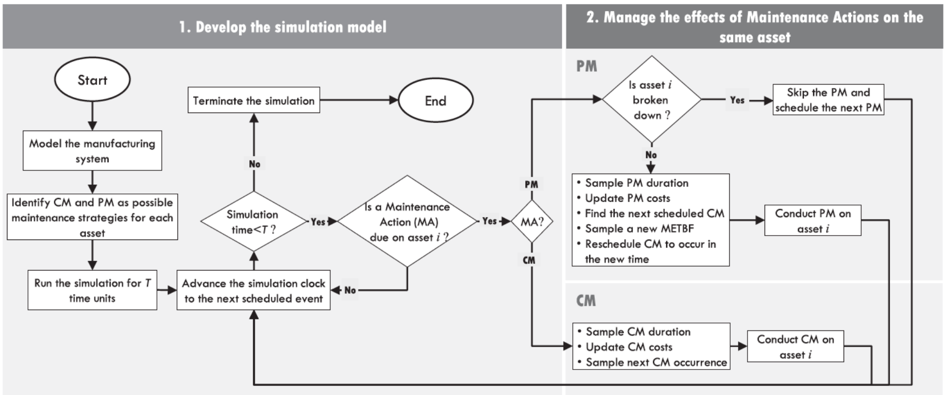


Figure 5.3: Approach for TBM modelling (Alrabghi and Tiwari, 2016)

Approach for Modelling CBM Policy

The CBM polices aims to further enhance the performance of the asset, by only conducting PM when needed. This is achieved by determining condition threshold for PM actions and condition monitoring for each asset. Only when the condition exceeds the maintenance threshold a PM action is conducted. Figure 5.4 illustrates a modelling approach for CBM, proposed by Alrabghi and Tiwari (2016), where the assets condition is monitored by periodic inspections.

The approach for CBM is similar to the approach for TBM, however here CBM and CM are defined as the possible maintenance actions for asset i. Thus, the variables related to the preventive actions are different.

The process illustrated in figure 5.4 evolves by the simulation clock, which simulates the time of the next event, where a failure of asset i has occurred or the asset is subjected to an inspection. When a failure has occurred, CM is conducted and the associated variables are updated. When an inspection is conducted, the degradation level of the asset is checked. If the degradation level exceeds the maintenance threshold PM is conducted, and if the degradation level is lower then the given threshold a new inspection is scheduled. For both events, the variables are updated before simulating the occurrence of the next event.

1. **Develop the simulation model:** CBM and CM are defined as maintenance actions. Set CBM variables, including inspection frequency, inspection cost, maintenance threshold, repair times, repair cost. CM variables are identical to TBM modelling approach.

2. **Manage the effects of maintenance actions the same asset:** The maintenance effects are manage with the same principle as in the TBM model. However, with

the degradation level of the asset, one now manage the effects of maintenance by reducing this level to a given state or value.

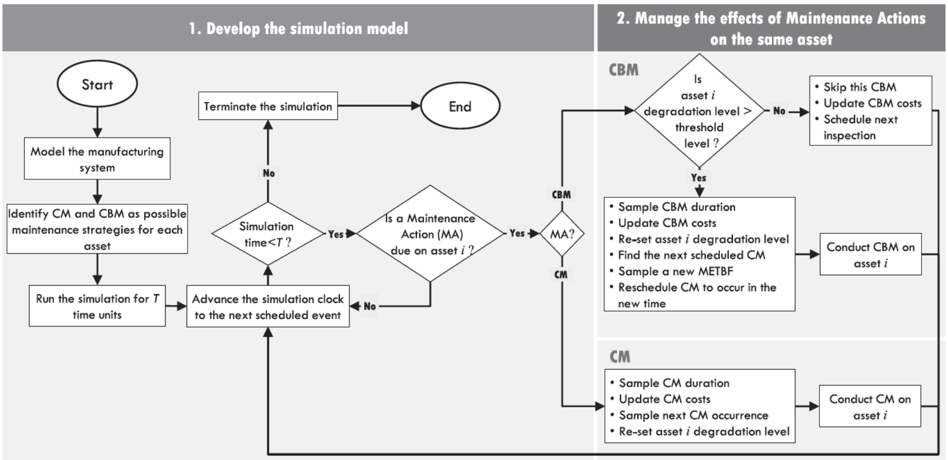


Figure 5.4: Approach for CBM modelling (Alrabghi and Tiwari, 2016)

5.6 Degradation Modelling

In a maintenance modelling, the degradation processes of the units is an important input. Especially for CBM models where the condition of the unit provides the information for maintenance decisions, e.g. when to perform maintenance. The degradation process characteristics should match the real degradation of the system as close as possible. Many degradation models are proposed in the literature. Where the easiest methods to model the failure behavior is by probability distributions, e.g. exponential, Weibull, normal, etc, which is well established in reliability engineering (Pintelon and Van Puyvelde, 2006).

In general, the regular reliability approaches are often being utilized to model the lifetime behavior of the system. However, these methods may be inaccurate and therefore only give a realistic image of the long-term behavior of the system. Thus the growing interest of implementing prognostic models in order to model the degradation of the unit in a more complex manner, to obtain a precise short-term behavior of the system.

For CBM models, the degradation can be modeled by discrete-state and continuous-state degradation. Where Markov processes are usually utilized for modelling discrete-state degradation, when precise measurements of the degradation process cannot be obtained (Alaswad and Xiang, 2017). Although Markov process is often used, the method has some disadvantages. Thus makes it unsuitable for complex cases, when transition probabilities are difficult to estimate and the classification of the degraded states is arbitrary (Van Horenbeek et al., 2010).

For system where the degradation is gradual over time, and it is difficult to classify the multiple degraded states, continuous-state degradation modelling may obtain a more realistic model behavior. When condition information obtained from sensors monitoring the degradation process are available, continuous-state models are preferred. Thus widely implemented in CBM models in the literature, by utilizing approaches such as; Gamma process, Wiener process and Inverse Guassian process (Alaswad and Xiang, 2017).

5.7 Statistics

Statistics plays a vital part in maintenance modelling. In this study, exponential distribution and two-parameter Weibull distribution is utilized to establish lifetime models of the respective components. The following subsections will provide the theoretical background for the statistical distributions used later in the thesis.

5.7.1 Exponential Distribution

The exponential distribution is a commonly used lifetime distribution for reliability analysis. Due to its simplicity, and that it is realistic for certain types of items (Rausand and Høyland, 2004).

Considering an item, the PDF for $t > 0, \lambda > 0$ is given by:

$$f(t) = \lambda e^{-\lambda t} \tag{5.7}$$

The distribution is given by the parameter λ, which denotes failure rate of the item. The survivor function ($R(t)$), for $t > 0$, of an item is given by:

$$R(t) = Pr(T > t) = \int_t^\infty f(u)du = e^{-\lambda t} \tag{5.8}$$

The MTTF is;

$$MTTF = \int_0^\infty R(t)dt = \int_0^\infty e^{-\lambda t}dt = \frac{1}{\lambda} \tag{5.9}$$

and the variance of T is given by:

$$var(T) = \frac{1}{\lambda^2} \tag{5.10}$$

An item with exponential life distribution has a constant failure rate, i.e. independent of time. Due to this characteristic the survivor function of an item that has been functioning for time t, is equal to the survivor function of a new item. Hence, the exponential distribution has no memory.

Therefore, the use of exponential law requires the assumption that:

- A used item is as good as new.
- The age of the item is of no interest, thus sufficient to estimate the reliability function on hours in operation and the number of failures.

5.7.2 Weibull Distribution

The Weibull distribution is one of the most used lifetime distributions in reliability engineering, as well as other disciplines. The distribution adequately describes observed failure times for different component types and failure phenomena (Lai, 2013).

Probability distributions are used for reliability predictions, by estimate future failures based on historical failure data. In many cases exponential distribution is applied, although the distribution has some shortcomings. In this regard, the Weibull distributions provide a more adaptive alternative, with its ability to take into account a broader specter of data and life characteristics by changing the distributions shape parameter. The Weibull distribution, popularly referred to as the "bathtub curve", illustrated in figure 5.5 where the effect of different shape factors are illustrated.

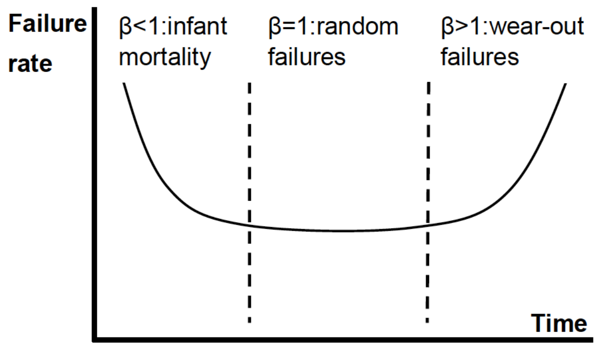


Figure 5.5: Illustration of the Weibull distribution (Zhai et al., 2013)

The Weibull family includes many distributions, either as an approximation or exact. The distributions that are included are the normal, the exponential ($\beta = 1.0$), the Rayleigh, and sometimes also the Poisson and the Binominal can be included. This gives a wide specter of opportunities to obtain the best fit of the failure data. This feature unlocks Weibull analysis ability to provide reasonably accurate failure prognosis and failure analysis with small samples of data. Which can be very valuable since failure data often are either small in size or incomplete (Zhai et al., 2013).

Basic of Weibull Distribution

The probability of failure at time t, also referred t as the Weibull distribution or the CDF, can be expressed as (Zhai et al., 2013):

$$F(t) = 1 - e^{-(\frac{t}{\eta})^{\beta}} \tag{5.11}$$

Thus, the Weibull reliability at time t, is defined as;

$$R(t) = 1 - F(t) = e^{-(\frac{t}{\eta})^{\beta}} \tag{5.12}$$

and the PDF is given by the equation:

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-(\frac{t}{\eta})^{\beta}} \tag{5.13}$$

The mean of the Weibull distribution is used to find the MTTF for the unit, and is given by;

$$MTTF(T) = \Gamma\left(\frac{1}{\alpha}+1\right) \tag{5.14}$$

while the variance is given by:

$$var(T) = \Gamma\left(\frac{2}{\alpha}\right) - \Gamma^2\left(\frac{1}{\alpha}+1\right) \tag{5.15}$$

5.7.3 Methods of Estimating Weibull Parameters

To unlock the potential of the Weibull distribution, accurate estimations of the shape and scale parameters are essential. There exist many different methods that can be applied for parameter estimation.

For parameter estimated based on failure data, the methods may be classified into two categories; the statistical methods and the graphical techniques. For parameter estimation without available failure data, generic data sources as OREDA are often utilized.

In the following, two different method for estimating the Weibull parameters is presented. One based on only the MTTF, and one where failure data is available.

Parameter Estimation Based on MTTF and Standard Deviation

In many cases, incomplete or no field data is available for estimating the parameter. Thus, utilizing generic data sources as OREDA is possible to obtain MTTF values. Barros and Lefebvre (2018) present a method for parameter estimation based on a given MTTF and a chosen Standard Deviation (SD) (σ), used for modelling Weibull lifetime law.

Considering a Weibull distribution with the parameters, α and β, we can then tune these parameters to fit the MTTF($1/\beta_{ref}$) and a chosen SD (σ). The chosen SD (σ) is calculated with the coefficient k, which denotes the wanted percentage of σ_{ref}. σ_{ref} is given by;

$$\sigma_{ref} = \frac{1}{\beta_{ref}} \tag{5.16}$$

By tuning the Weibull parameters, one obtains;

$$\sigma = k \times \sigma_{ref} \tag{5.17}$$

and:

$$MTTF = \frac{1}{\beta_{ref}} \tag{5.18}$$

in which gives a Weibull distribution with the corresponding parameters to the given MTTF and the chosen SD.

Weibull Probability Plot

The Weibull probability plot (WPP), involves plotting the empirical distribution function ($\bar{F}(t)$), with a log scale on the horizontal axis and a log-log scale on the vertical axis. One way to estimate $F(t)$ is by:

- $\hat{F}(t_i) = \frac{i}{n+1}$, the "mean rank" estimator.
- $\hat{F}(t_i) = \frac{i-0.5}{n}$, the "median rank" estimator.

The data set consists of successive failure times $t_i, t_1 < t_2 < ... < t_n$.

The technique is simple and can easily be done in spreadsheet software with unit scale for plotting, and are therefore a favorable technique for reliability engineers. By taking log twice of both sides of the survival function:

$$log(-log\bar{F}(t)) = \alpha log(t) - \alpha log\beta \tag{5.19}$$

Let $x = log(t)$ $y = log(-log\bar{F}(t))$, thus one obtain a linear equation:

$$y = \alpha x - \alpha log\beta \tag{5.20}$$

Now the plot is on a linear scale, and that the WPP indicate a straight line if it is plausible to assume that the data set is given by Weibull law. From 5.20 one can find the initial estimates of the Weibull parameters with $\hat{\alpha}$ = regression coefficient and $\hat{\beta} = exp(-(y - intercept/\hat{\alpha}))$ (Lai, 2013).

Chapter 6

Case Study - Gas Compressor Station

This chapter regards the case study of the Gas Compressor Station at Kollsnes, where the modelling characteristics will be presented, including: problem statement, failure and repair characteristics, modelling approach. Furthermore, a presentation of the maintenance models established for analysis and optimization will be provided.

6.1 Kollsnes Gas Compressor Station

As presented in chapter 2, the Kollsnes gas compressor station is a crucial part of the gas export network from Norway to the European market. Thus, the system needs to have a high performance to meet the demands. By establishing effective maintenance policies the performance can meet these demands, in addition to reducing the total maintenance cost. Hence, the objective to evaluate different maintenance policies, i.e. TBM and CBM, by establishing a maintenance model of the system, and search for the optimal policy.

6.1.1 Problem Statement

The main problem under investigation is when to conduct PM on the systems components, to make as little impact as possible on the system availability. The seasonal variations of the system is the key, where one can utilize the extra capacity in the time periods with a reduced production demand. With a reduced number of CDS's needed to fulfill the production demand there is room for conducting PM without causing downtime of the station. Hence, PM is only conducted when the action is not a direct cause of downtime.

By establishing a maintenance model with the characteristics presented, it is possible to solve this problem and obtain a maintenance policy that provides the optimal system performance, given the system information that is available for this study.

6.1.2 Modelling Method - Petri Nets with Predicates

PN is chosen for the maintenance models, which is a powerful method utilizing discrete-state space. The reason why it fits this case is the dynamic capabilities due to the communication between different sub-models or sub-nets. This is possible by using predicates and simulation of the PN.

In the literature PN are not widely used for maintenance modelling by researchers. However, some papers are published utilizing the modelling method. Santos et al. (2015) utilizes PN for modelling of the operation and maintenance of offshore wind turbines, and Blondel et al. (2014) for modelling of a gas compressor station, in a non-published paper.

DES would also be a suitable method for modelling the system. The reason for choice of modelling method is based on the authors limited knowledge in computing and lack of available DES software.

Software

On today's market one can find a large variety of simulation software, both generic and industry-specific. This report has chosen to use GRIF-Workshop, a software developed by Total. A systems analysis software platform for determining indicators of dependability, as performance, reliability, availability and safety. GRIF-Workshop provides a simulation package that consist of a Petro module, used for modelling of complex oil and gas multi-flow system; the BStock modul, based on stochastic block diagrams; and the Petri module, used for model large and complex system utilizing stochastic Petri Nets with Predicates (SATODEV - Safety Tools Development, 2018).

The Petri Module has the ability the model systems with little constraints on the abilities from the software. Hence, it makes the Petri Module suitable for modelling dynamic systems and maintenance strategies as PrM. A further explanation of the how PN and the software works will be provided in the presentation of the maintenance models later in this chapter.

6.1.3 Model Assumptions and Simplification

Due to the limitations of the study, various assumptions and simplifications are done to be able to model the behavior of the gas compressor station. A maintenance optimization model should be based upon information and data obtain from various of analysis, as presented in chapter 5, to be able to establish a rich and accurate maintenance model. However, this is not done in this study, hence the model is based on a limited data source and system information.

The simplifications of the gas compressor station comprehends a reduction in number of CDS's, where only two of the six CDS's are modeled. However, the same maintenance problems are subjected for 2 as 6 CDS's, thus the results will give a guideline for handling such maintenance problems. Furthermore, the gas demand is also simplified. In real-life the gas demand is fluctuating throughout the year, thus the number of CDS's needed to fulfill production demand varies. A simplification of this matter is done, by assuming a gas demand with two season, summer and winter, where the demand is constant. Hence, 50% and 100% of production capacity is needed to fulfill the demand, for summer- and winter operations respectively.

The degradation processes is assumed to be independent from the work load on the components, e.g. if a CDS is set in standby the degradation process will continue to evolve. For the degradation modelling, the model proposed by Heimdal (2017) on the degradation of the PD failure mode on the electrical motor is assumed to be given, and utilized to describe the degradation of the entire component. In addition, the MTTF obtained from the model is utilized to configure the Weibull distribution for the component in the TBM model. It is further assumed perfect inspection for the CBM policy, where the condition of the respective component is determined without any error.

In the following sections, additional assumptions will be presented and discussed in association with the respective characteristic.

6.2 System Characteristics

This section comprehend the system characteristic, i.e. failure and repair, where the input data for the maintenance model will be presented. Furthermore, the establishment of lifetime distributions for the components.

First, a presentation of the system configuration will be provided. Figure 6.1 illustrates the system in a Reliability Block Diagram (RBD) with respect of the two seasonal variations, summer and winter. For the system to deliver the production demand 1 out of 2 CDSs needs to be functional during summer, while 2 out of 2 CDSs needs to be functional during winter.

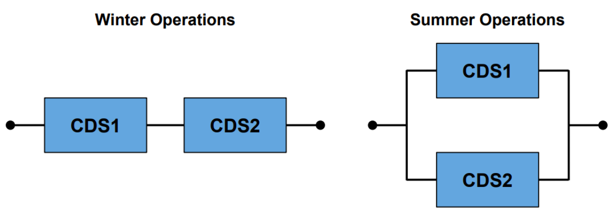


Figure 6.1: RBD of the gas compressor station with regards of seasonal variations

Figure 6.2 illustrates the RBD for one CDS. All the four components are in series, meaning that if one of the component fails to deliver its initial purpose the CDS is regarded as in a failed state.

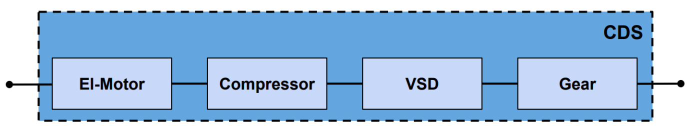


Figure 6.2: RBD of the CDS, with the four components

6.2.1 Failure Characteristics

The model the failure characteristics of the components two different approaches are used. For the TBM policy, regular reliability approach is utilized based on the MTTF, where the failure characteristics are modeled by Weibull law. To model a CBM policy, degradation models is needed.

Table 6.1 presents the MTTF values for the different components. Due to no condition or failure event data is available for this study, the respective Weibull distributions will be estimated based on the MTTF and different chosen SD, as presented in previous chapter. In appendix A, one can find the MatLab code used for estimating the parameters. The objective with the different SD for the distribution is to investigate how the SD influences the system performance with the different maintenance policies.

Table 6.1: MTTF values

Components	MTTF
Compressor	$4.5000E04$
Electrical Motor	$6.9018E04$
VSD	$1.0000E08$
Gear Box	$1.0000E08$

The most critical components are identified as the compressor and electrical motor, since these components are the biggest contributors to system unavailability. Due to low amount of failures for the VSD and gear, the impact of failures of the VSD and gear are assumed to be negligible, and will therefore not be implemented in the maintenance models. For further to focus on the optimization and analysis for the component regarded as critical, i.e. have the most severe impact on the optimization criteria.

TBM - Lifetime Distribution for Compressor

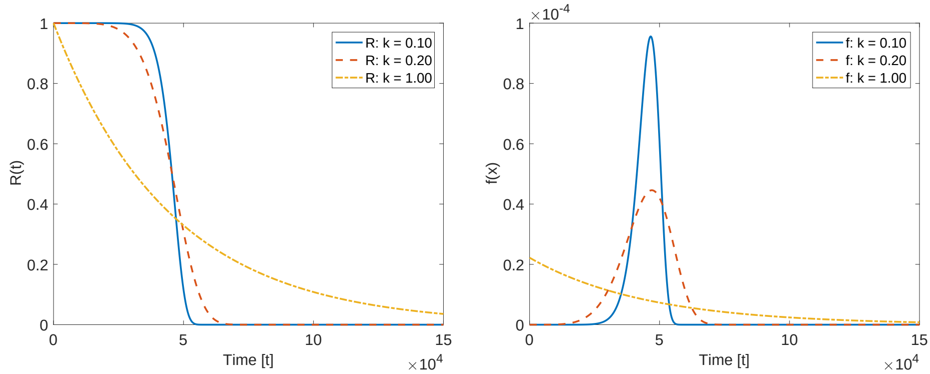
To characterize the lifetime distribution for the compressor, reliability approach is utilized. The estimated parameters for the three Weibull distributions are presented in table 6.2, for SD equals to 0.10% and 0.20% and 1.00% of the MTTF. The distribution with $K = 1.00$ is equal to an exponential distribution with the same MTTF.

Table 6.2: Weibull distribution - Estimated parameters for compressor

K	β_C	α_C	SD_C
0.10	$2.1306E-05$	12.1534	$4.5E03$
0.20	$2.0577E-05$	5.7974	$9.0E03$
1.00	$2.2222E-05$	1.00	$4.5E04$

Figure 6.3 illustrates the failure characteristics of the compressor, given the three different Weibull distribution parameters. In figure 6.3a the reliability function is presented, and in figure 6.3b, the PDF is presented. Both plots illustrates the different behavior

obtained with the different parameters. The Weibull distribution for $K = 1.00$, has a significant SD, while the other distributions are clearly centered around the mean.



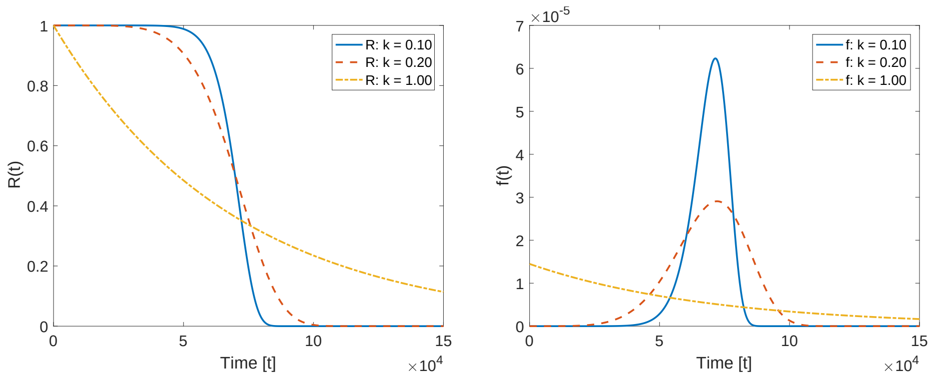
(a) Survivor function **(b)** PDF

Figure 6.3: Weibull distribution: Compressor

TBM - Lifetime distribution for Electrical Motor

The lifetime distributions of the electrical motor is is found in the same way as the compressor, with the same values for the K coefficient, for its respective MTTF. Table 6.3 presents the estimated parameters for the Weibull distributions.

In figure 6.4a the survivor functions of the different distributions are presented. The PDF of the different distributions, figure 6.4b, is centered around the MTTF of 69018 hours.



(a) Survivor function **(b)** PDF

Figure 6.4: Weibull distribution: Electrical motor

Table 6.3: Weibull distribution - Estimated parameters for electrical motor

K	β_M	α_M	SD_M
0.10	$1.3891E-05$	12.1534	$6.9018E03$
0.20	$1.3416E-05$	5.7974	$1.3804E04$
1.00	$1.4469E-05$	1.00	$6.9018E04$

CBM - Degradation Model for Electrical Motor

As presented previously, in one of the models proposed as follows has the objective to obtain a CBM model, for this one needs a degradation model for the electrical motor. In chapter 3, previous studies where reviewed where two different degradation models for the electrical motor where presented, utilizing probability-based approach.

Heimdal (2017) provided a Markov process model with discrete state space, in which can be directly employed in the maintenance model. Islam (2017) provided a continuous state degradation model. Since the PN model is a discrete state model, only Heimdal's degradation model can be utilized. For the gamma process, discretification is necessary to be able to utilize in a PN model. Thus, more research have to be conducted to provide a discrete state gamma process of the degradation phenomena.

The transition rates are estimated from censored data obtain from the PD failure mode. Hence, the degradation model is only based on the PD failure mode, however the model will characterize the degradation of the entire component.

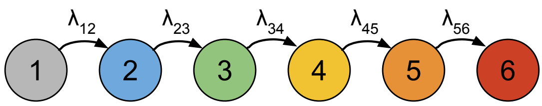


Figure 6.5: Adopted state transition diagram of degradation model (Heimdal, 2017)

The degradation process utilizes exponential law. In table 6.4 the transition rates (λ_{ij}) from each respective state is presented.

Table 6.4: Estimated transition rates for degradation model

From	To	Transition rate, λ_{ij}
State 1: Excellent	State 2: Good	$3.780E-5$
State 2: Good	State 3: Average	$4.700E-5$
State 3: Average	State 4: Acceptable	$8.760E-5$
State 4: Acceptable	State 5: Inspection Recommended	$1.423E-4$
State 5: Inspection Recommended	State 6: Unreliable	$3.517E-4$

CBM - Degradation Model for Compressor

For the degradation behavior of the compressor reliability approach based on the MTTF is utilized for the transitions between the respective degraded states. In this case a other approaches, as probability-based approach, would be preferable to obtain a more accurate and short-term prediction. However, due to lack of available condition monitoring data and the limitation of this study reliability approaches are used for predicting the degradation process.

The degradation characteristics of the compressor is modeled by four discrete states, as illustrated in figure 6.6. Where state 1 is new condition, state 2 is good condition, state 3 is bad condition, and state 4 is faulty condition.

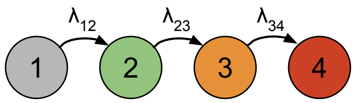


Figure 6.6: State Transition Diagram of Degradation Model

For the parameters of the degradation model for the compressor, no condition monitoring data was available. Hence, the transitions rates are based on dividing the failure rate for the entire component to fit the arbitrary states. To further utilize the same approach for estimating parameters for the Weibull distribution, as done previously. Table 6.5 displays how these rates are divided for the four different states.

Table 6.5: Transition rates for degradation model

From	To	Transition rate, λ_{ij}
State 1	State 2	$1.0000E-04$
State 2	State 3	$4.0000E-05$
State 3	State 4	$1.0000E-04$

In table 6.6 the estimated transition rates, for the the three K coefficient values are displayed. These parameters will be used in the following analyzes and optimization.

Table 6.6: Weibull distribution - Estimated parameters for degradation model

From	To	K	β_C	α_C	SD_C
State 1	State 2	0.10	0.9587 E-04	12.1534	1.0 E03
State 2	State 3	0.10	3.8350 E-05	12.1534	2.5 E03
State 3	State 4	0.10	0.9587 E-04	12.1534	1.0 E03
State 1	State 2	0.20	0.9259 E-04	5.7978	2.0 E03
State 2	State 3	0.20	3.7038 E-05	5.7974	5.0 E03
State 3	State 4	0.20	0.9259 E-04	5.7978	2.0 E03
State 1	State 2	1.00	1.0 E-04	1.00	1.0 E04
State 2	State 3	1.00	4.0 E-05	1.00	2.5 E04
State 3	State 4	1.00	1.0 E-04	1.00	1.0 E04

6.2.2 Repair Characteristics

The repair characteristics are modeled by transitions between states, which can have many different behaviors. In many maintenance models probabilistic distributions (e.g log-normal, exponential, normal) are utilized for describing the behavior of the repair transitions, due to the characteristics of the process used (e.g. Markov process) or due to uncertainties in the repair characteristics (e.g. weather window, spare parts, etc.). In this case the repair of the system is accurate with little deviation, and one can therefor utilize deterministic values for the transitions in the model. The transition times are displayed in table 6.7, where one can see that the maintenance delay, is substantial for both the components compered to the maintenance duration. Hence, a CM action may have a more significantly impact on the availability of the CDS then a PM action.

Table 6.7: Values for maintenance activities

	Duration of activity in hours				
Components	Inspection	PM Delay	CM Delay	PM Duration	CM Duration
Electrical Motor	12	4380	4380	365	365
Compressor	12	2190	4380	182	365

The components in each CDS is dependent, meaning that if on of the components fail the CDS is regarded as failed. Thus, it may be convenient to plan a PM action and maintain both components at the same time, since the CDS is taken out of production anyway. This will further be investigated in the analysis and optimization chapter.

With respect of maintenance effectiveness, imperfect repair is chosen for PM to obtain the most realistic behavior. Hence, the unit is restored to a state where the MTTF is reduced compered to the initial value, see table 6.8. For CM, the unit are subjected to renewal, meaning that the unit is restored to perfect condition. For the CBM policy, the components are subjected to periodic inspections, with a duration of 12 hours, where the CDS is taken out of production while undergoing inspection. The inspection is assumed to be perfect, meaning that the condition of the unit is revealed without error.

Table 6.8: Post-PM MTTF

Components	Post-PM MTTF [hour]
Electrical Motor	42 563
Compressor	35 000

The maintenance resources aspect may be important to include in the maintenance model. It can give a clearer view on how the organization works influences the maintenance performance, including all the aspects of the organization (i.e. working time, spare part handling, etc). In this case the aspect of maintenance resources is simplified by embedding the different aspects in the transitions time. Meaning that the transitions cover the delay time for spare parts and human resources. This still gives a detailed understanding and gives answers to the problem statement. However, in the future it may be interesting to investigate the effects of maintenance resources in the models, and can therefore be implemented in a latter stage of the respective case.

6.3 Maintenance Models

Two different maintenance strategies will be modeled, TBM model and CBM model. All models are subject to condition constraints, meaning that the models have a more opportunistic characteristics. The transitions are therefor not only triggered by the time parameter, but also guards. This provides more real-life characteristics of the maintenance activities, due to the fact that it is not common to look blindly on repair and inspection intervals without taking into account the affects of these interventions.

6.3.1 Common Petri Nets Models

The models are quite the same, and here I will provide a presentation of the different PN that are common for all the following models. This includes seasonal variation, CDS availability and system availability. There will be small differences on the guards and assignments on the nets for the respective models, however this presentations objective is to establish a understanding of how the PN are built and communicate with each other.

Seasonal Variations

To be able to obtain results with respect of seasonal variations, and make decisions on the basis of which season the system is in at a certain time. A PN is dedicated to simulation the seasonal variation.

The PN model, illustrated in figure 6.7 simulates the seasonal variations. The model has two discrete states: summer and winter. The transitions between these states are under Dirac law, meaning that it takes an deterministic value, in this case the value is 4380.0 hours. When a transition is fired, an assignment is triggered to change the Boolean variable ”Summer” from true to false, vice versa, dependent on which state the process is moving to. The variable is used as a ”guard” in other PN,

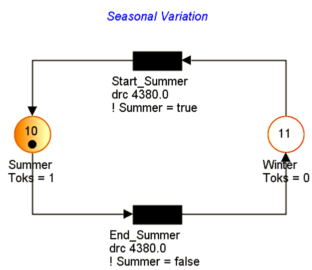


Figure 6.7: PN model for seasonal variations

CDS Availability

For the availability of each CDS a PN is dedicated to simulate the state of the CDS, available or unavailable.

The transitions are under Dirac law with the value 0.0, where the "guard" for the transition is the one that trigger the transition. In the PN in figure 6.8 the transition from available state the transition is guarded by the Boolean variables from each respective component, where if one of the components is unavailable the transition is triggered and the "token" moves from available to unavailable.

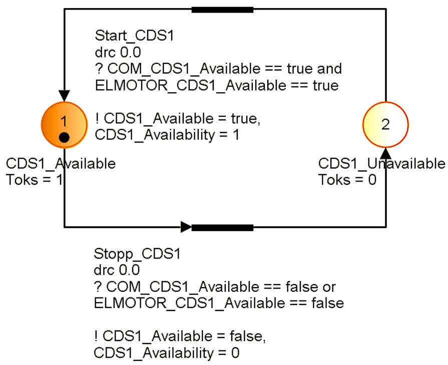


Figure 6.8: PN model for CDS availability

System Availability

To solve the optimization problem the PN of the entire systems state is important, and is dependent of both CDS availability and seasonal variations. The PN in figure 6.9 is dedicated to simulate the systems availability upon the production demand.

The transitions are triggered if the "guards" is fulfilled. There are two different conditional constrains for the system state to move from available to unavailable. If one of the following conditions are fulfilled the "token" moves from available to unavailable;

- One out of two CDS is unavailable in winter operation.
- Two out of two CDS unavailable.

The same applies for the transition from unavailable to available, however the conditions are different. The following conditions has to be fulfilled for the "token" to move from unavailable to available;

- One out of two CDS unavailable in summer operation.
- Two out of two CDS available.

The guards used as predicates for the PN is obtain throw the simulation of the CDS availability for both CDS and the seasonal variation.

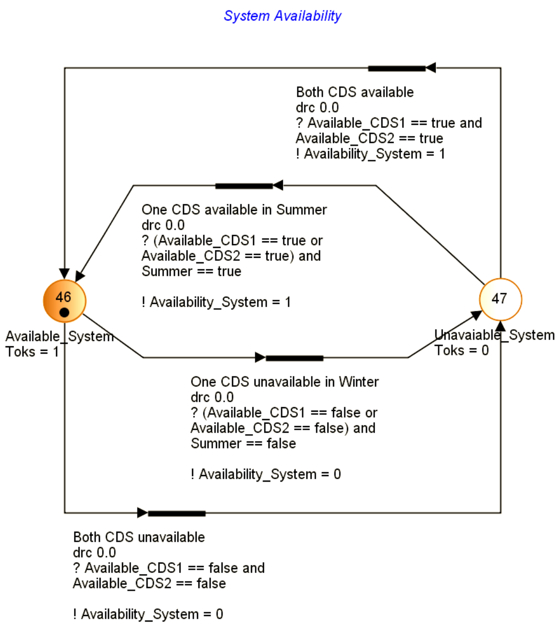


Figure 6.9: PN model for system availability

6.3.2 Time-Based Maintenance Policy Model

The TBM policy model consist of the above mentioned common PN models, and a PN model for each component.

The PN models is build as shown in figure 6.10. Which consists of an ”OK” state, where the component is functioning, and two loops, for CM and PM respectively. In addition, the PN in the left corner simulates the PM demand, which is needed because the PM action is triggered on a time interval and guards. When having a Dirac transition and guards, the transition will not be triggered if the guards are not fulfilled at the same moment as the Dirac time is obtained. The guards associated to the PM action is saying that;

- PM will not be conducted on the respective component if the other CDS is not available, and
- PM will only be conducted in summer operations.

With these guards, the policy can be regarded as time-based with a opportunistic aspect, thus the PM will not start if it is a direct cause of system unavailability.

To be able to model the maintenance effects, assignments are triggering parameter changes for the failure transition. Meaning that the MTTF of the transition changes after maintenance action. The CM action is regarded as renewal (i.e. good as new state) of the component, in which sets the MTTF back to initial value. When the component is subjected to PM action the component is not regarded as ”good as new”, thus the MTTF value is set to a given post-PM value (see table 6.7).

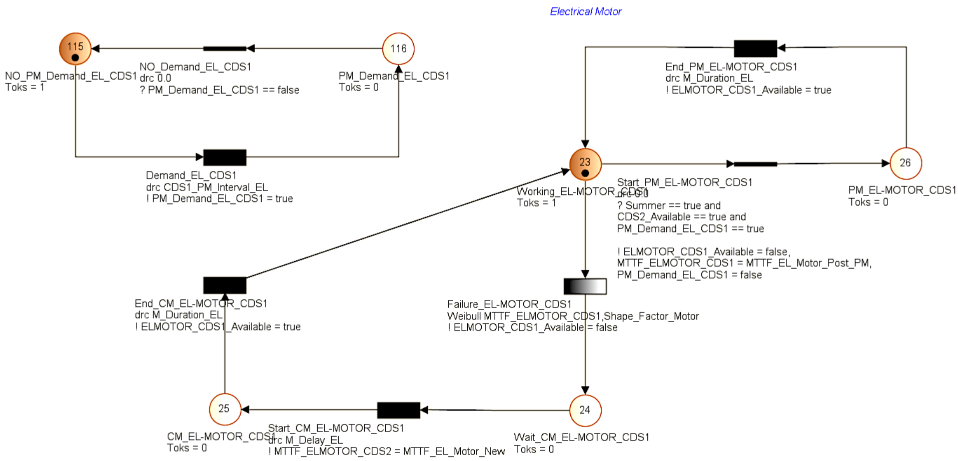


Figure 6.10: PN model for electrical motor (TBM)

6.3.3 Condition-Based Maintenance Policy Model

For the CBM model, degradation models of the components have to be established. In the following the PN for the degradation, with the associated repair PN will be presented for both compressor and electrical motor.

Electrical Motor

The model utilizes the degradation model proposed by Heimdal (2017) and is evolved to include maintenance processes. To model such policy, the model proposed as follows is divided into three sub PN, degradation process, repair process and inspection demand. These model communicate with each other using Boolean variables and predicates.

Figure 6.11 illustrates the PN of the degradation process with respective transitions. The six states on the bottom of the model is Heimdal (2017) degradation model, with identical transitions rates under exponential law. The development implemented on the model is the maintenance- transitions and states. The maintenance transitions proposed is set as a starting point for the model, where the final configuration will be addressed in the analysis and optimization chapter as follows.

The behavior of the maintenance is configured in the way that PM may be conducted on the motor when it is in the states ”Acceptable”, ”Inspection Recommended” and under some circumstances from ”Unreliable”, and are thereafter restored to ”Good” state. CM is conducted from ”Unreliable”, and are renewed to ”Excellent” state. The respective transitions are under Dirac law and are triggered by Boolean variables controlled in the repair PN. The repair PN uses input variables from the degradation PN on which state the degradation process is in.

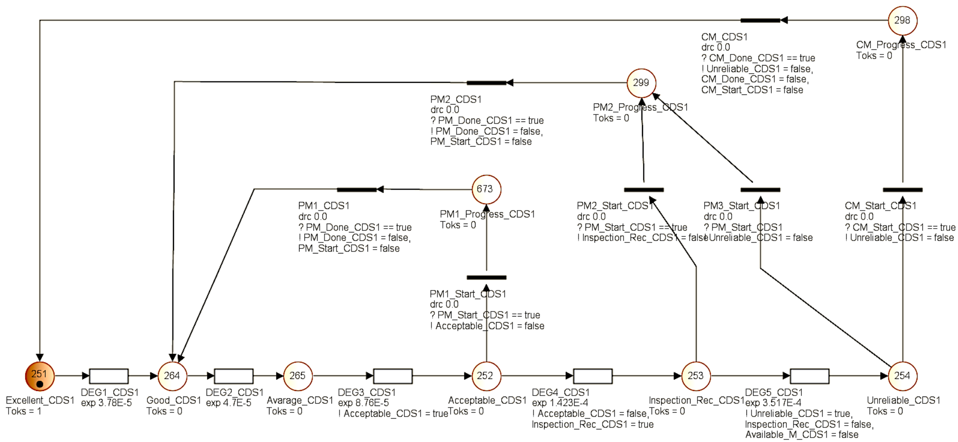


Figure 6.11: PN degradation model, electrical motor

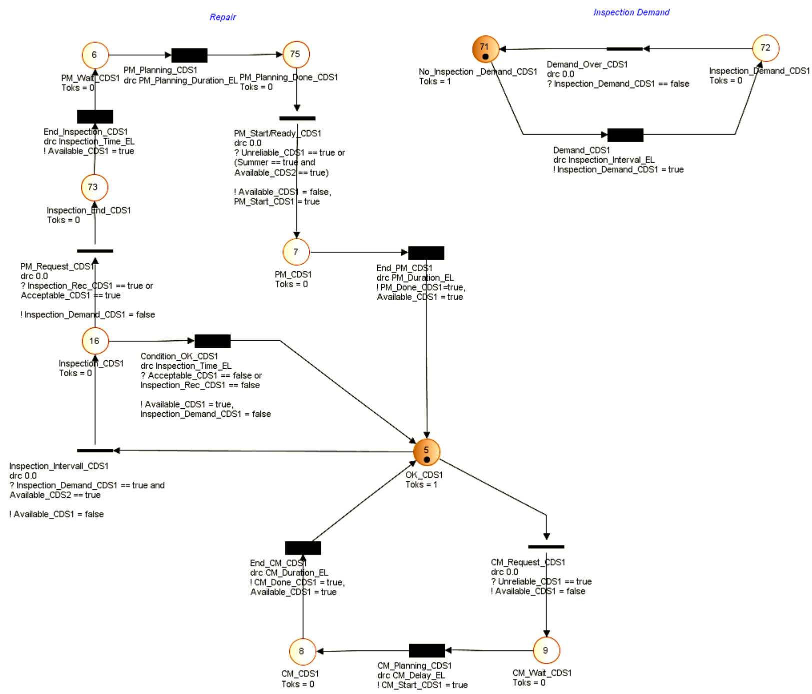


Figure 6.12: PN repair model, electrical motor

Figure 6.12 illustrates the PN model for the repair process. Which is divided into two separate PN, repair and inspection demand. The reason for this is that the activation of an inspection is based on both time interval and guards.

Moreover, the repair process is divided into two loops, one for PM and one for CM. The CM loop is the one at the bottom, where CM is requested if the motor is in ”unreliable” state. The PM loop is more advanced, where a inspection demand occurs at a given interval and are activated if the other CDS is available. During inspection, the state of the system is checked, if the system is not in ”Inspection Recommended” or ”Acceptable” state, the process returns to ”OK” state. If the process is in on of the respective states, PM is activated and the PM planning start, while the system is set back to production. The PM intervention starts when the planning is done, the system is in summer operation and the other CDS is available, or that the electrical motor is in ”Unreliable” state.

It is important to notice that the PM intervention only takes place in summer operations. However, if all the conditions are valid right before winter the CDS is taken out of production and is a direct cause of downtime if the system shifts to winter operation.

Compressor

The PN model for the degradation and maintenance of the compressor is illustrated in figure 6.13. The four states at the bottom is the degradation process, which utilizes transitions by Weibull law. The PN model is similar to the degradation model of the electrical motor.

The maintenance threshold condition is set to state 3, ”bad condition”, when the inspection finds the system in state 3, PM is activated and the planning of the action starts. When the action is ready, and all the guards are fulfilled, the PM intervention restore the compressor to state 2, ”good condition”. If a failure occurs, the CM intervention will conduct replacement and restore the compressor to state 1, ”new state”. The repair PN is identical for both electrical motor and compressor.

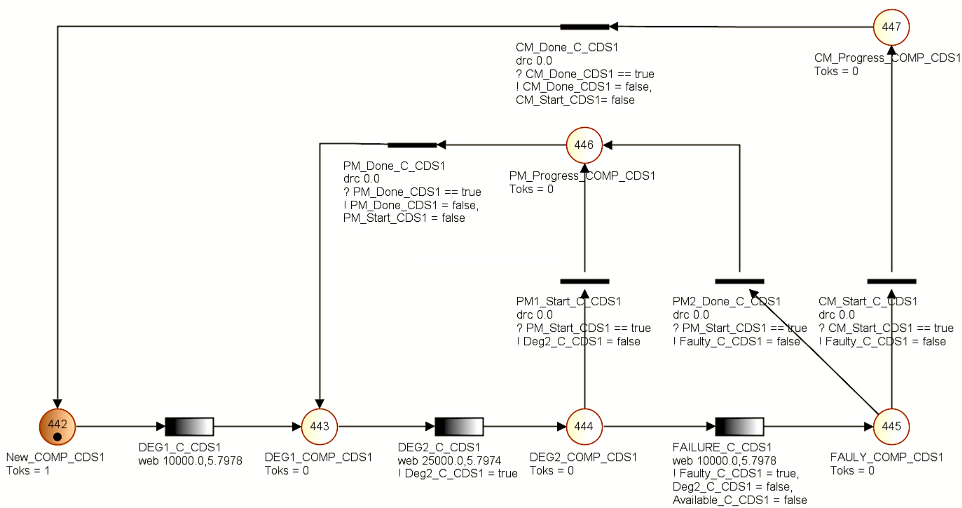


Figure 6.13: PN degradation model, compressor

Chapter 7

Analysis and Optimization

In this chapter, the different models presented in chapter 6 will be analyzed and optimized with respect to the optimization criteria. The different results from the models will be presented and discussed, on the basis of model behavior and comparison between the different models.

7.1 Analysis Configuration

The simulator established can be configured in different ways. In the CBM models, the tokens can be placed in arbitrary states in the degradation process, to obtain a different starting point for the simulation in the PN. However, for the analysis and optimization, the components are set to perfect condition at simulation time $t = 0$. The configuration may not be realistic and could have an impact on the system performance, since the components in each CDS has equal failure characteristics.

In the Petri Module one configure the simulator characteristics. The following configurations are set for the simulation:

- Time-span = 175 200 hours (20 years)
- Number of histories = 2000
- Confidence interval = 90%

The choice of the number of histories simulated was evaluated through simulating a model with different number of histories, to see where the results obtained from the simulation where stable. Further, the confidence interval of 90% was chosen on the basis of the system characteristic, even though the system is a critical part of a gas network, there is no significant safety risk associated with the components. Thus a 90% confidence interval is sufficient for analyses and optimization.

In last chapter three different configurations of the Weibull distribution where presented for each component (i.e., $K = 0.10$, $K = 0.20$ and $K = 1.00$). Due to time limitations, only $K = 0.20$ will be used for the optimization of the CBM policy. Furthermore, when the different optimal policies are obtained, these policies will be tested for all the values of K, to investigate the impact of the SD of the failure prediction with respect to maintenance performance.

7.2 Optimization Criteria

The optimization of the models will be based on system availability, with a discussion over the number of CM and PM activities. Due to lack of information on the associated cost of the different activities. For the optimization, the following KPIs will be utilized as criteria for evaluating the optimal solution:

- System availability.
- Number of maintenance actions (MA).
- Number of PM actions.
- Number of CM actions.
- Number of inspections.

Of these KPIs, availability is the only one that gives a direct value for optimization. The other KPIs only gives an indirect value. By combining the availability performance with the number of interventions, one obtain an understanding of the maintenance policy behavior. Exact numerical results for each optimization is provided in appendix B.

7.3 Failure-Based Maintenance Policy

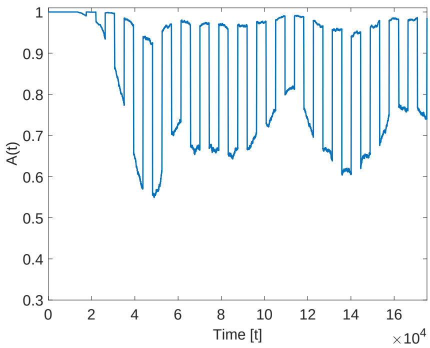
As a baseline for evaluating the system performance with the other policies, it is interesting to assess the system performance with an FBM policy, hence only CM activities.

The evaluation is based on availability performance and the total number of MA, the KPIs are presented in table 7.1 for the three different configurations of the Weibull distribution. One can see that the system availability and total MA (i.e., CM actions) are similar for the different configurations. However, with smaller SD of the distribution gives a slight increase in system performance. This is due to the simulation time-span, where for low SD the failures have periods with higher failure occurrence, which may be right outside the simulated time. For an infinite time horizon, the amount of MA would be equal for all lifetime model configurations.

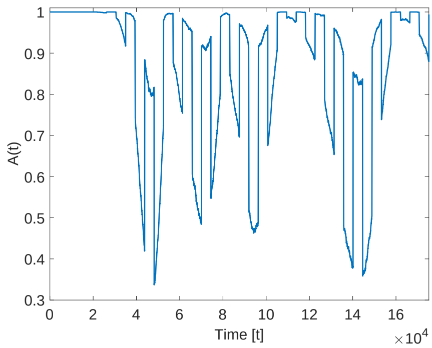
Table 7.1: KPIs for FBM policy

K	Total MA per CDS	System Availability
0.10	5.05	0.8656
0.20	5.36	0.8573
1.00	5.72	0.8477

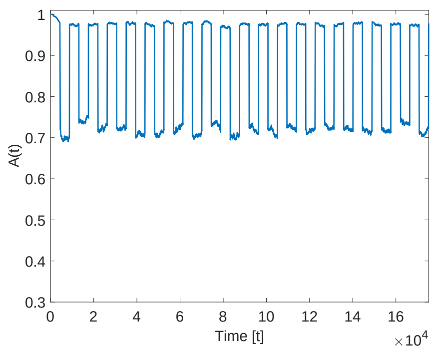
Even though the system KPIs do not differ significantly from each other with the different SD configurations of the Weibull distribution, the system behavior is totally different. Figure 7.1a illustrates the system availability over the analysis time-span of 20 years, for $K = 0.20$. The plot displays that the system availability has time periods with significantly reduced availability, thus also periods with high availability. This phenomenon is due to the SD of the failure times for each component, we therefore have a much higher probability of failure in certain time periods, hence higher availability after these periods when the components are maintained and restored to perfect condition.



(a) Availability plot, $K = 0.20$



(b) Availability, $K = 0.10$



(c) Availability plot, $K = 1.00$

Figure 7.1: FBM availability plot

Figure 7.1b and 7.1c illustrates the system availability plot of $K = 0.10$ and $K = 1.00$, respectively. Here, the phenomena is clearer, in comparison to the plot in figure 7.1a. However, it is important to take into account the fact that all components are in perfect condition at the starting point for the simulation. Hence, for low SD the same components for each CDS will have a tendency to suffer failure in approximately the same time, making a huge impact on the system availability.

The plot displays that with low SD the failure impact on the system availability is more substantial in certain time periods. Wheres, with exponential law ($K = 1.00$) the failure impact is evenly distributed throughout the time-span, due to the characteristic of constant failure rate.

7.4 Condition-Based Maintenance Policy

The CBM policy model is built by the PN degradation models for the electrical motor and compressor, with associated repair PN models. In this section, different optimization processes will be conducted to find the optimal configurations of the models, including maintenance threshold and inspection interval. By evaluating the KPIs presented in optimization criteria.

7.4.1 Maintenance Optimization for the Electrical Motors

For the degradation model for the electrical motor the model from Heimdal (2017) is utilized; thus the MTTF of the electrical motor has a significant SD. The following analysis and optimization comprehend the two electrical motors for each CDS.

On the CBM PN model for the electrical motor two optimization processes will be conducted: maintenance threshold- and inspection interval optimization. First, it is interesting to investigate the effects of the maintenance threshold in the model. The questions to be answer is; ”in which state of the degradation process is it most effective to activate PM action?”. Secondly, it is interesting to optimize the inspection interval, with the objective to find the optimal frequency, i.e. the inspection frequency that achieve the best system performance.

To find the answer, the optimization is conducted on two configurations of the PN model, and simulated for different inspection intervals. The configurations of the maintenance threshold are as follows:

- Configuration 1: PM triggered at ”Acceptable” and ”Inspection Recommended” state.
- Configuration 2: PM triggered at ”Inspection Recommended” state.

As a baseline for this optimization, an FBM policy for the two electrical motors obtains a system availability of 0.9440. Figure 7.2 illustrates the system availability achieved for each inspection interval, for respective configuration. Configuration 1 (blue line) accomplishes a much higher availability performance then configuration 2 (orange line). Where the plot demonstrates that for configuration 1, the optimal inspection interval with respect to system available is 1460 hours. However, there is little difference between 1460 and 2920 hours. Based on the number of inspections, illustrated in figure 7.3a, the inspection interval of 2920 hours is recognized as the optimal inspection frequency.

Furthermore, it is interesting to see that the availability is reduced for inspection interval of 730 hours. This behavior is explained by the impact of the inspection of the system availability during winter operations, where the inspection is a direct cause to downtime. Thus, the optimal interval recommend the midway, where the gained benefits in preventing downtime is higher then the disadvantage of causing downtime.

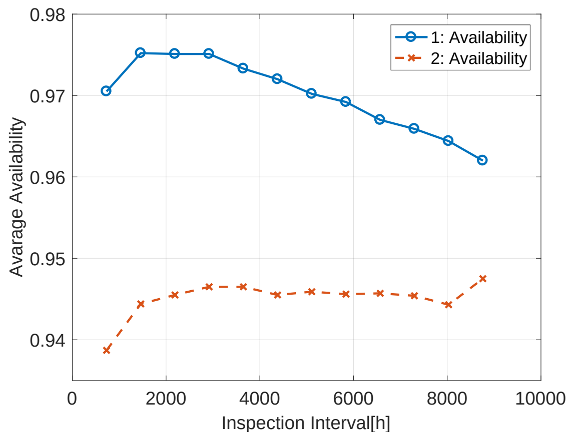
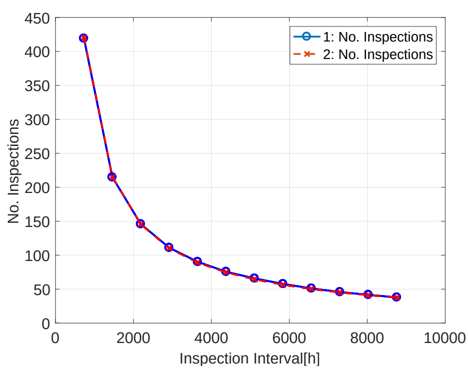


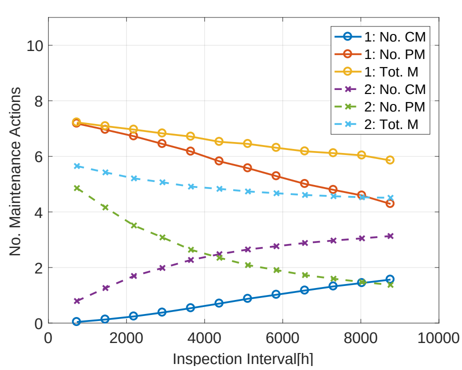
Figure 7.2: Inspection interval optimization: Availability

The other KPIs are illustrated in figure 7.3. 7.3a displays the number of inspections in each inspection interval, for both configurations. We see that the different configurations do not influence the number of inspections since the lines for each respective configuration are overlapping.

In figure 7.3b, the number of MA is displayed, differentiated in: number of CM, number of PM, and total number of MA, for each respective configuration. From the plot, we see a clear difference between the two configurations. While configuration 1 has an evident behavior where the number of PM constitutes almost all MA when the inspection interval is 730 hours, configuration 2 suffers a significant amount of CM failures for all inspection intervals. It is also interesting to observe that the occurrence of CM actions is higher than PM for inspection interval 4110 hours.



(a) Number of inspections



(b) Number of MA

Figure 7.3: Inspection interval optimization: MA

The behavior of configuration 2 is due to the late triggering of the PM action, i.e. too high maintenance threshold. Hence, the ”Inspection Recommended” state is not observed, or the PM action is triggered in ”Inspection Recommended” state, and the degradation process evolves to ”Unreliable” state during the PM delay before the PM is conducted. The analysis highlights a problem with the way the PN model is constructed. If the token has started the PM loop in the repair PN when a failure occurs, it will be recognized as a PM action in the analysis. Thus, the amount of PM actions for configuration 2 is much higher then it actually is. In some cases this assumption can be non-problematic, however for a system where the failure cannot be repaired in a regular manner if the degradation has evolved too far, the model has to be arranged in another way. Furthermore, the PN model behavior explains why the availability of configuration 2 is just a little bit higher than for an FBM policy. Due to the fact that the electrical motor suffers failure before the PM action is over.

On the basis of the analysis, configuration 1 is considered to be the optimal way to configure the maintenance threshold for the electrical motor, due to higher system performance. Configuration 1 is therefore utilized in the following system perspective model.

7.4.2 System Perspective for Maintenance Optimization

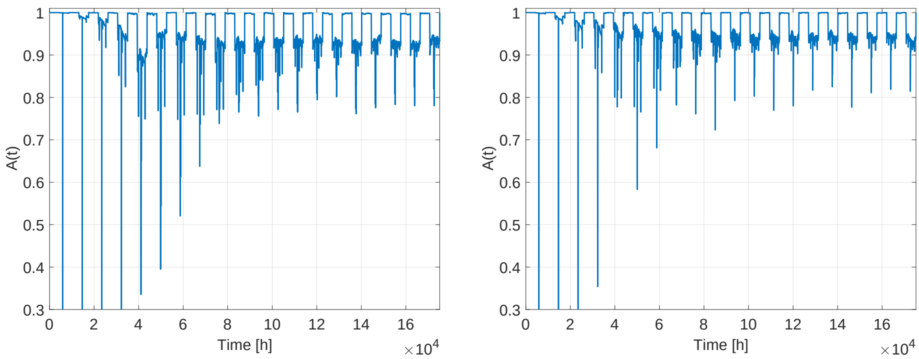
The system perspective is now consider, with a PN model for both the compressor and electrical motor. The objective is to investigate how these components affect each other, and to find the optimal configuration and inspection interval when taking into account both components for each CDS.

Dependent vs. Independent Maintenance Strategy

The components in each CDS is regarded as dependent, since a failure of one of the components causes unavailability for the respective CDS. Hence, it is interesting to investigate the impact of an dependent maintenance strategy, where both components are maintained when one of the components are over the pre-defined maintenance threshold. Compared to a strategy where all components are maintained independently, based on the maintenance threshold for each component.

For the dependent strategy, the maintenance time (i.e., delay and duration) is set to the highest value. Hence, the maintenance characteristics of the electrical motor are utilized to characterize both components. While for the independent the components are given their respective maintenance characteristic values (table 6.7). Figure 7.4 illustrates the availability plots of the two maintenance strategies, with an inspection interval of 2920 hours. Which displays no evident behavior characteristic to distinguish the two strategies.

The impact of the inspections during winter operations is clearly displayed in the plot, where the system is not able to deliver the production demand due to the 12-hour downtime caused by the inspection. Since the plot is based on average system availability, the impact of the inspections is clear in the first years of operation where few MA is performed on the system, while the impact gets more distributed over time due to the affects of the MA.



(a) Independent strategy: Availability **(b)** Dependent strategy: Availability

Figure 7.4: Independent vs. dependent strategy

Table 7.2 provides the KPIs obtained for the two maintenance strategies. The inspection and maintenance values are actions per CDS, which gives a better view since the dependent strategy has common actions for both components in the CDS, while for the independent the MA are conducted individually for all components.

Table 7.2: KPIs by maintenance strategy

Strategy	No. Insp.	No. CM	No. PM	Tot. MA	Availability	Downtime/Year
Dependent	106.58	0.37	10.62	10.99	0.9743	225.13
Independent	111.34	0.38	8.64	9.02	0.9656	301.34

Based on the KPIs, the dependent strategy imply to be the most suitable strategy. However, the organizational aspects should also be taken into account when choosing such strategy; it may be difficult to organize and implement in an effective manner, besides have a increase in maintenance cost.

Inspection Interval Optimization - Dependent Maintenance Strategy

It has been demonstrated that a dependent maintenance strategy for each CDS award a higher system performance, however the inspection interval for the last analysis were based on the optimal interval for the electrical motor. If a dependent maintenance strategy is going to be utilized, one wants to utilize the global optimal inspection interval for the CDS.

Figure 7.5 display the average availability achieved by the different inspection intervals. The optimal global inspection interval for the CDS with a dependent strategy is 1460 hours, with respect to average availability. However, from figure 7.6a we see that the interval has a high number of inspections, in which may not be favorable.

Furthermore, from the different plots we see that with an inspection interval of 2190 hours the KPIs does not decrease significantly. When no cost data is available it is difficult to evaluate the different KPIs against each other and obtain an absolute answer to the optimization problem. Hence, the only quantity that can be recognized as an absolute value is the average availability, thus the inspection interval of 1460 hours is recognized as the optimal inspections interval.

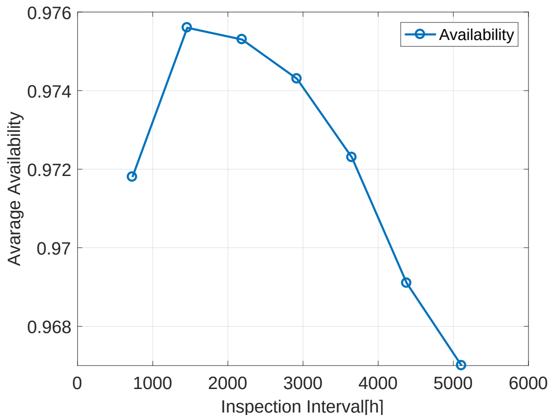
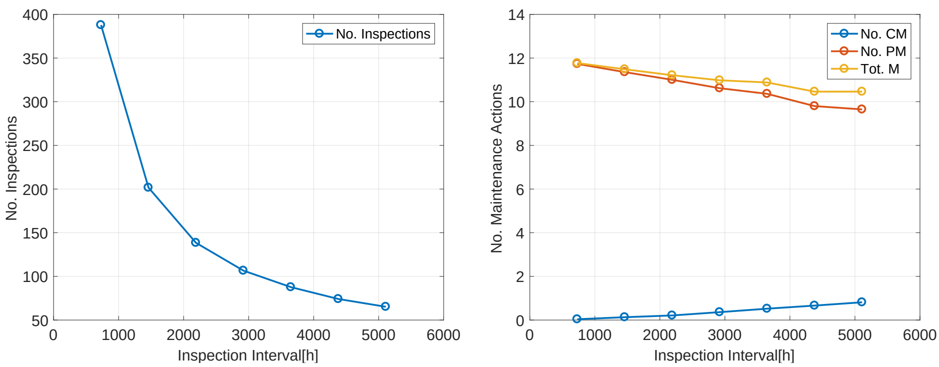


Figure 7.5: Inspection interval optimization: Availability



(a) Number of inspections

(b) Number of MA

Figure 7.6: Inspection interval optimization: MA

Impact of Weibull Distribution Configuration for Compressor

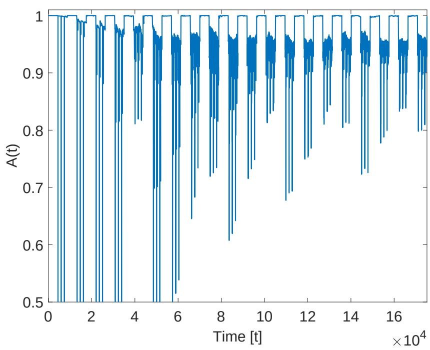
The transition rates in the degradation model for the electrical motor is given by Heimdal (2017). Hence, the following results are obtained by changing the shape parameter of the Weibull distribution for the compressor.

In table 7.3 the analysis results of three Weibull distribution configuration are presented. We see that the results for $K = 0.10$ and $K = 0.20$ are quite similar for every KPI. However, for low SD the performance is higher. For $K = 1.00$ (i.e., exponential law), the availability is reduced compared to the other configurations, as well as a slight increase in the number of MA.

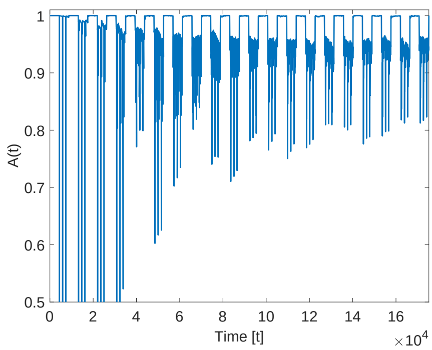
Table 7.3: KPIs for CBM policy with different Weibull distribution configurations for compressor.

K	No. Insp.	No. CM	No. PM	No. MA	Availability	Downtime/Year
0.10	200.70	0.12	11.32	11.43	0.9767	204.11
0.20	201.63	0.13	11.36	11.49	0.9756	213.74
1.00	198.13	0.55	11.52	12.07	0.9540	402.96

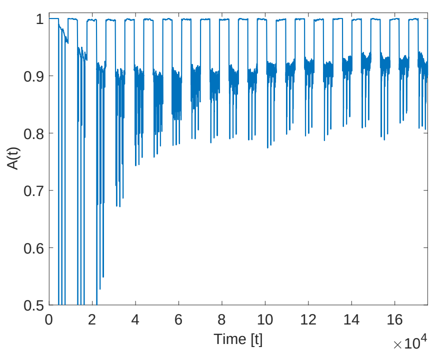
Figure 7.7a, 7.7b, and 7.7c, presents the system availability plot for $K = 0.10$, $K = 0.20$, and $K = 1.0$ respectively. The plots display that there are no clear difference between the different characteristics, except that for $K = 1.00$ the system availability is reduced in winter operations. The similarities can be explained by the fact that the electrical motor utilizes exponential law for all configurations. Thus changing the Weibull parameter for the compressor does not change the system behavior in a radical manner.



(a) Availability plot: $K = 0.10$



(b) Availability plot: $K = 0.20$



(c) Availability plop: $K = 1.00$

Figure 7.7: CBM availability plot

7.4.3 Remarks & Discussion

The building blocks of modelling a CBM policy is the degradation models, for a respective component, system or failure mode; in this case on the component level. The accuracy of the failure prediction provided by the degradation models plays a pivotal part, where inaccurate models will provide a wrong behavior of the model.

From the maintenance threshold- and inspection interval optimization of the electrical motor. It was recognized that with the maintenance threshold in "Inspection Recommended" state, the degradation process has a tendency to evolve to a failed/"Unreliable" state in the time between a PM is triggered and the action is performed on the component Hence, "Acceptable" state was recognized as the optimal maintenance threshold, which obtained a higher availability performance, for every inspection interval analyzed. Furthermore, the inspection intervals of 1460, 2190 and 2920 hours obtain a similar system availability. However, due to the amount of inspections is significantly reduced from inspection interval of 1460 hours to 2920 hours, the latter was recognized as the optimal inspection interval. Heimdal (2017) advocated that inspections should be carried out as often as possible due to the high SD of the failure prediction, to reduce the probability of unexpected failure for the electrical motor. However, the analysis contradicts this statement, which displays that the impact of inspections is higher than the impact of failures with an inspection interval of 730 hours. Thus it is essential to investigate the effects of inspections and MA to aid optimal maintenance decision.

For the system perspective analysis and optimization, it was recognized that a dependent strategy gave a higher performance than an independent strategy, for an inspection interval of 2920 hours. An optimization with regards to inspection interval was not conducted for the two strategies, which could have provided a different result. Furthermore, a global optimal inspection interval was obtained through optimization of the dependent strategy, which displayed that an inspection interval of 1460 hours achieves the best system availability. However, there is little difference in the performance obtained from the dependent and independent strategies in regards to system availability. Thus, the choice of strategy should also be based on which strategy that is easiest to implement and provides balance to the maintenance organization.

7.5 Time-Based Maintenance Policy

The TBM policy is considered to be a static policy, due to its nature where the maintenance decision is only dependent on the time-interval between PM actions. Hence, the analysis of the TBM policy aims to optimize the system performance with respect to PM interval for all K coefficient values, and to investigate the behavior of the system with respect to these characteristics.

7.5.1 PM Interval Optimization - Dependent Strategy

As presented previously, the CDS sub-system is considered to be dependent. Hence, this optimization utilizes the same PM interval for both components in the CDS.

The PM intervals are configured to be alternating, meaning that one CDS is maintained with a shorter interval for the first PM, for further utilizing the regular time interval. The PN is also modeled with guards, stating that a PM action will not be conducted at the time of PM demand if the other CDS is unavailable, or if it the system is in winter operations. Thus, the MA does not influence the system availability.

Figure 7.8 illustrates the average availability KPI, with respect to PM interval, for the three Weibull distribution configurations. The plot displays that for $K = 0.10$ (blue line) and $K = 0.20$ (orange line) the system availability is almost 100% for the PM intervals, 8760 hours and 17520 hours. Before the system availability for $K = 0.20$ drops at PM interval, 26280 hours. The behavior is due to the SD of the two Weibull distributions. Hence, for $K = 0.10$ the occurrence of failures are absence for PM intervals equal or less to 26280 hours. We see that for low SD of the Weibull distribution, the PM interval can be set closer to the MTTF for the respective unit, without increasing the number of failures.

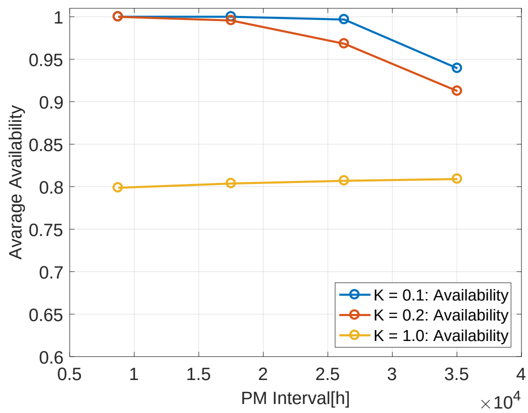
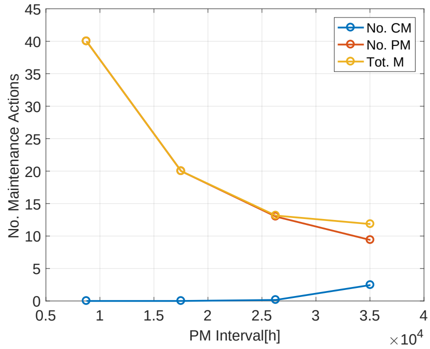


Figure 7.8: PM interval optimization: Availability

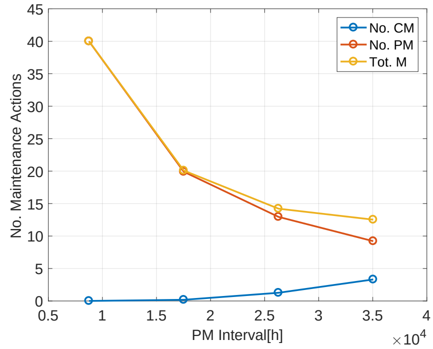
The behavior of the Weibull distribution with K coefficient, $K = 1.00$, is equal to the exponential law. The plot (yellow line) illustrates that the availability of this configuration is not significantly influenced by the PM interval. It is interesting to see that the system obtains a higher availability for higher PM intervals.

Figure 7.9 illustrates the maintenance KPIs, with respect to PM interval. In figure 7.9a and figure 7.9b we observe that the behavior of the number of MA is quite similar, except that the number of CM actions is increased at PM interval 26280 hours for $K = 0.20$, due to the higher SD. For the PM interval of 17520 hours, the total number of MA per CDS is 20.0, where all of these are PM actions.

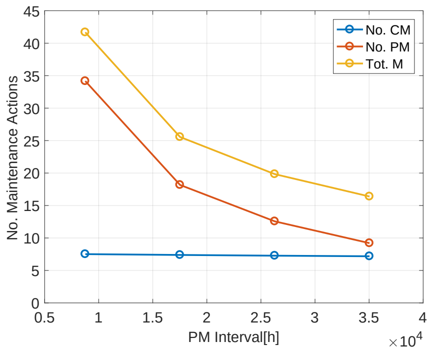
For $K = 1.00$, illustrated in figure 7.9c, the amount of CM actions stay constant for every PM interval, thus are independent from the PM actions. Hence, the total number of MA per CDS is only dependent on the PM actions, which is reduced by the PM interval.



(a) $K = 0.10$



(b) $K = 0.20$



(c) $K = 1.00$

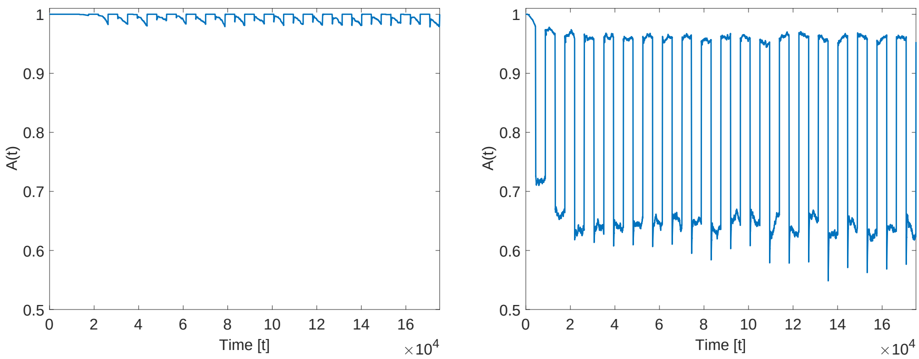
Figure 7.9: PM interval optimization: MA

In table 7.4 the KPIs obtained with a PM interval of 17 520 hours are presented, for the three different distribution configurations.

Table 7.4: KPIs for TBM policy with different Weibull distribution configurations

K	No. CM	No. PM	Tot. MA	Availability	Avg. Downtime/Year
0.10	0.001	19.999	20.000	1.0000	0.00
0.20	0.181	19.906	20.087	0.9956	38.54
1.00	7.385	18.171	25.556	0.8037	1719.60

Furthermore, it is interesting the display the system performance over the simulation time-span. For $K = 0.10$ the system availability is equal to 100%, over the entire simulated time-span. While, figure 7.10 displays the system availability plot for $K = 0.20$ and $K = 1.00$.



(a) Availability, $K = 0.20$ **(b)** Availability, $K = 1.00$

Figure 7.10: TBM system availability plot

7.5.2 Remarks & Discussion

The analysis and optimization of the TBM policy it was assumed that a dependent strategy is the best choice; where both components of the CDS is maintained with the same PM interval.

It was recognized that the SD of the failure prediction plays a crucial part in establishing the optimal PM interval. The two Weibull distributions with low SD obtained a high system availability for all the PM interval tested, where 17 520 hours (2 years) was identified as the optimal interval for $K = 0.20$. With low SD it is possible to push the PM interval closer to the MTTF, since the failures occur more centered around the MTTF. For $K = 1.00$, it was recognized that the PM actions do not influence the number of CM actions. Thus, the PM actions are not contributing to reducing the number of CM actions. Besides, it is important to state that the PM interval is independent of the occurrence of CM. Hence, the PM may be executed right after a CM action a PM demand occurs, which A more realistic and preferable way to model the PM interval is to reschedule PM actions with regards to CM. Hence, the system performance obtained for $K = 1.00$ is worse then it should be. While this model behavior does not influence the system performance for low SD, where few CM actions occur.

7.6 Policy Comparison & Discussion

From the analysis and optimization of the two maintenance policies, we have obtained an optimal strategy for each respective policy. In table 7.5 the KPIs for the two policies are presented for each policy with respect to the K coefficient value. It is important to state that the optimization for the CBM policy is based on the Weibull distribution configuration with $K = 0.20$. Thus, other inspection frequencies may be optimal for the different values of the K coefficient. For the TBM policy, the values presented are based on a PM interval of 17 520 hours, in which was established as the optimal frequency for $K = 0.20$. Besides, the lifetime distributions for the different components are not equal for the TBM and CBM policy, due to the state evolution in the degradation model. However, they are assumed to be equal for the sake of simplicity with regards to the comparison of the policies.

Table 7.5: KPIs by maintenance policies and K coefficient

Policy	K	No. Insp. per CDS	No. CM per CDS	No. PM per CDS	Tot. M. per CDS	Average Availability
	0.10	N/A	5.05	N/A	5.05	0.8656
FBM	0.20	N/A	5.36	N/A	5.36	0.8573
	1.00	N/A	5.72	N/A	5.72	0.8477
	0.10	200.70	0.12	11.32	11.43	0.9767
CBM	0.20	201.63	0.13	11.36	11.49	0.9756
	1.00	198.13	0.55	11.52	12.07	0.9540
	0.10	N/A	0.001	19.999	20.000	1.0000
TBM	0.20	N/A	0.181	19.906	20.087	0.9956
	1.00	N/A	7.385	18.171	25.556	0.8037

The CBM policy aims to find the midway between excessive and deficient maintenance. From table 7.5 we see that the amount of MA are significantly lower for the CBM policy then the TBM policy, for all K coefficient values. Due to the characteristics of the policy, where the PM action is triggered dynamically based on the condition of the components. Thus, the policy requires inspections. The number of inspections is around 200 over a time-span of 20 years, this activity may be costly, which is recognized as the disadvantage of the policy.

The TBM policy achieves higher system availability than the CBM policy for low SD. Hence, with low SD the TBM policy is suitable due to the MTTF is concentrated around the mean, which makes it easy to obtain an optimal PM interval where few failures occur. However, a static policy where the MA are only triggered by a predefined time-interval may lead to excessive maintenance, where the units are maintained even if the condition of the unit is acceptable.

Furthermore, it is recognized that for $K = 1.00$, a TBM policy does not increase system availability compared to an FBM policy, due to the fact that the evaluation of the degradation does not follow a pattern. Hence, if the system follows the behavior of exponential law, a TBM policy is not suitable. One of the assumptions that have to be taken into account for exponential law, is that an ”old” component is regarded to be ”as good as new”, due to the constant failure rate. Which emphasizes that utilizing a TBM policy is inadequate, since the PM action maintains the components from an ”as good as new” state to an ”as good as new” state.

For the CBM models with exponential law, this characteristic is avoided due to the degraded states. Nevertheless, the behavior of the model still has a high SD. However, the impact of high SD is not that substantial for the CBM policy, due to the fact that the PM action is triggered dynamically.

The system availability plots illustrating the behavior of the system over the simulated time-span, displays that the behavior is dependent on the maintenance policy. For TBM, the system performance is also significantly dependent on the SD, while for CBM the impact of SD is less significant. Hence, the choice of maintenance policy has to be taken upon the failure characteristics of the respective components, to obtain an optimal maintenance policy.

Chapter 8

Conclusion

The purpose of this chapter is to summarize and conclude the results of the maintenance models associated with the presented theory. Recommendations for further work is also presented.

8.1 Summary & Conclusion

The aim of this thesis was to investigate aspects of PrM and maintenance modelling in association with a case study provided by Equinor. The objective was to establish a maintenance model of a gas compressor station for analysis and for optimization of maintenance actions. The possibilities and challenges within the field of PrM and maintenance modelling were also highlighted.

Throughout the study, the importance of data availability has been emphasized. Sufficient system information and data is the foundation of all aspects of PrM, including maintenance modelling and PHM, thus also one of the most significant challenges. To overcome this challenge, the maintenance organization should establish a solid framework for data acquisition. By utilizing the improvement cycle presented in the study, one can identify the data needed to obtain accurate prognostic- and maintenance models. Furthermore, to acquire data in an adequate manner for use in future modelling.

Maintenance modelling can be utilized for multiple objectives concerning performance assessment and maintenance optimization. Generally, the objective is to establish a model which describes the behavior of the system, including organizational and/or technological aspects. Further, to assess the improvement under investigation and implement into the real-life system if proven to be of utility. In this case, maintenance modelling was utilized to analyze and optimize a TBM- and a CBM policy, in order obtain the optimal strategy within each policy. The case study's system characteristics demand considerable computational capabilities from the modelling method in order to consider the systems' many aspects. The aim was to model an advanced maintenance policy that would consider the system's multiple components and seasonal variations. Three modelling methods were proposed for modelling the system: Multi-Phase Markov process, DES and PN. The simulation methods DES and PN were considered the most suitable, due to the ability to take in to account system complexity and dynamic behavior. Thus, PN was utilized in the case study. Were the predicates allow implementation of conditional aspects needed to attain realistic behavior of the model. However, the method is best suited when the system characteristics can be adequately modeled in a discrete-state space.

Predictions of the future condition of the respective unit or system is essential to PrM. Generally, well-established reliability approaches are utilized for failure prediction in maintenance modelling, however this approach may be insufficient to obtain the level of accuracy needed for PrM. Hence, more advanced methods have been developed in the scheme of PHM, to obtain more accurate failure predictions. The previous reports on this case study proposed two prognosis based degradation models. The reports aimed to estimate the RUL of the failure mode, PD, in the electrical model. Both of these investigations used a probability-based approach in their respective degradation model, although two different techniques where used. Heimdal (2017) proposed a degradation model based on Markov process, discrete-state space and exponential law, and Islam (2017) utilized a non-homogeneous Gamma process with continuous-state space.

In the CBM model, the degradation model proposed by Heimdal (2017) was applied directly in addition to a degradation model for the compressor. A two-parameter Weibull distribution was used to model the failure characteristics of the respective components in the TBM model and the compressor in the CBM model. The Weibull distribution was based on the MTTF, and distinctly selected SD, 10%-, 20%-, and 100% of the MTTF.

The problem statement was to optimize MA to enhance system availability. Due to the seasonal variations, only one out of two CDSs is needed in summer operation to fulfill production demand. Therefore, PM actions can be conducted during summer operations without causing system downtime. Hence, the maintenance problem at hand became:" When should PM actions be performed, in order to minimize the impact on system availability?". To answer this question, the system availability was considered to be the primary optimization criteria. Additionally, the number of MAs were up for discussion. Through the optimization process, optimal strategies were proposed for both policies. However, many aspects and configurations of MA still need to be explore further. For instance, it would be interesting to investigate a non-periodic inspection strategy for the CBM policy, where the frequency is a variable dependent on the condition of the last inspection. Considering that a long-term optimal inspection interval is not necessarily optimal interval at a given time. The strategy may be a better choice due to the low failure rates of the components, and the downtime caused by inspections during winter operations.

The proposed maintenance model was based on a variety of assumptions, simplifications, and limited data without being assessed expert judgment. A definitive conclusion is therefore not given on the basis of the results obtained from the optimization and analysis, although the results highlight interesting aspects of the system characteristics. From the results, one can observe that the CBM policy achieves high system availability with a significant reduction in MA compared to the TBM policy. Also, due to its dynamic nature, the SD of the failure predictions proved to have an insignificant impact on the performance of the policy. For low SD, the TBM policy achieved an even higher system availability compared to the CBM policy. When SD increased however, the negative impact on performance was substantial. Besides, the policy relies on a large number of PM actions, in which is acknowledged to be excessive. The effects of utilizing RUL estimate, in this case in the form of a discrete-state degradation model, for maintenance decisions will reduce the number of MA. However, the effects on the availability of the system depend on the failure characteristics. In this case, there is a significant time-window to execute PM actions without causing downtime. TBM can therefore be used in the specified time-window to achieve a higher system availability by employing extensive maintenance, however this may not be favorable due to significant maintenance costs. The results exhibit that the lifetime behavior of a component with respect to SD is important for the choice of maintenance policy. This again emphasizes the importance of data to obtain accurate failure predictions.

The study highlights the aspects needed to build an adequate maintenance model. The model proposes a starting point for further work, where many aspects can be improved and implemented to enhance the accuracy of the model behavior. Through improvement, one can reach the case study's initial goal; a simulator that aids optimal maintenance decisions.

8.2 Recommendations for Further Work

As emphasizes previously, the case study concerns a variety of aspects within PrM, in which makes it important to subject this study case for further work.

The short-term aim should comprehend acquisition of data. Firstly, a standardized framework for acquisition condition monitoring data is needed to provide a rich data source, that will nurture the models, enhancing the accuracy of the PrM. Through a comprehensive FMECA on the CDS, one can acquire data and information on each critical failure mode. On the basis of the information, degradation models for the critical failure mode can be established. Two degradation model for the PD failure mode on the electrical motor already exists. It is recognized in previous studies that the non-homogeneous Gamma process is the most suitable technique for modelling the degradation phenomena. Thus a discrete-state Gamma process should be established and implemented in the maintenance model. Moreover, it may be interesting to determine the effects of failure interaction from the different failure modes. Hence, to integrate dependence factors for the different degradation models.

When a satisfactory model of the CDS is established, one can move away from the simplifications of the system. By including all 6 CDS, as well as more advanced operational patterns. This study assumed that the degradation of the components does not dependent on operational patters (e.g. standby mode, operational load). Thus, a study should be conducted on the effects of operational patterns on the degradation of the components.

By implementing accurate degradation models of each critical failure mode in the maintenance model, one obtains a simulator that provides a realistic short-term behavior of the system, which can be used to aim optimal maintenance decision. However, the model has to be subjected to V&V, to configure the system in a way that it best describes the system behavior, with regards to both failure and maintenance characteristics. This may be executed on the basis of acquired condition monitoring data in combination with expert judgment. Finally, cost data on the different activities should be included to be able to optimize the maintenance policy based on cost-effectiveness.

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Appendix A

Weibull Parameter Estimation

The MATLAB code for Weibull parameter estimation is based on the theory for: Parameter Estimation Based on MTTF and Standard Deviation. Presented in section 5.7.3.

A.1 MATLAB Code

```
%Weibull - Compressor

%=============
%Parameters1

lambda1 = 2.13055e-05;       % scale parameter
alpha1 = 12.1534;            % shape parameter
k1 = 0.1;                    % SD aim factor
t= 1:150000;                 % timespan
%=============
%Calculations1

%Mean Time To Failure1
MTTF1 = 1/lambda1 * gamma(1/alpha1+1);

%Variance2
var1 = 1/(lambda1^2) * (gamma(2/alpha1+1) -
(gamma(1/alpha1+1))^2);

%Standard Deviation1
SD1 = sqrt(var1);

%=============
```

```
%Calibration Variables1

SDa1 = k1 * 1/(1/MTTF1);      %Standard Devation Aim
MTTFa = 4.5e+04;              %MTTF aim

%===========
%Graph1

%Reliability Function1
R1 = exp(-(lambda1 * t).^(alpha1));

F1 = 1 - R1;

%The probability density function1
f1=diff(F1);

%=============
%%Parameters2

lambda2 = 2.05765e-05;        % scale parameter
alpha2 = 5.7974;              % shape parameter
k2 = 0.2;                     % SD aim factor

%=============
%Calculations2

%Mean Time To Failure2
MTTF2 = 1/lambda2 * gamma(1/alpha2+1);

%Variance3
var2 = 1/(lambda2^2) * (gamma(2/alpha2+1) -
(gamma(1/alpha2+1))^2);

%Standard Deviation2
SD2 = sqrt(var2);

%===========
%Calibration variables2
SDa2 = k2 * 1/(1/MTTF2);      %Standard Devation Aim

%Graph2
%===========

%Reliability Function
R2 = exp(-(lambda2 * t).^(alpha2));
```

```
F2 = 1 - R2;

%The probability density function
f2=diff(F2);

%=============
%%Parameters3

lambda3 = 2.2222e-05;        % scale parameter
alpha3 = 1.0;                % shape parameter
k3 = 1;                      % SD aim factor

%=============
%Calculations3

%Mean Time To Failure3
MTTF3 = 1/lambda3 * gamma(1/alpha3+1);

%Variance3
var3 = 1/(lambda3^2) * (gamma(2/alpha3+1) -
(gamma(1/alpha3+1))^2);

%Standard Deviation3
SD3 = sqrt(var3);

%===========
%Calibration variables3
SDa3 = k3 * 1/(1/MTTF3);     %Standard Devation Aim


%Graph3
%===========

%Reliability Function
R3 = exp(-(lambda3 * t).^(alpha3));

F3 = 1 - R3;

%The probability density function
f3=diff(F3);


%===========
%Plot
```

```
%Survivor function(R)
figure(1)
plot(R1,'-','LineWidth',1.5)
hold on
plot(R2,'--','LineWidth',1.5)
plot(R3,'-.','LineWidth',1.5)
hold off
lgd = legend(
'R: k = 0.10, alpha = 12.1534, lambda = 2.1306-05',
'R: k = 0.20, alpha = 5.7974, lambda = 2.0577e-05',
'R: k = 1.00, alpha = 1.00, lambda = 2.2222e-05',
'Location','northeast');
title(lgd,'Survivor Function')
xlabel('Time (t)')                    %x-axis label
ylabel('Probability')                 %y-axis label

%Probability Density function:
figure(2)
plot(f1,'-','LineWidth',1.5)
hold on
plot(f2,'--','LineWidth',1.5)
plot(f3,'-.','LineWidth',1.5)
hold off
lgd = legend(
'f: k = 0.10, alpha = 12.1534, lambda = 2.1306-05',
'f: k = 0.20, alpha = 5.7974, lambda = 2.0577e-05',
'f: k = 1.00, alpha = 1.00, lambda = 2.2222e-05',
'Location','northeast');
title(lgd,'Probability Density Function')
xlabel('Time (t)')                    %x-axis label
ylabel('Probability')                 %y-axis label
```

Appendix B

Optimization Results

The appendix provide numerical results, obtained trough the maintenance optimization process for the different maintenance policies.

B.1 Condition-Based Maintenance Policy Results

Numerical results for maintenance optimization, in section7.4.

B.1.1 Transition and Inspection Interval Optimization

Table B.1: KPIs for different inspection intervals with configuration 1

Insp. Interval	No. Inspections	No. CM	No. PM	Tot. M	Availability
730.0	419.010	0.040	7.182	7.222	0.9705
1460.0	214.700	0.129	6.959	7.088	0.9752
2190.0	145.667	0.240	6.724	6.964	0.9751
2920.0	110.885	0.380	6.448	6.828	0.9751
3650.0	90.157	0.538	6.174	6.712	0.9733
4380.0	75.541	0.703	5.821	6.524	0.9720
5110.0	65.749	0.875	5.574	6.449	0.9702
5840.0	57.626	1.021	5.288	6.309	0.9692
6570.0	51.016	1.173	5.009	6.182	0.9670
7300.0	45.676	1.321	4.795	6.116	0.9659
8030.0	41.613	1.442	4.593	6.035	0.9644
8760.0	37.832	1.565	4.289	5.854	0.9620
N/A	0.000	4.175	0.000	4.175	0.9440

Table B.2: KPIs for different inspection intervals with configuration 2

Insp. Interval	No. Inspections	No. CM	No. PM	Tot. M	Availability
730.0	420.39	0.79	4.86	5.65	0.9387
1460.0	214.96	1.26	4.16	5.42	0.9444
2190.0	145.32	1.70	3.51	5.21	0.9455
2920.0	110.16	1.98	3.08	5.07	0.9465
3650.0	88.98	2.27	2.64	4.91	0.9465
4380.0	74.74	2.48	2.35	4.83	0.9455
5110.0	64.40	2.65	2.09	4.74	0.9459
5840.0	56.37	2.77	1.91	4.67	0.9456
6570.0	50.21	2.88	1.73	4.61	0.9457
7300.0	45.16	2.97	1.60	4.57	0.9454
8030.0	41.14	3.05	1.48	4.53	0.9443
8760.0	37.62	3.13	1.38	4.51	0.9575
N/A	0.000	4.175	0.000	4.175	0.9440

B.1.2 Global Inspection Interval - Dependent Strategy

Table B.3: KPIs for different global inspection intervals

Inspection Interval	No. Inspections	No. CM	No. PM	Tot. No. M	Availability
730.0	387.81	0.04	11.73	11.77	0.9718
1460.0	201.63	0.13	11.36	11.49	0.9756
2190.0	138.46	0.21	11.00	11.21	0.9753
2920.0	106.58	0.36	10.62	10.98	0.9743
3650.0	87.69	0.52	10.36	10.88	0.9723
4380.0	74.11	0.66	9.80	10.46	0.9691
5110.0	65.21	0.81	9.65	10.46	0.9670

B.2 Time-Based Maintenance Policy Results

Numerical results for maintenance optimization, in section 7.5.

B.2.1 PM Interval Optimization

Table B.4: KPIs for $K = 0.10$, with respect of PM Interval

PM Interval	No. of CM per CDS	No. of PM per CDS	Total M per CDS	System Availability
8 760	0.000	40.000	40.00	1.0000
17 520	0.001	19.999	20.00	1.0000
26 280	0.158	12.999	13.157	0.9967
35 040	2.454	9.391	11.845	0.9393

Table B.5: KPIs for $K = 0.20$, with respect of PM Interval

PM Interval	No. of CM per CDS	No. of PM per CDS	Total M per CDS	System Availability
8 760	0.007	39.993	40.000	0.9999
17 520	0.181	19.906	20.087	0.9956
26 280	1.262	12.954	14.216	0.9682
35 040	3.313	9.212	12.525	0.9125

Table B.6: KPIs for $K = 1.00$, with respect of PM Interval

PM Interval	No. of CM per CDS	No. of PM per CDS	Total M per CDS	System Availability
8760	7.513	34.163	41.676	0.7987
17520	7.385	18.171	25.556	0.8037
26280	7.274	12.561	19.835	0.8069
35040	7.185	9.205	16.389	0.8090