Master's thesis

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

Astrid Vormdal

Maintenance Optimization by Use of a Markov Model

A Steam Trap Case Study Using Empirical Plant Data

Master's thesis in MORG - Organisation and Management - Safety, Reliability and Maintainability
Supervisor: Jørn Vatn

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RAMS
Reliability, Availability,
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Preface

This study report is a master thesis within the specialization of safety, reliability and maintenance as a part of the experience-based study program of organisation and management at NTNU. The study was carried out in the period between September 2019 to the end of October 2020. The study involves a study case with empirical plant data collected from Equinor, which also has been the student’s employer during the study period.

The intention of this project was initially to create a contribution to improvement of maintenance management strategy, and by this contribute to obtain a sustainable, competitive advantage to a branch that is influenced by varying and potentially decreasing margins, thorough utilizing the access to empirical maintenance data and working experience in combination with maintenance optimization theory and models. Therefore, it is assumed that the average reader of this master thesis is familiar within maintenance management theories and strategies in general.

Batnfjordsøra, 2020-10-30

Astrid Vormdal

Astrid Vormdal

Acknowledgment

I would like to express my gratefulness to professor Jørn Vatn for excellent guidance, especially related to development of the mathematical models but also in general, during this master's study.

I also want to thank my family, my friends and my employer Equinor including my leaders and many great colleagues for being supportive about this study. The most work intensive work periods of the study have required adaptions from the surroundings, mainly represented by my partner Vidar, my loving children Erlend and Magnus and my mother Åshild. This is highly appreciated and have also been decisive to enable this work.

A.V.

Summary

An already established Markov degradation model was further developed and utilised in order to model failure development and cost optimization, thorough a steam trap case study carried out by using empirical plant data from an Equinor methanol production plant. Data collection included maintenance data from the company's computerized maintenance management system SAP and also inspection reports, process data from process control and acquisition system and qualitative information about maintenance routines and practise collected from maintenance personnel.

Data from steam trap failures were collected and used for degradation modelling. Some assumptions regarding failure development was made, due to incomplete data sets according to the Markov degradation model. The model was then utilized to calculate optimal inspection intervals and to simulate alternative maintenance strategies. There were also tried to simulate a continuous monitoring case.

The Markov model showed ability to model alternative maintenance strategies in addition to inspection interval optimization, enabled by the many input parameters the model requires, and especially the inspection matrix. The results indicated potential for optimization of maintenance performance and strategy. Costs were mainly related to maintenance and less to energy loss. The online condition monitoring system case had the highest savings, but not all cost related to the online monitoring system was included. Improvement and optimization of maintenance strategy should be considered against other aspects like the company's overall maintenance strategy.

The model and the study case could need some additional validation before conclusion.

Sammendrag

En tidligere utviklet Markov degraderingsmodell ble videre utviklet og benyttet for å modellere feilutvikling og kostandsoptimalisering gjennom en case-studie av kondensatpotter, utført ved å bruke reelle, empiriske data fra et Equinor metanolproduksjonsanlegg. De viktigste kilder til datainnsamlingen var bedriftens elektroniske vedlikeholdsstyringssystem SAP, historiske inspeksjonsrapporter, prosessdata fra bedriftens prosesskonstrollsystem og kvalitativ informasjon fra internt og eksternt vedlikeholdspersonell.

Data fra feil- og vedlikeholdshistorikk ble samlet inn og videre benyttet for å modellere degradering. Noen antakelser angående feilutviklingstid måtte gjøres på grunn av ufullstendige datasett i henhold til Markovmodellens design, for å oppnå en god modell. Modellen ble så benyttet til å beregne optimale inspeksjonsintervall og til simulering av alternative vedlikeholdsstrategier. Det ble også forsøkt simulert en case med kontinuerlig tilstandsovervåkning.

Markovmodellen viste god evne til å modellere ulike vedlikeholdsstrategier i tillegg til optimalt vedlikeholdsintervall, spesielt grunnet inspeksjonsmatrisen. Resultatene av analysen indikerer et potensiale for forbedring av vedlikeholdsstrategi for det studerte caset. Det viste seg at kostnader for det valgte utstyret i all hovedsak var knyttet til vedlikeholdet og mindre til energitap. Online tilstandsmonitorering viste størst potensiale for besparelser, men da før kostnader knyttet til innkjøp, drift og vedlikehold av systemet for online tilstandsovervåkning var inkludert. Forbedring av vedlikeholdsstrategien må også vurderes opp mot andre aspekt som overordnet målsetting og strategi for vedlikehold i bedriften.

Modelleringen og studiecaset kan trenge noe validering og potensialt forbedringer før endelig konklusjon.

Contents

List of Figures

List of Tables

Abbreviations

BP	Balanced Pressure
CM	Corrective Maintenance
CMMS*	Computerized Maintenance Management System
FMECA	Failure Mode, Effect and Cause Analysis
HP	High Pressure
LP	Low Pressure
MCS	Monte Carlo Simulation
MP	Medium Pressure
PCDA	Process Control and Data Acquisition
PdM	Predictive Maintenace
PFD	Probability of Failure on Demand
PM	Preventive Maintenance
RCM	Reliability Centred Analysis
SAP*	System Analysis and Software Development (CMMS system in Equinor)
VBA	Visual Basic
WSN	Wireless Sensor Network

*Same software

Chapter 1

1 Introduction

This chapter will, in addition to introduce the state of the art regarding maintenance optimization methods, present the business context for and motivation to development of maintenance optimization methods for a production plant. Further, the problems, objectives, and the approach to investigate these questions will be presented together with some limitations for the study.

1.1 Background

Maintenance optimization is in any industry one possible measure to achieve business objectives related to cost and production, as well as other important objectives like safety level, energy efficiency and environmental emissions. Successful maintenance optimization requires not only high level of professional, technical competence, but also good knowledge of failure development behaviour, maintenance costs, maintenance optimization methods and all types of consequences as a result of failure impact.

Predictive maintenance (PdM) is one type of modern maintenance approach that, if used in the right cases, could be very cost efficient. PdM is, to be brief, much about doing correct maintenance to the right time (before failure), which over time can be an important contributor for production plants to achieve sustainable competitiveness. A modern predictive maintenance concept requires equipment condition indicators or metering, which in turn shall be used to predict time to function failure. The last years technology development and automation of human tasks have led to new, interesting, and more efficient maintenance methods. This has been a quite interesting backdrop during this study.

In this work, a maintenance case study from an Equinor Methanol production plant has been performed. The methanol plant produces more than 920 000 tons methanol from natural gas every year. The plant consists of tons of process equipment like compressors, piping, boilers, vessels, pumps, and separators that contain process medium like gas- and liquid hydrocarbons, steam and water with a wide range of temperature and pressure. Correct maintenance is decisive to achieve safe, reliable and efficient operation of the production plant. And as a consequence to this, maintenance makes up a considerably part of the operation costs. Therefore, maintenance optimization *can* contribute to improve results, both economic and related to the other objectives as mentioned above, and further competitiveness for the plant.

Literature on the Maintenance Optimization field contains a lot of models and frameworks with a variety of point of views.

Horenbeek (2010) stated in 2010 that on that time, “the gap between academic models and application in business specific context” was still a “big problem on the field”. Horenbeek contributed to the Maintenance Optimization field with a literature study that contains a “Maintenance optimization classification framework”. This framework introduced the more practical aspects of this problem, like maintenance optimization criteria’s, and illustrates the complexity for maintenance optimization problems. It was declared that “data availability is often seen as the biggest obstacle to overcome to make the implementation of maintenance optimization models possible in real-life case studies”. Gilabert, Fernandes, Arnaiz and Konde (2015) also points on a maintenance information gap, from several reasons, as an obstacle to maintenance cost improvement and developed a Monte Carlo Simulator (MCS) to illustrate a methodology to overcome this information gap. The article also provides an improvement model inspired by the Deming cycle. Xiang, Cassady and Pool (2011) demonstrated and presented degradation and lifetime simulation of a single unit system by using a Markov model. The simulation model was further utilized for maintenance cost optimization for maintenance strategy analysis and improvement purposes. Ewa Laskowskas (2018) study and publication “State modelling and prognostics of safety valves used in the oil and gas industry” demonstrates utilization of real time empiric data from a petrochemical plant to develop a Markov degradation model for reliability modelling purposes.

There has been performed several maintenance optimization studies and published many articles on this field, based on real, empiric data over the last years. Many of them points on the information gap and aims to overcome this gap. This master thesis has the purpose to close this gap by examining the possibilities that lies in an already established Markov model for condition monitoring and degradation modelling, from a cost optimization perspective. This involves, in light of the chosen case, pointing out what needs to be done to establish the actual model, identify the benefits and challenges from it, and propose how it can be used in an industrial context.

1.2 Objectives

The main objective of this master’s project is to demonstrate aspects of maintenance optimization related to a chosen case at Equinor Tjeldbergodden methanol plant

The following objectives are underlying the main objective:

1. Identification and further development of develop a real, suitable case suitable for degradation modelling and maintenance optimization
2. Utilize an already established and/or develop a failure development model for the chosen case in collaboration with supervisor from NTNU
3. A literature study of maintenance optimization methods from a PdM perspective
4. Identify and collect available data related to the chosen case e.g from CMMS system and PCDA system
5. Develop cost functions and perform maintenance strategy optimization calculations for the chosen case

6. Examine and discuss the opportunities and challenges related to the model from an industrial perspective

1.3 Approach

Data collection and further processing from CMMS system, inspection reports on G-disk and data from PCDA system makes up a big part of the approach. A motivation for the chosen case, was an assumption that failure costs related to energy loss and material degradation was high, and that there could be more optimal maintenance intervals than today. Another motivation was to examine whether optimized time based, manual inspections should be replaced with automatic sensors. Collected data from these systems have been processed and further calculated to failure rates and failure repair times as an input to the degradation model. This data was put into a Markov state model to model failure development with maintenance and cost optimization.

The other main part of this master's thesis is a literature study among journals, articles and other sources that can be accessed with the NTNU user licence. The aim of the literature study was:

1) To obtain a wider and deeper insight to acknowledged, both well established as well as modern, maintenance optimization methods that in turn ca be used to discuss and evaluate the alternatives and the chosen method.
2) To get a deeper insight in the equipment- and failure characteristics and inspection- and maintenance methods related to the chosen case
3) And in addition to this, demonstrate how to perform and utilize a successful literature search

Approach is illustrated in figure 1-1 Research approach step by step:

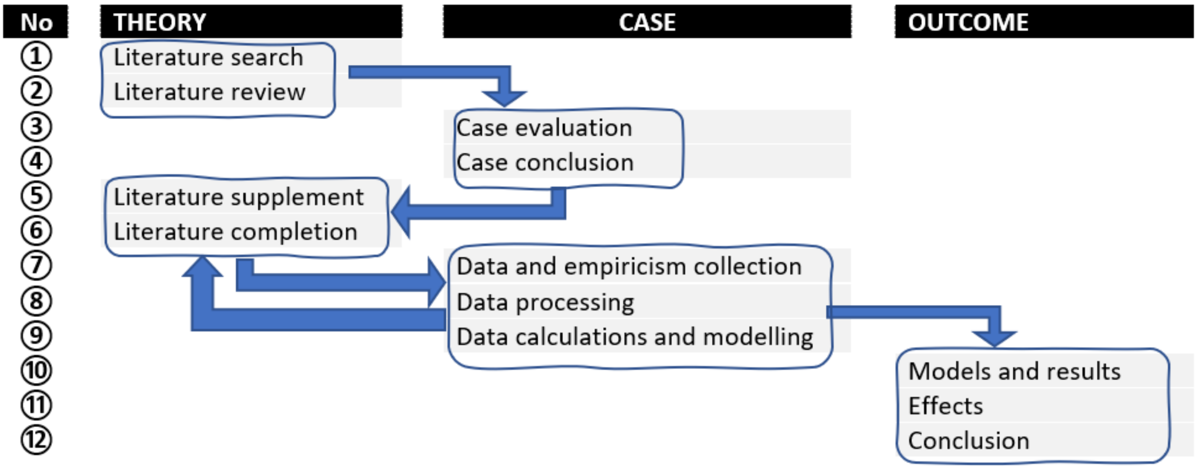


Figure 1-1 Research approach step by step.

The research approach for this study is separated into three main parts, where the first two, theory and case, overlaps each other. The study started with a literature search on predictive maintenance. The literature study on this field together with writer's experience and limitations as mentioned in section 1,5, formed the basis for case study selection. After case selection, some literature search for supplementary purpose should have been performed. During model development, some literature study on the maintenance management, system reliability theory and among this Markov analysis, and of the maintenance optimization field was executed. Maintenance data was collected from malfunction reports and work orders in SAP, inspection reports on G-disk and in addition to this, a separate excel spreadsheet containing for most the same information as the one from SAP and inspection reports. Collected equipment and maintenance data was in turn processed to lifetimes and repair times and failure- and repair rates was further calculated. The times and consequently the rates was further adjusted according to some assumptions made, due to incomplete data acquisition, to obtain a complete model as a result from the data collected. Empiric data with relevance for the case, like for example information about maintenance routines, was also collected thorough interviews of maintenance personnel. The modelling involves mainly two tasks – 1) development of a generic degradation model, for this case a Markov state model and 2) Further develop the model for the chosen case, including cost functions, to obtain the outputs. Part 3) of the study is the outcome of the model, including specific models, results, conclusions, and discussions.

In sum, the approach as described in the section above, should function to obtain the main objective and the six underlying objectives from chapter 1,2 Objectives.

1.4 Contributions

This study will contribute to the maintenance optimization field by demonstration of how to utilize empiric maintenance data from CMMS for developing a Markov state model for modelling degradation and for cost optimization purpose. This study is performed from an industrial point of view, which is a common and realistic point of view for many maintenance optimization practitioners. For the business sector, the study can present an overview of the opportunities and the challenges a Markov state model can provide for optimization purposes, and also the work and the data that is necessary to develop a useful model.

1.5 Limitations

1.5.1 Data Collection

When data is collected in general, it is practically impossible to get bet better quality of the results than on the input data. It was already well known, even before the data collection started, that maintenance history data in CMMS system have varying quality and precision over time. These data are often not standardized and a result of human evaluation. It is obvious, thorough observations, that data past 2013 is reported with much more precision and it contains more information. Data form before 2010 are rarely documented in CMMS system. Data collection was due to the need of quality control, quite time consuming. Due to time available in combination with factors mentioned above, it was decided to collect failure data from the last five years.

1.5.2 Writers Profession and Pre-knowledge

The models and equations used, are the same as used in the courses in the master’s programme. The writers background excludes the use of more advanced modelling tools than those. The writers background and process experience from operations and maintenance set a limitation related to some equipment specific problems. This limitation has an impact of the chosen case and its relevance.

1.5.3 Life Cycle Perspective

Life cycle perspective is not considered for the case, which practically means that it is assumed that components are replaceable. Equipment is provided both with replaceable (maintainable) and non-replaceable component, the first one is somehow more expensive than the other one.

1.5.4 Modelling

There are possibilities for further model development, for example phase type modelling and also to vary maintenance intervals during lifetime. Such models are quite more complicated than the model used in this case and they are not a part of this scope.

1.6 Outline

Following is an overview of the remaining chapters and structure in this report.

Chapter 2 provides the theoretical background to the study. This includes maintenance theory in general and a short literature review of PdM implementation, maintenance optimization, Markov modelling, Markov processes and human and organizational factor.

Chapter 3 introduces the steam trap study case. System configuration, background and maintenance practice at plant are mentioned in this chapter.

Chapter 4 describes method, assumptions, results and analysis for data collection.

Chapter 5 presents the maintenance modelling, the Markov model that were developed and the modelling simulation cases.

Results and result analysis are described in chapter 6 and chapter 7 provides a summary og the findings together with a conclusion and discussion.

Chapter 2

2 Theory

A theoretical basis for the maintenance modelling and optimization study, including some maintenance-managerial aspects, followed by the findings from the literature review will be presented in this chapter. The first part, chapter 2.1 contains fundamental maintenance optimization theory that is primarily collected from the course literature at NTNU. The background for the literature review in chapter 2.2 is presented in chapter 1.3 “Approach”, while the search method is presented in the introduction to chapter 2.2 “Literature review” and discussed later in the discussion-chapter of this report.

2.1 Theoretical Background

2.1.1 Maintenance Management

The following items listed below are pointed out in NS-EN 13306 as the main objectives for maintenance management:

- Availability (at optimum costs)
- Safety
- Environment impact
- Durability and/or product quality.

Especially the first and the second item, but also the last two, are important targets for maintenance optimization problems.

2.1.2 Maintenance Strategy Approaches

A classic presentation of maintenance approach is categorization into preventive, corrective and “improvement” maintenance. The two first categories are further divided as illustrated in figure 1-1 Maintenance Approach. The chosen of approach has directly impact on maintenance costs as well as other relevant maintenance targets and are often found by an RCM analysis.

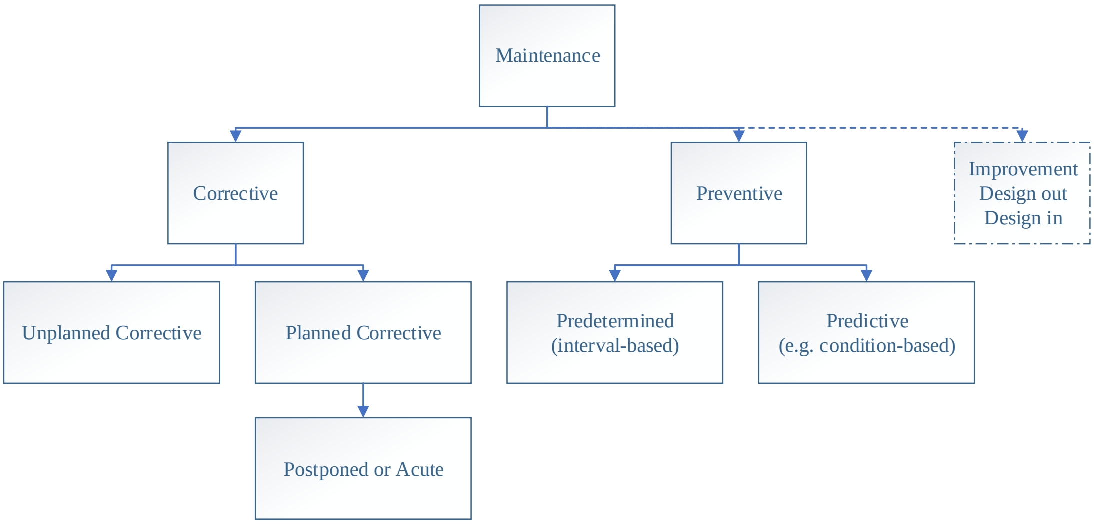


Figure 2-1: Maintenance Approach (inspired by Wilson, 2017, Chapter 2).

2.1.3 RCM Analysis

An RCM analysis is a recognized method for decision of maintenance approach (and activities), and eventually maintenance optimization after that. The RCM analysis is systematic mapping of system functions in order to identify system- and equipment function failures, causes and effects. (Vatn, 2018). The following bullet points describes main steps in RCM and figure 2-2 illustrates an example of an RCM logic.

- System and system limits decision
- Functional fault analysis
- Selection of critical units (FSI – Functional significant Items)
- Data collection, analysis
- Failure mode- and effect analysis (FMEA/FMECA)
- Decision of maintenance approach (and activities)
- Maintenance interval set up
- Implementation
- Updates of RCM process

Bullet points are collected from Vatn, 2018.

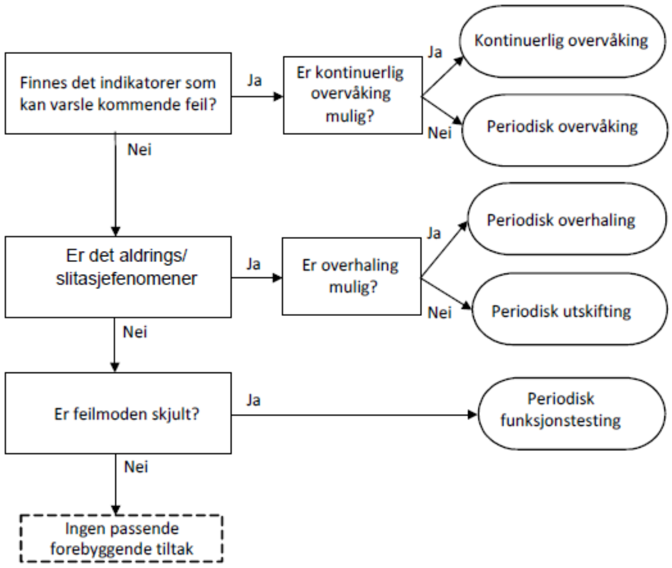


Figure 2-2: Example of an RCM decision logic (Vatn, 2018)

2.1.4 Failure Development Modelling and Optimization

Failure models can express probability (failure/lifetime) distributions over time, failure rate and failure development (degradation) time. The two most common probability distributions will be shortly presented below.

Classic maintenance optimization methods can be utilised to set an optimal maintenance interval for individual activities or for groups of activities (typical for turnaround and partial stop) and to establish optimal number of spare parts (Vatn, 2018).

2.1.5 Probability Distribution f(t)

Weibull distribution and exponential distribution are the two most common probability distributions used in maintenance modelling. Lifetimes for components that degrades due to aging is often Weibull distributed. Lifetimes for components with constant probability for failure (failure rate) is often expressed by the exponential distribution. This is often common for electrical components that is not exposed for degradation due to aging. Probability distributions are expressed f(*t*).

Weibull Distribution

Weibull distribution is expressed as:

$$f_T(t) = \alpha\lambda(\lambda t)^{\alpha-1}e^{-(\lambda t)^{\wedge}\alpha}$$

where α is referred to as the shape parameter and λ is the referred to as the scale parameter. α value depends on the degree of aging and failure rate is constant and α=1. The higher the α is, the stronger is the aging (faster aging process). Weibull distribution is flexible and commonly used “to model life distributions, where the failure rate function is decreasing, constant or increasing” (Raussand and Høyland, 2004).

Input parameters α and λ can be found in supplier's documentation or calculated thorough data analysis of at set of empiric maintenance data or test data. Lifetimes without maintenance (when $\tau \rightarrow \infty$) is preferred.

Exponential Distribution

The exponential distribution is expressed as:

$f_T(t) = \lambda e^{-\lambda \tau}$

2.1.6 Failure Rate Function z(t)

Failure rate function for a component or equipment expresses the probability of failure in a short time interval (t), given that it still works at that time. Failure rate function is expressed z(t). The failure rate curve is often referred to as the bathtub curve because of its shape. Example of a bathtub curve is illustrated in the figure 2-3 below.

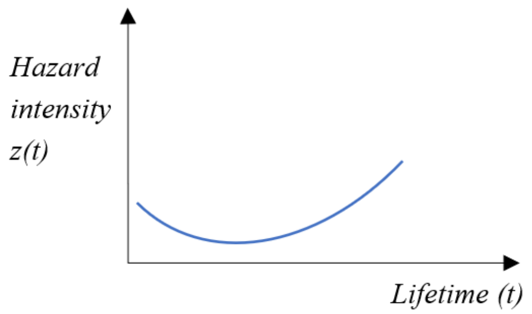


Figure 2-3: Bathtub curve example

2.1.7 Failure Rate λ

Failure rate is expected number of failures per time unit. Failure rate is expressed as λ. Failure rate can be calculated with or without maintenance. Effective failure rate $\lambda_E(\tau)$ express the failure rate per time unit as a function of time-based preventive maintenance interval (τ). Effective failure rate $\lambda_E(\tau)$ is a central term in maintenance optimization cost function calculations. Exponential distribution has constant failure rate.

2.1.8 Failure Development Modelling

Type, consequence, and behaviour of failures are important factor for decision of maintenance. Failure development models can according to Vachtsevanos (2006) be categorized in three main approaches:

1) Model-based prognostic; Remaining useful lifetime estimation by using a mathematical model of the degradation.

2) Data-driven prognostic; Predict degradation by using monitoring data. Bayesian networks and Markov models are methods that belongs to this category.
3) Experience-based prognostic; Rest useful lifetime estimation by using reliability models developed from empiric data (statistical). This category is close to the data-driven prognostic one.

From a point of view where condition based and/or predictive maintenance strategy is preferred, it is important to understand the failure development and degradation behaviour. Realistic failure development models can provide a high, mathematical insight in failure development, wich in turn can act as effective decision support regarding efficient maintenance according to maintenance objectives.

2.1.9 Observable Failures

For observable failures or loss of function, failure development can be modelled. Inspection of function / failure development could be a natural maintenance approach to such failures. Thus, failure development models form good basis for decision of inspection intervals for periodic condition monitoring. Example of such maintenance cases could be wall thickness in pressure vessels or piping due to failure mechanisms like corrosion and erosion.

PF Model

The PF-model is a common model for observable failures that start to develop after a long time in state new or maintained as good and after that develop fast. The PF-model describes the time and failure development that runs in the period from detectable failure (potential) to critical failure (loss of function according to failure state and predetermined criteria) – *The PF interval.* Figure 2-4 illustrates an example of a PF-model.

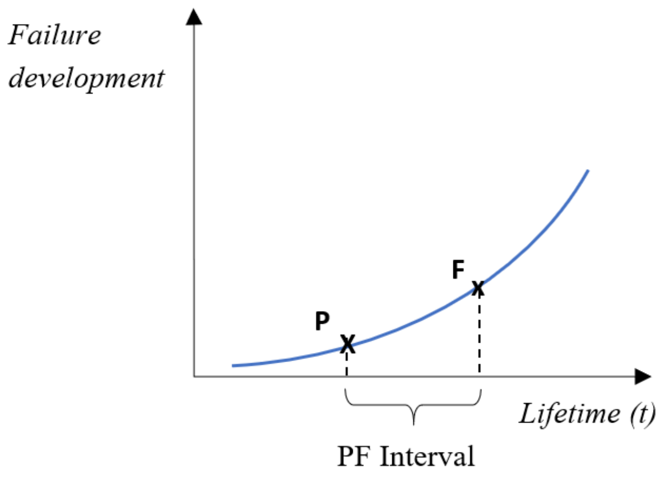


Figure 2-4: PF-model example

From the PF-model, calculations of effective failure rate $\lambda_E(\tau)$ and maintenance cost optimization can be done.

Observable, Gradually, Failure Development

Other failures start to develop practically at t≈0, e.g. right subsequent the state new or maintained as good as new. A characteristic of this failure is that it would typically develop more slowly. This can be modelled, and a Markov state model, presented in the following section, is a common model for this purpose. Figure 2-5 illustrates a general example of observable, gradually, failure development.

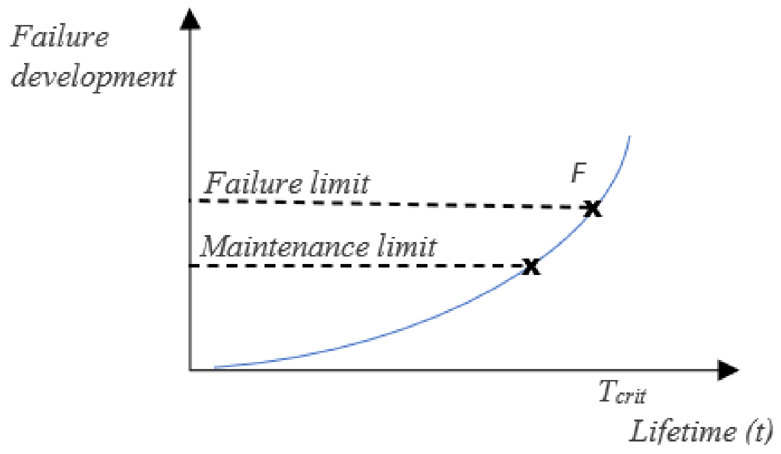


Figure 2-5: Example of observable, gradually, failure development with maintenance- and failure limits (Vatn, 2018)

2.1.10 Markov State Modelling

Markov processes can be utilized to analyse the reliability of a system as a function of time, with a wider number of defined (system) states (Rausand and Høyland, 2004). This makes Markov analysis to an applicable method for failure mechanisms that develop and affects the system reliability and availability over time, and for systems that can be in more than two system states.

Markov chains are a type of stochastic processes that models the transition rates from one state to another state. Stochastic processes are by Rausand and Høyland (2004) defined as "a collection of random variables". For this purpose, it is the continuous-time stochastic processes that are of interest. More specific, the (repairable) system states as a function of time, the number of failures within a time interval, mean time to first system failure, mean time between system failures and sojourn time for each state. Failure(s) and failure development, repair times and decision processes can be modelled with Markov processes. In a traditional Markov analysis, transition between system states only depends on "present" state, which means that historic transitions and states and sojourn time up to the present have no impact as the model practically has no memory. This is what give the Markov characteristic and the belonging process is named Markov process (Holen, Høyland and Rausand, 1988).

Figure 2-6 illustrates a simple example of how failure development can look like. For a Markov process, the failure development differentiated in 3 steps from 'functioning, beginning in state 0 at time 0 to failure at state 2 is illustrated. λ represent failure rates and μ represents repair rate.

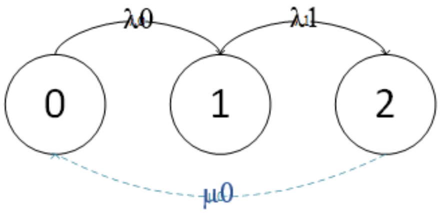


Figure 2-6 Simple Markov diagram

For a stochastic degradation process in interval of $\{Y(t), t\epsilon\theta\}$, system states can be defined as as *y0* to *yr* where *y0* is state "new" or "good as new" and state *r* is failure (to function) state. X(*t*) expresses the process state at time t. Further, the probability that the system is in state *i* at time *t* expressed as $P_i(t)$ is derived by numerical integration of standard Markov differential equations (Laskowska 2018, Vatn 2020):

$$P_i(t+\Delta t) \approx P_i(t)(1-\lambda_i\Delta t) + P_{i-1}(t)\lambda_{i-1}\Delta t \tag{1}$$

(mean time to failure) can then be found by the integral of Equation (1):

$$\text{MTTF} = \int_{t=0}^{\infty}[1 - Pr(t)]dt \tag{2}$$

Equation (1) can be used as a basis but will not be useful for a degradation model because it allows only one step and also because it allows transition both to the left and to the right. For situations where transitions between any state shall be modelled, matrices with defined transition states must be used. This leads to the Markovs differential equations (based on Kolmogorov's differential equations):

$$\mathbf{P(t)}\cdot\mathbf{A} = \dot{\mathbf{P}}(t) \tag{3}$$

And this leads to Equation (4):

$$\mathbf{P}(t+\Delta t) \approx \mathbf{P}(\mathrm{t})[\mathbf{A}\Delta \mathrm{t}+\mathbf{I}] \tag{4}$$

Where:

- **P**(*t*) is time dependent probability vector for the various states defines in transition matrix **A**
- $\dot{\mathbf{P}}(t)$ is time derived
- **A** is a transition matrix (λ and τ)
- **I** is an identity matrix

and the diagonal elements summarized equals zero.

These differential equations can be used to find probabilities for being in each state as well as probability for being in state *i* as a function of time *t* (Vatn, 2018).

The A-matrix reflects the transitions between the system- or degrading states. Depending on the nature of the failure and failure development, transitions "move" gradually or quicker. A quick failure development can also go from one early state to a late state without visiting states between, for example like a shocking occurrence. All such behaviour can be modelled in the A-matrix. The A-matrix also can include repair rates from late states to good a new or early state.

For inclusion of inspections into the Markov model, an inspection matrix has to be introduced. The inspection matrix models what happens from an inspection at defined intervals. In addition to that, other probabilities like decision process can be modelled with the inspection matrix. In the Markov diagram presented as virtual help states.

The Markov model has both benefits and backdrops. The model is flexible and easy to configure to a variety of cases. The number of states can be chosen to reflect the natural behaviour of the system and it enables decision process modelling. The model can be used where a hight number of censured lifetimes are available. One backdrop of the model is that it often requires assumptions to create a good degradation model, due to incomplete datasets. And when the Markov characteristics of a system is questionable, there Markov Model might not be the best alternative.

2.1.11 Maintenance Optimization

Background and Historic Overview

Maintenance optimization is a discipline within the operations research field that was established by Great Britain during 2nd world war. The field covers quantitative methods for use in decision-making processes (Helbæk, 2012), often related to economics. Maintenance optimization was founded by researchers early in the 1960's (Dekker, 1996). The object of maintenance optimization problems is to utilize mathematical models to balance costs and benefits related to maintenance and failure, thus find the optimum solution that leads to the minimum of costs (Vatn, 2018; Dekker, 1996).

Back in the 1950's and 1960's, preventive maintenance was utilized to reduce failures and unplanned down time. Time based preventive maintenance programs was established. On that time, research models were developed to optimize those programs. In the next decade, the 1970's, condition-based maintenance arose, using information about equipment state to predict failure. This approach proved to be more cost efficient than the time based one. And in the decade after that, design improvement and "design out" failures and weaknesses got its attention (Dekker, 1996).

Reliability centred maintenance (RCM), now an important fundament for maintenance management in many industries, was first introduced for airplane maintenance in the 1960's. It was first about 20 years later, in the 1980's, that this approach had its breakthrough in many other industries (Dekker, 1996). Nowadays, RCM, focusing on system reliability and function(s), is a well-recognized method and common fundament for a successful maintenance program that intend to balance safety, availability, and costs.

Maintenance optimization is one of the many important areas of maintenance management in manufacturer industry to obtain central objects related to safety, productions, energy consumption, environmental emissions, product quality and costs.

2.1.12 Maintenance Optimization Modelling

Problem-solution in a general decision-making process is illustrated in figure 2-7:

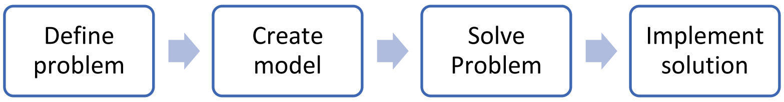


Figure 2-7: Problem Solution Process (copied from Helbæk, 2012).

Years of research in the field have resulted in a variety of methods and models for maintenance optimization.

Basically, maintenance cost optimization intends to minimize two set of costs (per time unit), often as a function of maintenance interval (τ, decision criterion). This is illustrated in figure 2-8:

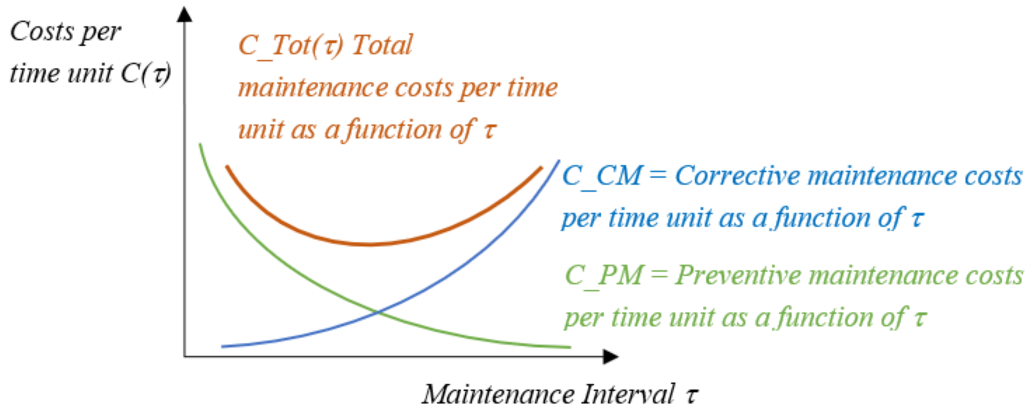


Figure 2-8: Cost optimization example in general

The figure, that in this case is only drawn to exemplify the theory, shows the balance between PM costs and CM costs. For a long maintenance interval, the PM costs per time unit will decrease and the CM costs will increase due to increased failure rate. And in the opposite way, for a short maintenance interval, the PM costs per time unit will increase while the CM costs will decrease due to decreased failure rate. An optimal solution to a maintenance interval decision problem is at the minimum point of the total maintenance costs (CM+PM per time unit as function of τ). The solution of this problem for the previous example illustrated above, is pointed out in figure 2-9.

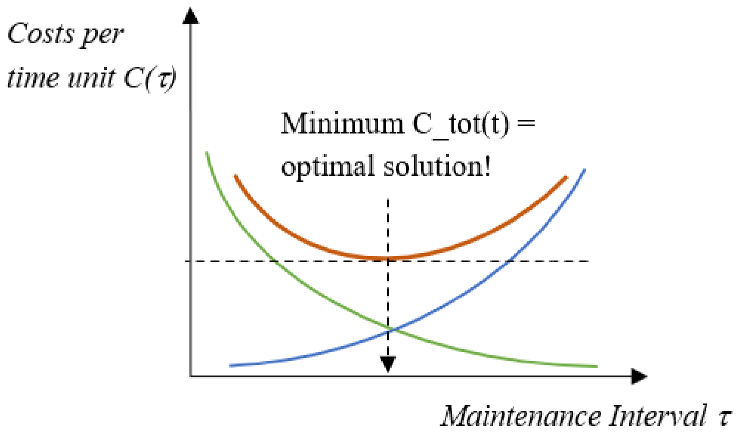


Figure 2-9: Maintenance optimization graphic example of optimal solution where the point of minimal total costs

Cost Function

A standard cost function model for interval optimization can be written as written below:

$$C(\tau) = C_{PM} / \tau + \lambda_{E(\tau)} [C_{CM} + C_{EP} + C_{ES} + C_{EM}] \quad (5)$$

Where the result C(τ) is cost per hour or other time unit for a defined system failure given a component failure.

And the input parameters are:

- τ = Maintenance interval, preventive maintenance
- $\lambda_{E(\tau)}$ = Effective failure rate as a function of maintenance interval τ.
- C_{PM} = PM cost
- C_{CM} = CM Cost
- C_{EP} = Expected production loss due to one failure
- C_{ES} = Expected safety loss due to one failure
- C_{EM} = Expected costs due to material loss after a component failure

Cost function

The optimal solution of an interval optimization problem is the value of τ that minimizes C(τ). Different mathematical methods can be used to find τ. (Vatn, 2018).

The cost equation shown in this section is the basis function. For maintenance optimization modelling, the cost equation and effective failure rates has to be adapted to the specific case. There are developed several functions for this purpose. Some of them are presented in Vatn (2018).

2.2 Literature Review

2.2.1 Literature Search

The literature search was focused on different aspects related to predictive maintenance and made out at an early stadium of the study, where PdM was planned to dominate the study more than it actually did. A detailed method for search and scanning of the findings was developed. The systematic literature search are summarized in table 2-1 by sources, key words, inclusion/exclusion criterias, number of hits and comments. Different aspects of PdM was studied, as implementation, practical use of modelling and decision support tools (Markov and Monte Carlo Simulation), sensor architecture technology, impact on human/organisational factor and maintenance optimization.

Table 2-1 Systematic literature search

Litterature source	Key word(s)	Inclusion criteria	Exclusion criteria	Number of hits	Comment
Scopus	Predictive maintenance + Wireless sensor network	-	-	9	
	Predictive maintenance	2010 - 2019		42	Large number of hits – articles were sorted on number of sites and then assumed relevancy
	Predictive maintenance + «sensor		Some businesses not relevant to chemical prosessing plant	45	Large number of hits – articles were sorted on number of sites and then assumed relevancy
Oria	Predictive+maintenance	Peer-reviewed journals		18 →10	
Web Of Science	Industry 4.0 + Predictive maintenance			9→6	

	+ cyber*physical system"				
Proceedings og ESREL 2018				7	"Manual scanning", no key words used

A pilot search in Scopus as summarized in figure 2-10 was made to get the experience to continue the search in more efficiently. Unfortunately, the rest of the literature search was not logged as detailed as the pilot search. Table 2-1 can therefore be somehow imprecise.

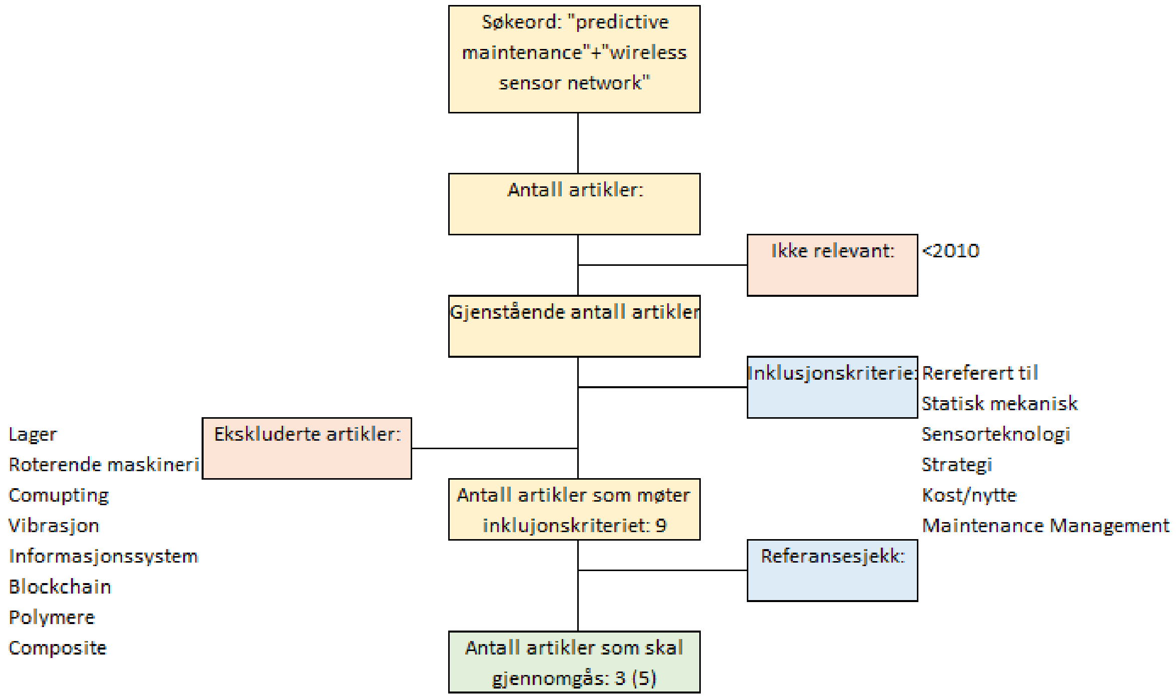


Figure 2-10 Systematic literature search - Scopus Pilot, logged.

During the pilot search, the following method for scanning of "hits" was developed:

1. The summary of all hits was red thorough.
2. Of the articles that looked relevant, the article was registered in an excel overview and given a score for assumed relevance to objectives (1-5).
3. The relevant articles were saved and printed
4. Complete review of relevant articles prioritized by score for assumed relevance.
5. Notes after review was collected in one document
6. Article was given a new, actual score for relevancy

There were also planned for a point 6 and 7 on this list, that said to 6) make an overall evaluation the result of the literature review and 7) Review original literature used in the most relevant articles. These two points were not prioritized.

The excel overview together with notes and score were used thorough case study.

2.2.2 Literature Review

PdM Implementation

Selcuk (2015) presented state of the art of predictive maintenance in an article that can be used as an starting point for maintenance management improvement. The article presents “suggestions for how to implement a predictive maintenance programme in a factory” and it provides a quite detailed overview of parameters that can be used for condition monitoring and what types of equipment that can be monitored as a part of a PdM strategy. In addition to this technical aspect, he also points on the need for decision-making support tools like Bayesian theory and neural networks to handle the data acquired. Gilabert et. al. (2015) developed a Monte Carlo Simulator tool (MCS) to compare different maintenance strategies as PM, CM, PdM, inspections, sensor quality vs cost based on specific business scenarios combined with reliability and/or cost targets. The article also provides an improvement model inspired by the Deming cycle. He, Han, Gu and Chen (2018) developed and proposed a cost-oriented dynamic predictive maintenance strategy based on their work with cyber-physical systems and operational data for a manufacturing system in combination with a mission reliability state model. Five kinds of costs related to mission reliability state were added to the model in order to optimize the predictive maintenance strategy. Based on the findings from a case study, it was implied that the dynamic predictive maintenance strategy can provide a more cost-efficient performance of the maintenance tasks compared to a conventional approach.

Maintenance Optimization

Horenbeek and Pintelon (2010) contributed to the Maintenance Optimization field with a literature study that contains a “Maintenance optimization classification framework”. This framework introduced the more practical aspects of this problem, like maintenance optimization criteria’s, and illustrates the complexity for maintenance optimization problems. It was declared that “data availability is often seen as the biggest obstacle to overcome to make the implementation of maintenance optimization models possible in real-life case studies. As a result of their literature review of maintenance optimization models in 2010, Horenbeek and Pintelon published a framework for maintenance modelling. This is shown in figure 2-11 and illustrates the complexity of information required to make a successful maintenance optimization model.

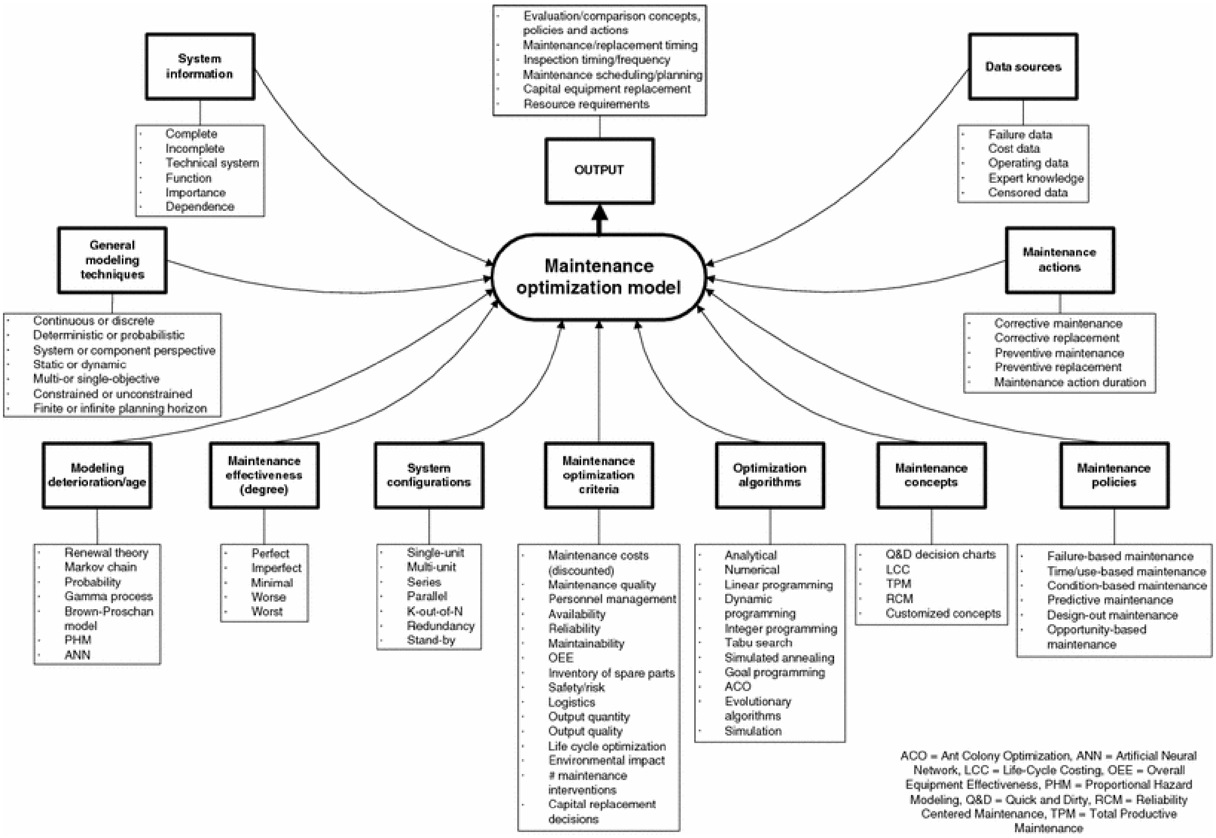


Figure 2-11: Maintenance optimization model (Horenbeek and Pintelon, 2010)

Input information are grouped in 11 categories and requires knowledge and information like system function- and configuration, failure development- and optimisation modelling, maintenance concepts, policies and actions are some of the categories.

Markov Processes

Xiang, Cassady and Pohl (2011) demonstrated and presented degradation and lifetime simulation of a single unit, repairable system by using a Markov model with a traditional Weibull distribution. The simulation model was further utilized for maintenance cost optimization for maintenance strategy analysis and improvement purposes. Common to many of the studies of cost optimization modelling is that the models indicate that there are potential for profit where periodic maintenance can be replaced with condition-based maintenance. Xiang et al (2011) also found that a prognostic error in system condition estimations, can lead to higher maintenance costs than periodic maintenance can do.

E. Laskowska (2018) developed Markov model for safety valves using real time empiric data from a petrochemical plant in her study and publication “State modelling and prognostics of safety valves used in the oil and gas industry”. The Markov degradation model was developed for reliability modelling purposes, in this case to verify whether the maintenance supports the valve performance requirements according to the safety integrity level, which is somehow different to the cost optimization object. E. Laskowska concludes, like Xiang et. al. that the model results, probability of failure as function of time (PFD), depends heavily on the maintenance activity considerations and the model assumptions. Cartella, Lemeire, Dimiccoli, Sahli and Xu (2015) pointed at model selection a crucial point for state space models, and then the defined number of states and density, also called model configuration. They developed and proposed automatic model selection to mitigate this point in condition monitoring and remaining useful lifetime estimation. In this work, a hidden Semi-Markov model for continuous or discrete observations for modelling state duration without limitations by density distributions. The conclusion was that the proposed method require few parameters to be estimated and that it can be used for a variety of applications.

Human and Organisation

The human and organisational aspect due to predictive maintenance and modern condition monitoring technologies are also worth attention in an industrial context. MacKinsey and Company (2015) pointed at Labour as one of 8 value drivers in an Industry 4.0 perspective, with a productivity increase for technical professions of 45-55 % thorough automation of knowledge work. Krason, Maczewska and Polak-Sopinska (2019) points on the need for constant development of maintenance skills and competence as the maintenance strategies and applications develops. Fields as IT, electronics, analysis and problem solvings will be even more dominating in the future. Ciocoiu, Siemieniuch and Hubbard (2017) revealed unclear processes, poor communicationand decision-making responsibility problems in their study of the organisational effects after the introduction of a remote condition monitoring system in a railway organisation. It seemed to be a missing link of information- and decision-making process flow between the between the condition monitoring output, the maintenance planning personnel and the teams that periodized maintenance interventions.

Chapter 3

3 Study Case Overview

For the maintenance optimization analysis, a case study from the Equinor Tjeldbergodden methanol plant was performed. In the study, empirical data from steam traps in the methanol plant was collected. Data from 57 malfunction reports form the basis for further reliability analysis. Most of those failures reported was after annual inspection.

3.1 Equinor Tjeldbergodden Methanol Plant

The methanol plant at Tjeldbergodden produces more than 920 000 tons methanol from natural gas every year. Figure 5-1 illustrates a simplified overview over man input and output in the production process streams.

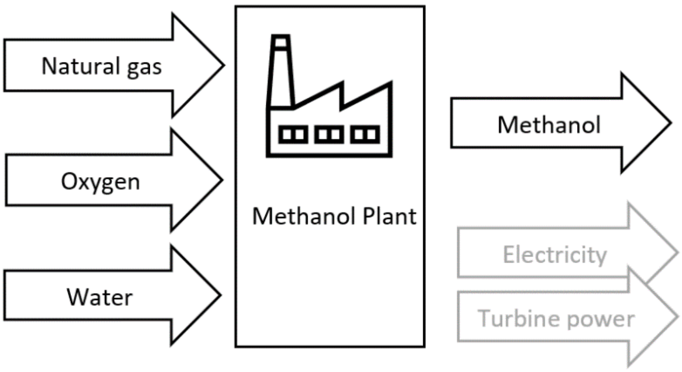


Figure 3-1: Simplified overview of main process input and output streams

The production plant consists of tons of process equipment like compressors, piping, boilers, vessels, pumps, and separators that contain process medium like gas- and liquid hydrocarbons, steam, and water with a wide range of temperature and pressure. Steam and water make up, in addition to and among the hydrocarbon systems, a considerable part of the plant.

3.2 Steam System and Steam Traps

3.2.1 Introduction to Function and Build-up

The main function of steam traps is to discharge steam condensate out from the steam systems to prevent steam pipeline rupture followed by heavy external steam leakage and possible critical consequences like personal injuries and production loss. The steam system of the methanol plant is separated in to three different pressures distributed in 4 steam nets:

-	Low pressure (LP):	5 barg	T ≈ 153 degC	Saturated
-	Medium Pressure (MP):	45 barg	T ≈ 400 degC	Overheated
-	Medium pressure (MP)	35-47 barg	T ≈ 250 degC	Saturated
-	High pressure (HP):	105 barg	T ≈ 515 degC	Overheated

Figure 3-2 and 3-3 illustrate a schematic overview of a typical thermodynamic and balanced pressure steam traps that is represented in the case study.

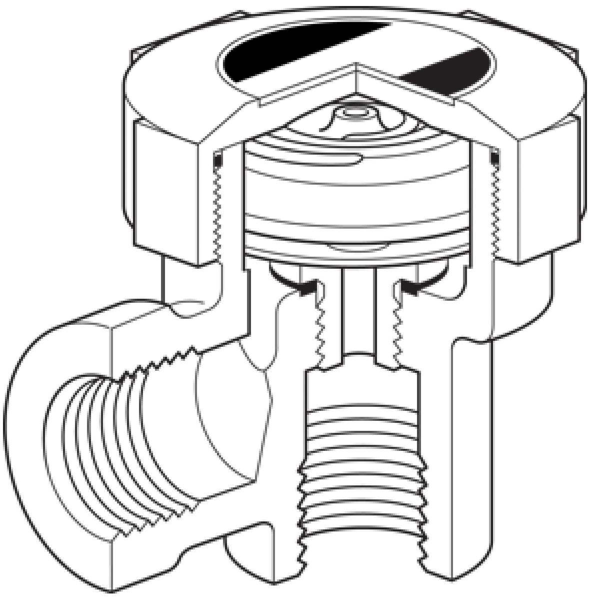


Figure 3-2: Balanced pressure steam trap with replaceable capsule. Figure is collected from https://www.spiraxsarco.com/learn-about-steam/steam-traps-and-steam-trapping/thermostatic-steam-traps

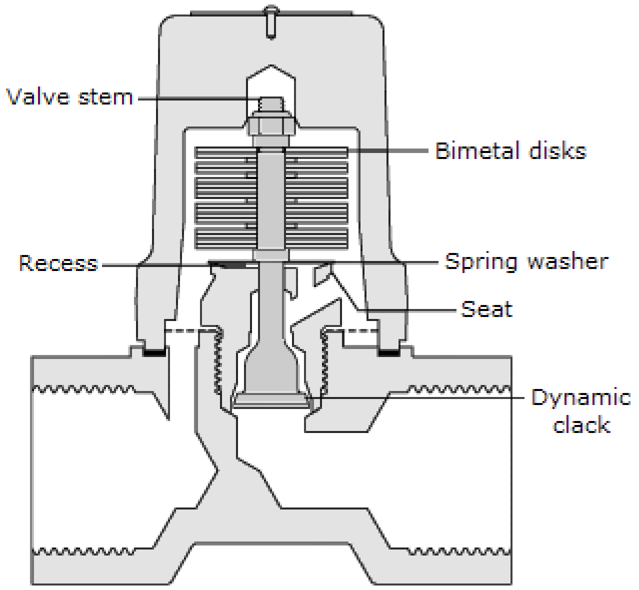


Figure 3-3: Thermodynamic, bimetallic steam trap. Figure is copied from https://www.spiraxsarco.com/learn-about-steam/steam-traps-and-steam-trapping/thermostatic-steam-traps

The discharged condensate is then transported out from the steam system to the condensate system, as illustrated in figure 3-4:

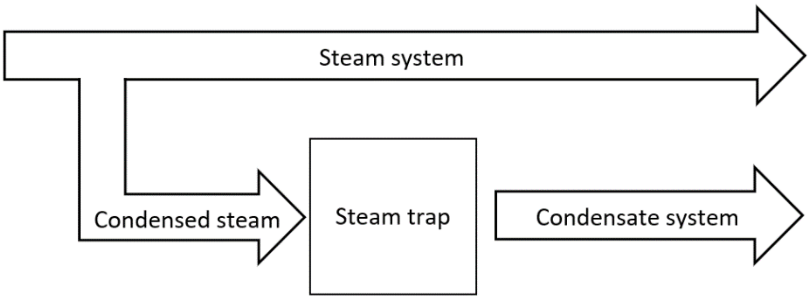


Figure 3-4: Steam trap and steam/condensate system interaction

3.2.2 Steam System

Steam system at the methanol plant has some local functions that are listed below:

- HP steam (from waste heat in production process) to electric power production in turbo generator
- MP steam direct into the chemical reactions of methanol production process

- MP steam to feed water pump turbine
- MP steam to gas turbine
- MP steam to different process heaters
- LP steam to different process heaters and distillation columns
- LP steam to utility stations (steam hoses for warm up, cleaning etc)

There are totally 157 steam traps in the methanol plant (Air Separation Unit included) distributed on the different steam nets:

- LP net: 127
- MP net: 36
- HP net: 14

From the temperature profiles in the first section of this chapter, one can see that the LP steam is saturated, the MP steam is both saturated and overheated and the HP steam is overheated. A saturated steam will do more harm to the surrounding materials than the overheated because of the moisture of a saturated steam.

3.2.3 Failure Modes, Failure Mechanisms and Consequences

The three most common failures are:

- Fail closed/no condensate flow/failure to open on demand: This failure prevents the main function – discharge steam condensate from the steam to prevent steam pipeline rupture followed by serious consequences as listed is introduction to function and build up. Reasons for this failure could be unsuccessful maintenance, that internal components for some reason are “stuck” inside the steam trap or clogged filter
- Failed open/internal leakage: This failure leads to steam loss into the steam condensate system. Immediate, the failure leads to an energy loss and as the failure develops, there will be a risk for external leakage as well as increasing energy loss. Common causes for this failure are aging and degeneration of internal components as a consequence of process load over time. As the internal leakage increase, the steam trap starts to erode inside because of steam flow.
- External leakage: This failure leads to steam and energy loss like the internal leakage. A common cause for this failure is increasing internal leakage and erosion thorough the steam trap outer material (“house”).

In other industrial settings, the consequences of failure could be different from this case, for example affecting product quality.

3.3 Maintenance and Inspection of Steam Traps

3.3.1 Periodic Condition Monitoring

All steam traps are annually inspected by supplier. Inspection method is acoustic emission that gives symptomatic information about the flow thorough the steam traps. The inspection is carried out by a local, manual instrument that in addition to acoustic emission also do temperature measurements.

The supplier market provides wireless sensors for acoustic emission that can be connected via wireless network to a monitoring program for automatic, continuous condition monitoring.

3.3.2 Maintenance of Steam Traps

Maintenance additional to condition monitoring by inspection, is condition based. Depending of the type and failure, whole steam trap or spare parts are replaced.

Maintenance are by experienced maintenance engineers characterized as hand work and a successful maintenance operation requires knowledge and experience in addition to general, industrial, mechanic competence. Unsuccessful maintenance task can result in failure right after maintenance is performed. This is useful information to the inspection matrix.

Most of the LP and LP steam trap can be maintained when the plant is in operation. Maintenance of the HP steam traps normally requires a full production stop, which practically means that they will be available for maintenance second year.

Chapter 4

4 Data Collection and Analysis

4.1 Data Collection

4.1.1 Steam Trap Maintenance Data

Failure history and maintenance data reported in SAP form the basis for input data the steam trap degradation model. Example of SAP malfunction report ("M2 notification") is shown in Appendix A and a work order example are shown in Appendix B. In addition to SAP, inspection reports sent by steam trap inspector and an internal excel spreadsheet overview of the same data were studied. Out of 157 steam traps, 57 failures were registered over a five-year period from 2014 to 2019. Approximately 85 % of the failures were reported from the annual stem trap inspection. The rest 15 % was observed and reported by Equinor operation technicians outside the annual inspection campaign. Of the three common alternative failure modes of steam traps failed open/internal leakage, external leakage and failed closed, only the first two, failed open/internal leakage and external leakage, were considered. The reason for this is that these failures have quite different failure rates and consequences. External leakage is not a frequent observation and based on experience, assumed to be a consequence of internal leakage the majority of the observations. Failure behaviour and consequences are described more detailed in the previous chapter.

The collected data was:

1. Tag number
2. Failure data
    a. Failure date
    b. Failure impact (registered in SAP and described in long text)
    c. Failure mode, internal/external leakage, qualitative or semiquantitative
    d. Type of maintenance activity
3. Maintenance history prior to point 2:
    a. Date for last maintenance activity
    b. Type of maintenance activity

These failure and maintenance data were registered into a spreadsheet. Appendix 3 contains a cut from this spreadsheet. Reported failure states according to maintenance management processes in the company where used. It was however, because of observed inconsistency in the SAP malfunction reports, a need to make a clear definition of the different states. The definitions are listed in table 4-1

Table 4-1 Steam trap state definitions

Steam Trap State Definition	State	Failure impact usually reported as
New	0	Ok[1)]
Used, ok (no inspection findings)	0	ok[1)]
New overhauled	0	ok[1)]
Overhauled	0	ok[1)]
Failed Open Minor	1	Unwell (U)
Failed Open	2	Seriously ill (S)
Failed Open large	2	Seriously ill (S)
External leakage	3	Dead (D)

[1)]*No malfunction reports and failure impact definition of this state, inspection reports ok*

Time between the different states was calculated and from this data, transition rates from time to failure and repair times were calculated and put into the Markov model. This is referred to as data processing in the research approach. Average values for the collected visiting times for the steam traps, grouped into pressure class and type the parenthesis are listed in table 4-2. Number of data points are registered in the parenthesis. Only the group of LP (BP all) traps was further modelled. This group makes up 65 of the 157 steam traps in the plants steam/condensate system. The selection of this group was made based on the fact that this group had the highest number of data points in combination with limited time capacity.

Table 4-2 Collected visiting times before assumptions [months]

Pressure	LP	LP	MP	HP	HP
Type	BP all *(n)*	TD all *(n)*	TD62 *(n)*	TD62 *(n)*	TD120 *(n)*
n	25	4	21	4	1
0	120,5 *(1)*		63,3 *(4)*	44,1 *(1)*	
1					
2					
0-2	41,5 *(20)*	48,5 *(4)*	39,4 *(16)*	48,5 *(4)*	58,8 *(1)*
0-3	82,6 *(4)*		42,9 *(1)*		
1-3					
2–1					
1–2					
1–0	2,0 *(1)*		2,1 *(3)*	18,0 *(1)*	

3–1					
3–0	2,4 *(4)*		6,0 *(1)*		
2–0	3,1 *(20)*	3,4 *(4)*	3,6 *(17)*	7,5 *(4)*	13,0 *(1)*

4.1.2 Cost Data

Cost data is differentiated into the two categories “direct maintenance costs” and “energy loss and downstream costs”, and presented in the following sections.

Direct Maintenance Costs

Direct maintenance costs cover all costs directly related to steam trap inspection, overhauling and replacement. This involves components and man hours. Cost data is found in work orders in SAP, purchasing orders and supplier’s sales offers. Costs are presented in table 4-3 and as the table shows, the costs vary for the different types of steam traps. One man hour is estimated to 850 NOK. Inspection cost per steam trap is calculated as the total annual inspection price divided on the number of steam traps inspected.

Table 4-3 Direct maintenance costs

Pressure / mechanism	Type	Replacement cost (C_REP)		Overhaul cost (C_OH)		Inspection cost (C_INS)
		Material	Man hours	Material	Man hours	
LP		[NOK]	[h]	[NOK]	[h]	[NOK/insp.]
BP	BPC32YCV	4700	20	2000	5	446
BP	BPT30Y	4500	20	2000	5	446
BP	BPC32Y	4500	20	2000	5	446
BP	BPC32CV	4400	20	1500	5	446
TD	TD62	0	0	0	0	446
TD	TD42LA	3300	20	1500	10	446
MP						
TD	TD62M	15000	25	4500	10	446
HP						
TD	TD62M	15000	25	4500	10	446
TD	TD120M	27000	50	5500	10	446

Energy Loss and Downstream Costs

As a consequence of internal leakage from steam to condensate system, less steam goes to production of electric power on the plant. And as a consequence of this energy loss, more electricity needs to be imported to cover the plants power consumption. Energy loss costs is calculated on the basis of steam loss converted to electric power production decrease, based on the machinery’s energy efficiency in 2019, for a normally optimized production case and with an assumed power import cost of 0,45 NOK/kWh.

Downstream costs also correlate to time in each state (failure mode) due to increasing erosion of downstream piping as steam trap internal leakage continues in time. Downstream costs cover extra inspection needs and repairment of eroded condensate piping downstream.

Energy loss and downstream costs per month is shown in table 4-4

Table 4-4 Costs due to energy loss and downstream damage

Pressure / mechanism	Type	Energy loss (C_ENL)		Downstream inspection and damage (C_DS)
		[kg/h]	[NOK/month]1)	[NOK/month]
LP				
BP	BPC32YCV	4,01	158	5000
BP	BPT30Y	4,12	162	5000
BP	BPC32Y	4,12	162	5000
BP	BPC32CV	4,58	180	5000
TD	TD62		-	5000
TD	TD42LA	1,60	63	5000
MP				
TD	TD62M	14,08	555	25000
HP				
TD	TD62M	34,5	1358	25000
TD	TD120M	121,81	4802	25000

1) *Energy loss is collected from the inspection reports and conservatively calculated with 40% flow thorough steam trap. This is not measured. Further assumptions regarding energy loss costs will be presented in the following section.*

4.2 Analysis and Assumptions for Data Collection

4.2.1 Failure Rates

Failure transition rates for each steam trap was calculated as: 1/equipment state sojourn time

and maintenance rates was calculated as: 1/(passive + active repair time).

The prolonged (passive) repair time is caused by the repair decision process that sets a required end for the failure to be fixed. A common approach to the required end decision process in the company is to postpone the repair as long as possible to avoid maintenance earlier than needed and to achieve enough time for planning phase.

Table 4-2: Collected visiting times before assumptions indicates that for most of the failures, a step from state 0=”Healthy” to state 2=”Seriously Ill” was observed thorough yearly inspection.

One reason for the many jumps from state 0 direct to state 2, is the absence of quantity of leakage rate in the inspection reports. “Failed open” was differentiated in to minor and major leakage only in the 2018 and 2019 inspections. Inspection reports before 2018 does not differentiate the leakage rate. Table 4-5 summarizes distribution between reported minor and major leakages in 2018 and 2019.

Table 4-5 Failure distribution LP (BP) traps.

Distribution data basis:			
	Failed open minor (unwell, 1)	Failed open large (S. ill, 2)	External leakage (Dead, 3)
2019	2	10	
2018	1	13	
Average	0,115	0,885	

Quality assurance of data was a time-consuming work. Failure alerting measurable indicator from inspection reports only comes up with a semi quantitative measure and failures are reported in SAP as states “unwell”, “seriously ill” or “dead”. The failure impacts reported was utilized as condition states in the Markov model, but had to be compared with failure descriptions and inspection reports, to mitigate the risk for inconsistency in failure reports. The data collection indicated that data post 2013 was the most reliable data and steam trap maintenance history and data pre 2010 is incomplete.

As a basis for the model, it is assumed that all failures go through all states in order. This assumption fits good with the equipment nature and degradation behaviour and contributes to a good Markov degradation model.

Data was further processed to “force” all failure development into all states. Assumptions was made on basis in a combination of interpretation of collected data and years of steam leakage experience. For the group of LP (BP all types) steam traps, the following assumptions was made:

- All the registered steam trap state 2-failures had visited state 1 before state 2
- All the registered steam trap state 3-failures had visited state 2 before state 3
- All the registered steam trap state 2-failures will develop to state 3 with a fixed development time if not maintained
- 11,5 % of reported failures from 2018 and 2019 was state 2. This part is used a basis for sojourn time for state 1 and led to the assumption that 11,5% of the time registered from state 0 to 2, was spent in state 1. In practise, this mean relatively rapid failure development from potential, observable failure to further failure development and therefore, most major leakages is observed at annual inspection.

All frequencies are [month^{-1}]

4.2.2 Costs

Energy loss is collected from the inspection reports and conservatively calculated based on the assumption of 40% flow thorough steam trap. This is not measured. Steam leakage rate due to erosion will develop over time. Therefore, the energy loss costs for LP (BP all) traps where further assumed to be as presented in table 4-6 Energy loss costs for LP (BP all).

Table 4-6 Energy loss costs for LP (BP all)

State	Monthly cost [NOK/month]
1 – Unwell	100
2 – Seriously Ill	200
3 - Dead	500

Chapter 5

5 Maintenance Modelling

In this section, the approach to the model will be presented, followed by the model itself.

5.1 Modelling approach

5.1.1 Feasible Maintenance Activities

By using the example RCM decision logic in figure 2,1, possible maintenance activities can be found. The following bullet points demonstrate use of the RCM decision logic:

- Is the function hidden? *No*
- NO → Does a failure alerting measurable indicator exist? *Yes, ultrasonic and temperature*
- YES → Is continuous monitoring feasible? *Yes, but not with existing equipment*
- Alternative pathways:
    - YES → <u>RCM decision logic suggests “Continuous on-condition task”</u>
    - NO → Increasing rate of “potential” failures? *Unknown*
        - Alternative pathways:
        - NO → <u>RCM decision logic suggests “Scheduled on-condition task”</u>
        - YES → <u>RCM decision logic suggests “Scheduled on-condition task and scheduled on-condition task”</u>

The RCM decision logic suggests tree alternative maintenance activities. Continuous on-condition task involves a continuous condition monitoring system. For the steam trap case, there are such online systems available commercially provided by wireless sensors and network but requires investment and implement of WSN (wireless sensor network) since WSN is not established at the methanol plant for now. Whether this is an interesting business case for or not, will depend on several factors like:

- For continuous condition monitoring system and activity:
    - Investment cost
    - Total cost optimized (cost optimization for continuous condition monitoring case)
    - Additional, positive effects of WSN implementation
- For scheduled task

- Total cost of optimized alternative maintenance task (scheduled task)

These factors will be discussed more in detail later.

5.1.2 Degradation modelling

As a basis for degradation development modelling, an already established Markov model application in Microsoft excel was adapted to the case and further developed. Degradation was modelled only for failure mode “failed open/internal leakage”

The Markov state model is based on the following Markov transition diagram shown in figure 5-1,

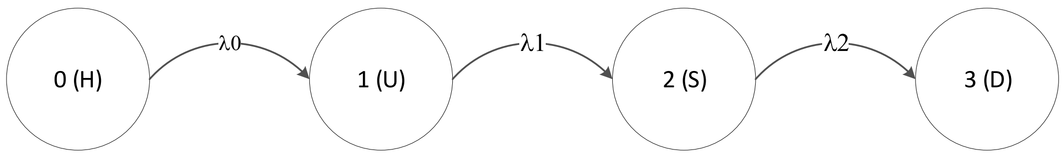


Figure 5-1: Markov transition diagram for Markov degradation model for steam traps

where the transition states represent the states that is reported in the Equinor computerixed maintenance management system SAP:

- 0 = H = Healthy; condition is good or as new, no failure reported)
- 1 = U = Unwell; defined in ISO 14224 as incipient (non-critical). For the steam trap case, this represent a minor leakage thorough the steam trap.
- 2 = Seriously ill, defined in ISO 14224 as degraded (non-critical). For the steam trap case, this represent a major leakage thorough the steam trap.
- 3 = Dead = not able to function as required or equipment is in a such state that requires the equipment to be shut down from for example safety or hazard reducing reasons. Defined in ISO 14224 as critical. For the steam trap case, this state represents an external leakage. Failure to open as required or fail closed is another failure typical for the steam trap case that belongs into this category. That failure is not considered for the steam trap case in this study.

The model also included repair rates, as shown in Chapter 6.

5.1.3 Model Selection Rationale

A Markov model for degradation modelling is a flexible model that can be used for modelling degradation, graded into a appropriate number of states. The model intends to provide, with its inspection matrix, simulation of different optimization strategies strategy, which can make the model feasible for maintenance optimization decision support. Failure and maintenance data for the chosen case, categorized into unwell, seriously ill and dead, can fit to the model demands for Markov a degradation model where condition should be graded into a specified number of states and also the times between the different states are available for data collection to a certain degree. There are however rules or guidelines for deciding an appropriate number of states, it is therefore not given that the chosen number of states on basis of the information available is the optimal number for a good model configuration. It is also positive for the chosen case that the Markov model supports the use of censured lifetimes as the failures observed seldom crossed the replacement limit. Markov modelling includes matrix calculations by a matrix program like Matlab or a VBA coded Microsoft excel application. For the modelling itself, this might not be a drawback, but it might set some target group limitations. The model configuration requires some assumptions, which can affect the results negative.

5.2 Presentation of the Markov Model

5.2.1 The Markov Diagram

The Markov diagram for Markov model is shown in figure 5-2.The model was developed fit to the available data as described in the previous sections. This model only allows transitions from the one to the next state at time. For repair rates, the probability of unsuccessful inspection and overhauling are integrated to the model thorough the inspection matrix, shown in the diagram below as the virtual states with the q's. The q's can also represent the probability for a "no maintenance"-decision e.g. run to failure. That is not considered in this model, but an optimisation case with no maintenance in state 1(U) was simulated. A basis for the model is that for steam traps that is at state 2 (S), it is assumed that a successful overhauling always is sufficient to get as good as new. Steam traps at state 3 (D) need replacement. This assumption fits good with steam trap types that comes with replaceable parts and new provided by a steam trap replacement kit.

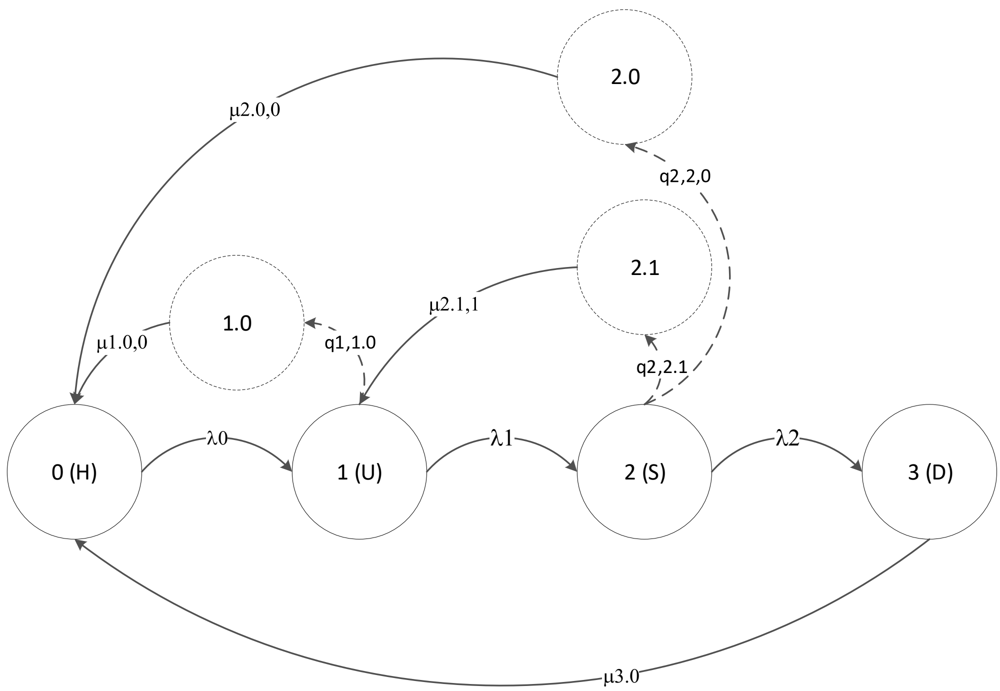


Figure 5-2: Markov model with repair rates

5.2.2 Degradation Curve

Data collection and assumptions led to the degradation curve for LP (BP all) traps as shown in figure 5-3.

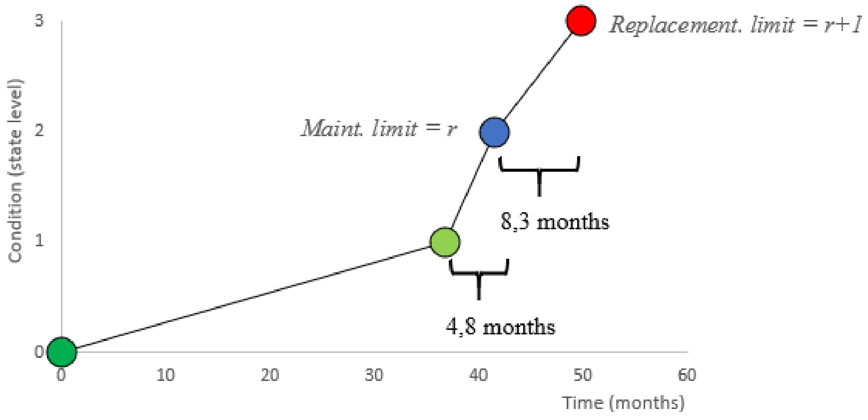


Figure 5-3: Degradation curve LP (BP all)

5.2.3 Transition Matrix

For the base case that intends to describe todays situation, the following transition matrix was made on basis of data collection and further assumptions.

Table 5-1: Transition matrix for LP (BP all) steam trap case

	To →	0	1	2	3	1.0	2.0	3.0
From	0		λ0					
↓	1			λ1				
	2				λ2			
	3	μ3_0						
	1.0	μ_0		λ1	λ2			
	2.0	μ2_0			λ2			
	2.1		μ2					

With lambdas and mus listed in table 5-2.

Table 5-2: Transition rates for LP (BP all) steam trap case

Parameter	Value
λ0	0,0272
λ1	0,2089
λ2	0,1205
µ0	0,0833
µ2_0	0,3226
µ3_0	0,4167

5.2.4 Inspection Matrix

Table 5-3 show the inspection matrix

Table 5-3 Inspection matrix

	To →	0	1	2	3	1.0	2.0	3.0
From	0	1						
↓	1		q1.0,1 + q1.1			1-(q1.0,1 + q1.1)		
	2			q2.2,2			1-(q2.2,2+q2.2,1)	q2.2,1
	3				1			
	1.0					1		
	2.0						1	
	2.1							1

And table 5-4 Inspection probabilities presents descriptions of matrix input

Table 5-4 Inspection probabilities

Parameter	Description
q1.0,1	Still at state 1 due to unsuccessful overhauling
q1.1	Still at state 1 due to unsuccessful inspection
q2.2,2	Still at state 2 due to unsuccessful inspection
q2.2,1	Go to state 1 due to unsuccessful overhauling

5.3 Optimization Cases for Decision Support

Seven cases were defined for simulation of alternative maintenance strategies, in addition to base case that models todays situation. The cases are listed in below.

Case L0 – Base Case

Parameter values as listed above. This case was developed to estimate todays costs to establish a baseline for optimization

Case L1 – Optimize Base Case Tau (τ)

This case simulates the effect of varying tau to find an inspection interval optimum of the base case maintenance strategy.

Case L2 - Check Effect of Lower μ at τ = 1-18

The intention of this case is to check the effect of decreased passive repair time.

Case L3 - Check Effect of Varying "Unsuccessful Overhauling" at τ = 5 and 12

This case can indicate two things, 1) the effect of using expert maintenance personnel compared to more available, not so expert personnel and 2) effect of wrong assumptions regarding this probability, more precise it will function as a sensitivity analysis to the assumption.

Case L4 - Simulate Online Condition Monitoring

A successful simulation of this case can indicate a break-even cost for an investment in condition monitoring system. This is not a complete condition monitoring profitability calculation, investments, operation and maintenance of such a system is not considered. For this case, $\tau = 1$, $\mu 0$ is optimized and $\mu 2.0$ and $\mu 3.0$ = base case repair rates. Probability of unsuccessful inspection is decreased and probability of unsuccessful overhauling unchanged for base case. Inspection cost is set to 0 NOK.

Case L5 - Check the Effect of Varying Probability for "Unsuccessful Inspection"

Like case L3, this case might indicate 1) the effect of not using expert personnel for inspections, but also 2) as a sensitivity analysis for the assumption regarding the probability of unsuccessful inspection.

Case L6a – Optimize $\mu 0$

The intention of this case is to check the effect of varying passive repair time for steam traps that has an early failure indication at state 1 unwell.

Case L6b – No Maintenance at State 1

The intention of this case is to check the effect of rejecting maintenance for steam traps in state 1 unwell.

5.4 Cost Optimization

The other costs used in the cost optimization are those listed in table 5-5 below:

Table 5-5 Costs for cost optimization

Cost parameter	Cost ([NOK]
C_I	446
C_{CMREP}	9 250
C_{CMOH}	38 000
C_{ENL}	Acc. to table 4-6
C_{DS} *[NOK/month]* - for time in state 3	5000

Abbreviations:

- P Pressure
- BP Balanced pressure
- C_I Inspection cost
- C_{CMREP} Corrective maintenance replacement cost
- C_{CMOH} Corrective maintenance overhauling cost
- C_{ENL} Cost energy loss per moth
- C_{DS} Cost material damage down stream

Chapter 6

6 Results and Result Analysis

6.1 Case Results

Case L0 – Base Case and Case L1 – Optimize Base Case Tau (τ)

Table 6-1 and figure 6-1 presents C(τ) for base case and for varying inspection intervals τ. Base case shows that one LP (BP all) steam trap costs 8542 NOK yearly. Result of cost optimization of τ indicates that 5 months would be an optimum inspection interval.

Table 6-1 Case L1 results

τ	2	3	4	5	6	8	10	12[2)]	14	16	18	24
C(τ)[1)]	8607	8063	7923	7914	7976	8163	8355	8542	8714	8865	8986	9298

[1)] *Yearly cost of one LP (BP all) steam trap*
[2)] *Todays inspection interval, case 0 base case*

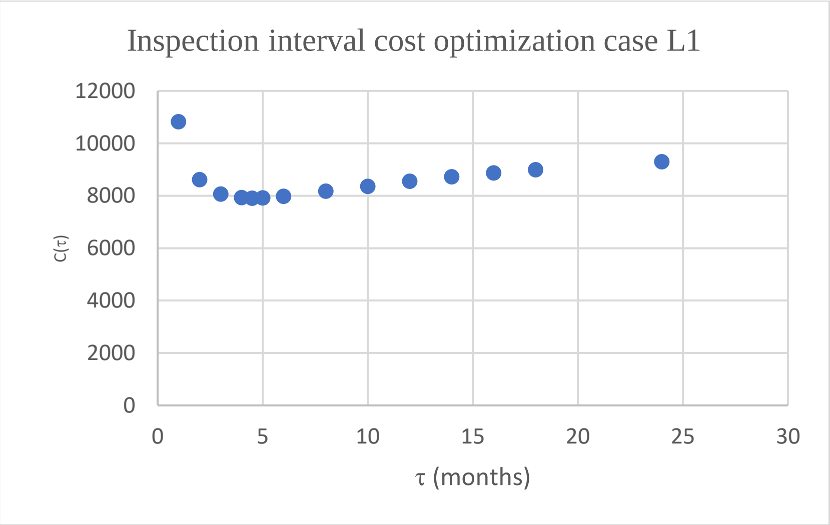


Figure 6-1: Cost optimization case L1

From the state model it is possible to see the probabilities for being in each of the defines states. Snips from the Markov Model on Microsoft excel are shown in the figure 6-2, 6-3 and 6-4. The first figure shows the average probabilities together with transition matrix (A) and the two following figure show the model configuration and the inspection matrix (M).

Costs (month-1)			A-Matrix==>		To -->				
Downstream	Steam trap maintenance	Energy loss	P_i			0	1	2	3
			0,773341358	From	0		0,0272		
		7,1	0,071234412	↓	1			0,2089	
		16,6	0,082812443		2				0,1205
54,1	474,2	15,0	0,029946184		3	0,4167			
	17,0	2,2	0,022081656		1_0	0,083333		0,2089	
	80,9	3,9	0,019735295		2_0	0,3226			0,1205
	3,5	0,2	0,001160875		2_1		0,3226		0,1205
Inspection cost	37,2								
		∑	1,000312224						
SUM Costs (month-1	711,9	Ved tau =	12			8542,807			

Figure 6-2 L0 base case transition matrix and cost calculations

Parameters	Value	Comment
nDim	7	Dim. of problem
initState	1	Row number of initial state
nPeriods	150	
tau	12	
lambda_0	0,0272	Failure rate
lambda_1	0,2089	
lambda_2	0,1205	
mu_0	0,0833	Repair rate
mu2_0	0,3226	
mu3_0	0,4167	Integrate
q2.2,1	0,05	Mislykket OH
q2.2,2	0,10	Mislykket inspeksjon
q1.1,0		
q1.0,1	0,05	Stående på U grunnet mislykket OH
q1.1	0,10	Stående på 1 grunnet misl. Ins

Figure 6-4: L0 base case model configuration

	To -->						
	0	1	2	3	1_0	2_0	2_1
From ↓ 0	1						
1		0,15			0,85		
2			0,1			0,85	0,05
3				1			
1_0					1		
2_0						1	
2_1							1

Figure 6-3: L0 base case inspection matrix

Markov modelling results show that maintenance costs make up considerably much more than costs due to energy loss. Average probabilities are not further reported in this result chapter because costs were the main objective for the optimization problem.

Case L2 - Check Effect of Lower μ at τ = 1-18

Results for case L2 are shown graphical in figure 6-5 Cost optimization case L2 – Check effect of lower μ. Simulation results from case L2 indicate that all μ=1 gives the best C(τ) and that optimal τ is practically the same compared to base case. All μ = 1 show a cost yearly reduction of 1823 NOK per LP (BP all) steam trap, which makes up a relative reduction of 21%.

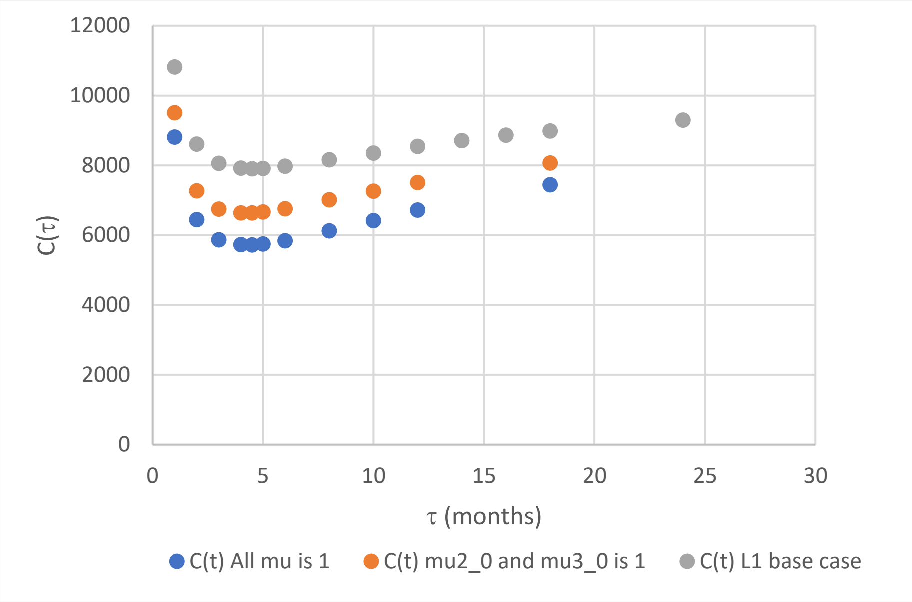


Figure 6-5 Cost optimization case L2 – Check effect of lower μ

Case L3 - Check Effect of Varying Unsuccessful Overhauling at τ = 5 and 12

Case was only calculated for τ=12. Calculations showed following impact (presented in table 6-2):

Table 6-2 Effect of varying overhauling result

$P_{Unsuccessful\ overhauling}$	0,01	0,05	0,10	0,15
C(12), yearly per trap [NOK]	7803	7914 1)	8060	8215
Cost impact [NOK]	-103	0	121	268
Relative impact [%]	1,2	0	1,4	3,1

1) *Base case*

Case L4 - Simulate Online Condition Monitoring

With the L4 case input parameters as described in section 5.3, result of online condition monitoring cost modelling at τ=1 (month) showed a yearly cost of 2061 NOK /year for one steam trap. This cost saving makes up 3614 NOK which 46% compared with todays modelled situation (base case).

Case L5 - Check the Effect of Varying Probability for Unsuccessful Inspection

Case was only calculated for τ=12. Calculations showed following impact (presented in table 6-3).

Table 6-3 Effect of varying inspection quality

$P_{Unsuccessful\ inspection}$	0,02	0,1	0,15
$C_{(12)}$, yearly per trap [NOK]	7746	7914 (base case)	8027
Cost impact [NOK]	-183	0	117
Relative impact [%]	-1,4	0	2,1

Case L6a – Optimize μ0

Table 6-4 shows the effect of varying μ0. Results is yearly costs per LP (BP all) steam trap in NOK.

Table 6-4 Cost optimization of C(τ) with different μ0.

μ0 [month-1]	τ =1	τ =5	τ =8	τ =12
0,33	9968	7342	7540	8031
0,50	9714	6959	7350	7875
0,08	10822	7914	8162	8542
0,06	11003	8071	8294	8650

The cost optimization showed that μ0 =0,5 at τ=5 gives the lowest maintenance cost. This corresponds to a required end of 6 month for maintenance from state 1. This cost result makes up a 12% cost reduction compared to base case with μ0 =1 and τ=12. For τ=12 in case L6a, the cost reduction is negligible.

Case L6b – No Maintenance at State 1

No maintenance at state one gave 4,7% cost increase for τ=12, higher average probabilities for state 2 and 3 and therefore higher maintenance costs.

6.2 Result Analysis

The Markov model showed ability to model alternative maintenance strategies as in addition to inspection interval, enabled by the many input parameters the model requires. A short analysis of the different case results is carried out in the following sections.

6.2.1 Cost Optimization of Inspection Interval

The results indicate that for the group of steam traps that were modelled, all types of balanced pressure traps for the low-pressure steam net, a lower inspection interval can be beneficial. From the maintenance model, five months seems to be an optimal interval. Steam trap inspections are carried out by external supplier and will therefore have minimal impact on the organisation.

6.2.2 Sensitivities and Alternative Maintenance Strategies

The results show low impact of varying the input probabilities for unsuccessful inspection and unsuccessful overhauling. Relative impact for both cases was in order of -1,4 – 3,1 % compared to base case. This indicates that the Markov model could be less sensitive to wrong assumptions and input data regarding these probabilities. Neither will the strategy according to these results be very sensitive to varying inspection and maintenance quality, which supports a flexibility regarding inspection- and maintenance performers. This is useful information for example for a consideration about whether the inspections and maintenance should be carried out by in house or external personnel.

6.2.3 Cost Optimization of Repair Rates

The cases with varying repair rates can contribute to assess the required end for maintenance task after observed failure. Simulation results from case L2 indicate that all μ=1 month^{-1} gives the best $C(\tau)$. This is higher repair rates than for base case. Increased repair rate might however influence other, alternative aspects, like spare part needs and capacity to perform other, more profitable maintenance tasks. These aspects must be considered but are not included in the Markov model.

6.2.4 Online Condition Monitoring Simulation

Online condition monitoring case resulted in 46% cost decrease, compared to base case. Somehow lower compared to maintenance optimization of today’s strategy. But the cost optimization does not include purchase, implementation, operation and maintenance of online condition monitoring system.

Chapter 7

7 Conclusion

7.1 Summary and Discussions

The Markov model showed ability to model alternative maintenance strategies in addition to inspection interval, enabled by the many input parameters the model requires, and especially the inspection matrix. The results indicated potential for optimization of maintenance performance and strategy for the chosen case. Costs were mainly related to maintenance and less to energy loss. The online condition monitoring system case had the highest savings, but not all cost related to the online monitoring system was included. Therefore, this strategy should be considered up against other aspects like the company's maintenance strategy in general. Locally stocked spare parts at stock could also be considered.

Data collection was time consuming. The quality of reported data was varying. Despite that SAP requires lot of data input, the data collection work showed that there is a potential for improvement in reporting if data shall be used for large volume data collection for analytical purposes. Consistently use of the "activities" tab in the SAP M2 notification module would have simplified data collection for maintenance analysis purposes. Work order operations are not very suitable for this work.

Several assumptions were made to create a good degradation model. So, when the modelling was complete, it would have been beneficial to validate the data thorough sensitivity analysis, experts and/or additional inspections. These inspections can be performed manual or automatic, online or offline. Some sensitivity analysis was carried out. Another, specific action to improve data quality and increase data volume for a better understanding of the degradation model, is to perform an inspection just before maintenance. Such actions could have improved the modelling. The Markov model itself could have been compared to other, recognised degradation model for validation.

Maintenance optimization for the study case might not result in really high total cost savings and for a optimization- and improvement study like this, there would have been beneficial to prioritize more expensive cases. The amount of data available however, made this case suitable for the study. There should also be noted that the optimization model is based equipment with replaceable parts. Not all steam trap models are delivered with replaceable parts.

For a more predictive and accurate model, various parameters like operational load should have been included in the modelling. This might involve using another model than Markov.

The data collected only included 25 failures for the group of LP-BP traps that consist of totally 65 steam traps. The reason for this was that the data collection approach involved study of failures over the last five years. For the most it was one failure per trap. It is therefore challenging to conclude that the degradation model is representative for the whole group of those steam trap (LP BP all), or only a part of the group.

7.2 Discussion of Objective Attainment

Aspects of maintenance optimization related to a chosen case were demonstrated and the results indicated that the model can be feasible as a decision support tool regarding maintenance optimization. A suitable study case was identified under the premises described in section 1.5 Limitations. The study case does not provide the highest maintenance cost for the company and could therefore seem somehow irrelevant, the data material basis was suitable for the degradation and optimization modelling. A high effort was made in data collection of failure- and maintenance data. An already established Markov Model were further developed by supervisor from NTNU and utilized and to fit the study case. Cost data were collected and cost functions were prepared.

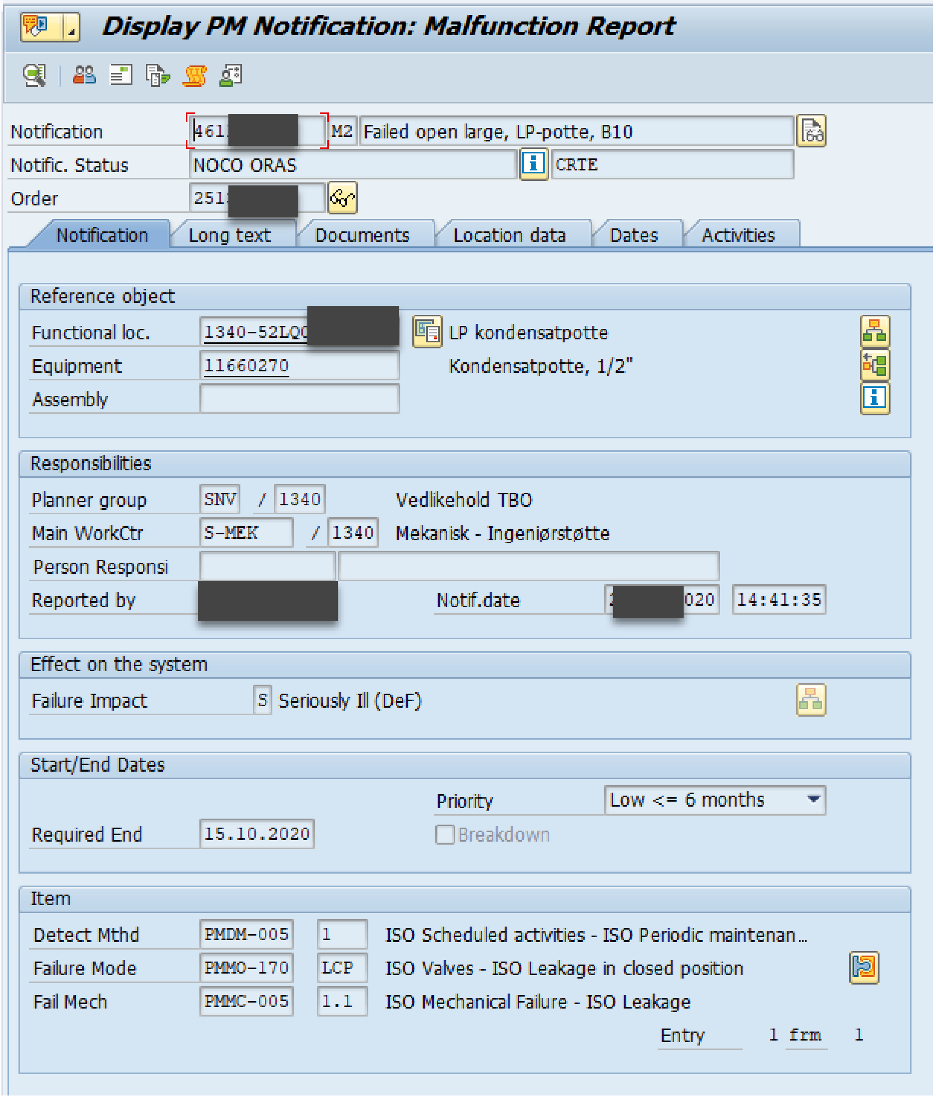
Most of the literature search was carried out in a systematic way in an early phase of the study, before study case and degradation model were concluded. Aspects such as PdM implementation, human and organisational factor and maintenance optimization and Markov Modelling in general were reviewed. Therefore, the literature review focuses more on general aspects related to PdM instead of a deeper understanding of Markov modelling and steam trap behaviour / degradation models. Unfortunately, time capacity did not allow much additional literature review in the late phases of the study. Further literature review to obtain a deeper understanding in Markov modelling and steam trap behaviour should have been carried out for a more successful attainment of the literature review objective.

7.3 Recommendations for Further Work

Further validation of the degradation modelling is recommended. Methods for validation can be additional inspections in order to collect more degradation data for the model, or expert opinions.

The case study only considered one group of 65 of the 157 steam traps at the plant. There are data collected also for the rest of the steam traps and it would have been natural to perform similar modelling for those as well, either before or after modelling validation.

Appendix A SAP Malfunction Report (M2 Notification)



Display PM Notification: Malfunction Report

Notification 461[redacted] M2 Failed open large, LP-potte, B10
Notific. Status NOCO ORAS CRTE
Order 251[redacted]

Notification | Long text | Documents | Location data | Dates | Activities

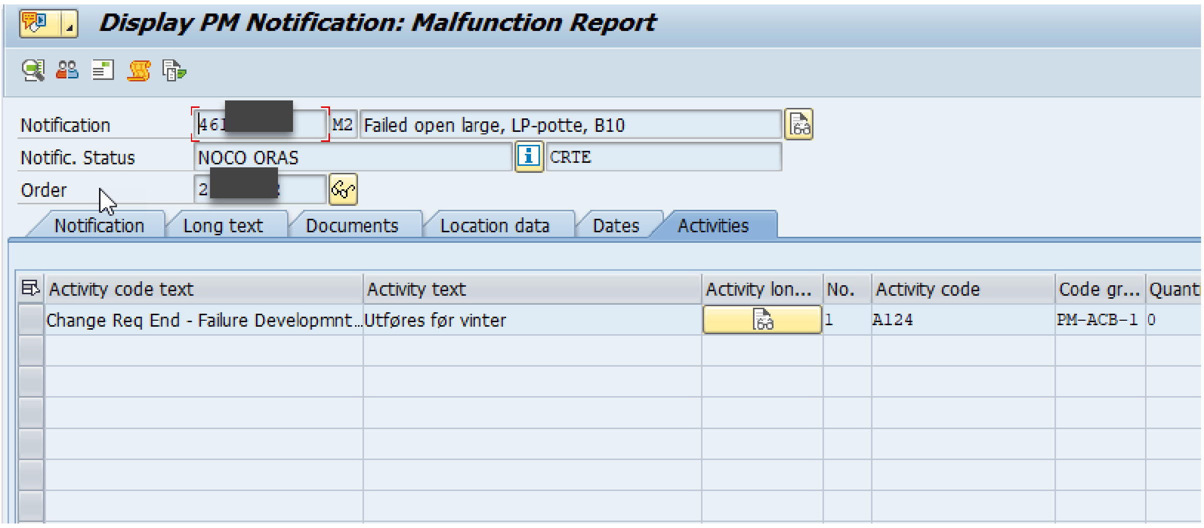
Reference object
Functional loc. 1340-52LQ[redacted] LP kondensatpotte
Equipment 11660270 Kondensatpotte, 1/2"
Assembly

Responsibilities
Planner group SNV / 1340 Vedlikehold TBO
Main WorkCtr S-MEK / 1340 Mekanisk - Ingeniørstøtte
Person Responsi
Reported by [redacted] Notif.date [redacted]020 14:41:35

Effect on the system
Failure Impact S Seriously Ill (DeF)

Start/End Dates
Priority Low <= 6 months
Required End 15.10.2020 Breakdown

Item
Detect Mthd PMDM-005 1 ISO Scheduled activities - ISO Periodic maintenan...
Failure Mode PMMO-170 LCP ISO Valves - ISO Leakage in closed position
Fail Mech PMMC-005 1.1 ISO Mechanical Failure - ISO Leakage
Entry 1 frm 1



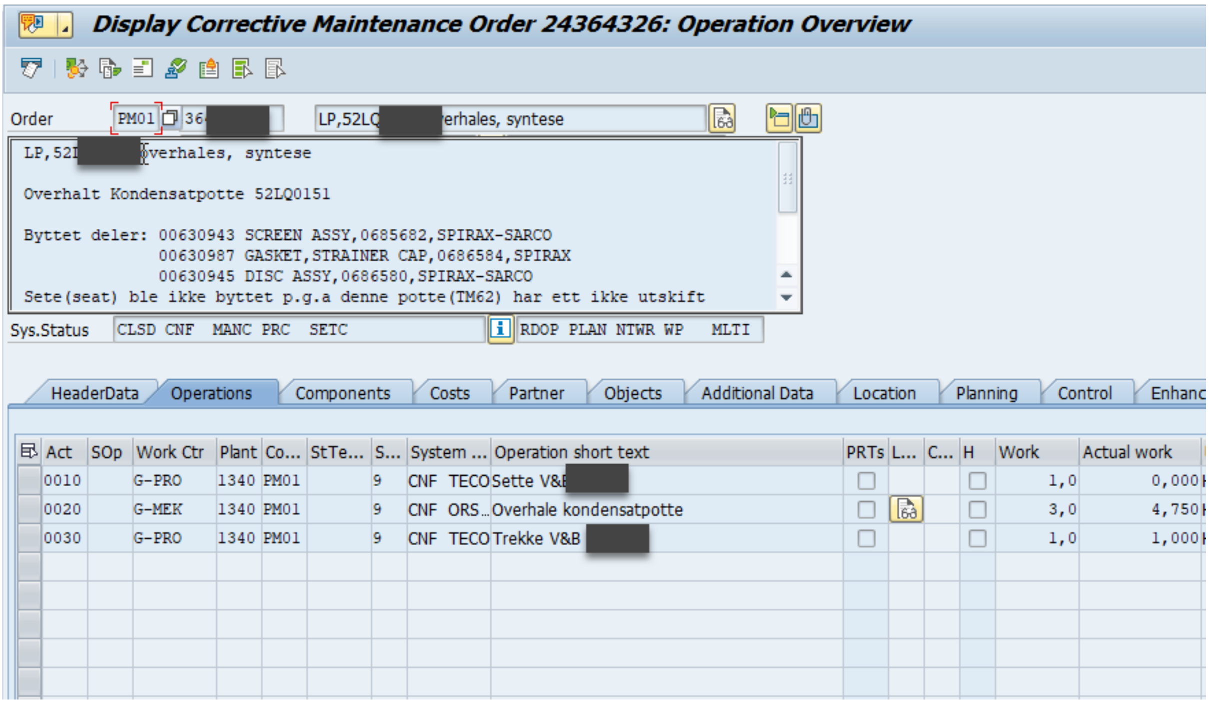
Display PM Notification: Malfunction Report

Notification 461[redacted] M2 Failed open large, LP-potte, B10
Notific. Status NOCO ORAS CRTE
Order 2[redacted]

Notification | Long text | Documents | Location data | Dates | Activities

Activity code text	Activity text	Activity lon...	No.	Activity code	Code gr...	Quant
Change Req End - Failure Developmnt...	Utføres før vinter		1	A124	PM-ACB-1	0

Appendix B SAP Work Order



Appendix C Data Collection of Failures and Repairs

Location	Functional Loc.	Description		TYPE	Innmontert 1	Overhalt 1	Feilmode 1	Rapportert 1	Innmontert 2	Overhalt 2	Feilmode 2	Rapportert 2	Datedif
B20	1340-52LQ0695	LP kondensatpotte	[redacted]	BPC32Y	Ukjent		FO	16.01.2015	28.04.2015				
~~B20~~	~~1340-52LQ0653~~	~~LP kondensatpotte~~		~~BPC32Y~~	~~Ukjent~~		~~FO~~	~~15.01.2017~~					
D20	1340-52LQ0931	LP kondensatpotte	[redacted]	FT14-4.5	Ukjent		FO	15.01.2017	25.04.2017				
D30	1340-52LQ0950	LP kondensatpotte		BPT30Y	Ukjent		FO	15.01.2017		19.04.2017			
B10	1340-52LQ0717	MP kondensatpotte	[redacted]	TD62	07.03.2011		FOL	31.01.18	04.07.2018				
D20	1340-52LQ0915	LP kondensatpotte	[redacted]	BPT30Y	01.09.2009		FOL	31.01.18	27.08.2018				
B20	1340-52LQ0732	MP kondensatpotte		TD62	25.09.14		FOL	10.05.19		20.09.19			
B10	1340-52LQ0064	MP kondensatpotte		TD62	01.09.14		FOS	31.01.18		16.07.18			
B10	1340-52LQ0680	HP kondensatpotte	[redacted]	TD120	12.06.14		FOL	10.05.19	05.06.20				
C00	1340-52LQ0026	LP kondensatpotte		TD42LA	18.04.14		FC	05.01.16		09.02.16	FC	31.01.18	
B20	1340-52LQ0365	MP kondensatpotte		TD62	03.12.2013		FO	16.01.2015		30.03.2015			
C00	1340-52LQ0547	MP kondensatpotte	[redacted]	TD62	06.11.13		FO	16.01.15	29.05.2015		RC	19.07.2017	
A00	1340-52LQ0543	LP kondensatpotte	[redacted]	BPT30Y	12.09.2013		FO	15.01.2017	06.06.2017				
B30	1340-52LQ0906	HP kondensatpotte		TD62	18.06.13		FO	15.01.17			FOL	31.01.18	
B10	1340-52LQ0727	HP kondensatpotte	[redacted]	TD62	11.06.2013		FO	05.01.2016	21.07.2016				
B30	1340-52LQ0907	HP kondensatpotte	[redacted]	TD62	01.06.2013		RC	15.01.2017	18.06.2018				
~~D20~~	~~1340-52LQ0191~~	~~LP kondensatpotte~~	[redacted]	~~BPC32YCV~~	~~09.11.12~~		~~FC~~	~~10.05.19~~		~~24.09.19~~			
B20	1340-52LQ0731	MP kondensatpotte		TD62	28.09.2012		FO	05.01.2016		27.02.2016			
D20	1340-52LQ0664	LP kondensatpotte		BPC32YCV	30.08.12		FO	04.02.13		06.11.13	FO	15.01.17	
~~B20~~	~~1340-52LQ0218~~	~~LP kondensatpotte~~	[redacted]	~~BPC32Y~~	~~28.08.2012~~		~~FO~~	~~15.01.17~~		~~18.04.2017~~			
~~B20~~	~~1340-52LQ0530~~	~~LP kondensatpotte~~	[redacted]	~~BPT30Y~~	~~23.08.2012~~		~~FC~~	~~16.01.15~~		~~03.04.2015~~	~~FC~~	~~05.01.2016~~	
C00	1340-52LQ0346	LP kondensatpotte		BPC32YCV	23.08.12		FO	15.01.17		10.03.17	FOL	31.01.18	
B30	1340-52LQ0947	LP kondensatpotte		BPT30Y	23.08.2012		FO	15.01.2017		08.03.2017			
C00	1340-52LQ0029	LP kondensatpotte		BPC32YCV	01.08.2012		FO	16.01.2015		16.03.2015			
B20	1340-52LQ0515	MP kondensatpotte		TD62	14.12.11		RC	03.07.15		09.07.15	FOL	31.01.18	
A00	1340-52LQ0187	LP kondensatpotte		BPC32Y	21.10.2011		FC	15.01.2017		19.04.2017			
A00	1340-52LQ0660	LP kondensatpotte	[redacted]	BPC32Y	29.06.11		EL	08.07.18	07.09.18				
E00	1340-52LQ4001	LP kondensatpotte		BPC32Y	30.05.11	02.04.14_16.03.15 (FOx2)	FO	18.01.16	09.03.16		FO	31.01.18	
D20	1340-52LQ0668	LP kondensatpotte		BPC32CV	13.05.11		FOL	10.05.19		01.10.19			
B20	1340-52LQ0137	LP kondensatpotte		BPC32YCV	03.03.2011		FO	15.01.2017		20.03.2017			

	Location	Functional Loc.	Datedif	Innmontert 3	Overhalt 3	Feilmode 3	Rapportert 3	Overhalt 4	Innmontert 3	Mekanisme	Catalog profile	Main Functic
2	B20	1340-52LQ0695								Balanced pressure	PM-170	1340-5210
3	~~B20~~	~~1340-52LQ0653~~								~~Balanced pressure~~	~~PM-170~~	~~1340-5210~~
4	D20	1340-52LQ0931								Flottør	PM-170	1340-6402
5	D30	1340-52LQ0950								Balanced pressure	PM-170	1340-5210
6	B10	1340-52LQ0717								Termodynamisk	PM-170	1340-2901
7	D20	1340-52LQ0915								Balanced pressure	PM-170	1340-5210
8	B20	1340-52LQ0732								Termodynamisk	PM-170	1340-1201
9	B10	1340-52LQ0064								Termodynamisk	PM-170	1340-1201
10	B10	1340-52LQ0680								Termodynamisk	PM-170	1340-1201
11	C00	1340-52LQ0026			07.07.18					Termodynamisk	PM-170	1340-5703
12	B20	1340-52LQ0365								Termodynamisk	PM-170	1340-8001
13	C00	1340-52LQ0547		08.12.17						Termodynamisk	PM-170	1340-5210
14	A00	1340-52LQ0543								Balanced pressure	PM-170	1340-5210
15	B30	1340-52LQ0906			13.06.18					Termodynamisk	PM-170	1340-5207
16	B10	1340-52LQ0727								Termodynamisk	PM-170	1340-5207
17	B30	1340-52LQ0907								Termodynamisk	PM-170	1340-5207
18	~~D20~~	~~1340-52LQ0191~~								~~Balanced pressure~~	~~PM-170~~	~~1340-5210~~
19	B20	1340-52LQ0731								Termodynamisk	PM-170	1340-1201
20	D20	1340-52LQ0664				FOL	10.05.19	30.09.19		Balanced pressure	PM-170	1340-5210
21	~~B20~~	~~1340-52LQ0218~~								~~Balanced pressure~~	~~PM-170~~	~~1340-5210~~
22	~~B20~~	~~1340-52LQ0530~~		~~07.04.16~~						~~Balanced pressure~~	~~PM-170~~	~~1340-5210~~
23	C00	1340-52LQ0346		21.03.18		FOL	10.05.19	04.07.19		Balanced pressure	PM-170	1340-3001
24	B30	1340-52LQ0947								Balanced pressure	PM-170	1340-1201
25	C00	1340-52LQ0029								Balanced pressure	PM-170	1340-5103
26	B20	1340-52LQ0515			16.07.2018					Termodynamisk	PM-170	1340-5210
27	A00	1340-52LQ0187								Balanced pressure	PM-170	1340-5210
28	A00	1340-52LQ0660								Balanced pressure	PM-170	1340-5210
29	E00	1340-52LQ4001			01.04.18	FOL	04.04.18		25.06.18	Balanced pressure	PM-170	1340-3401
30	D20	1340-52LQ0668								Balanced pressure	PM-170	1340-5210
31	B20	1340-52LQ0137								Balanced pressure	PM-170	1340-5210
32	B20	1340-52LQ0517			04.07.19					Termodynamisk	PM-170	1340-8001

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