MASTER

Developing a framework to decide upon which maintenance policy to use per component
a case study at the Service & Support department of Océ-Technologies Venlo

Teeuwsen, L.A.

Award date:
2016

Eindhoven, April 2016

Developing a framework to decide upon which maintenance policy to use per component

A case study at the Service & Support department of Océ-Technologies Venlo

by
L.A (Lonneke) Teeuwsen

BSc Industrial Engineering and Management Science – TU/e 2013
Student identity number 0748807

In partial fulfillment of the requirements for the degree of

Master of Science
in Operations Management and Logistics

Supervisors:
ir. dr. S.D.P. Flapper, TU/e, OPAC
dr. ir. R.J.I. Basten, TU/e, OPAC
M. ten Have, Océ-Technologies

TUE. School of Industrial Engineering.
Series Master Thesis Operations Management and Logistics

Subject headings: condition based maintenance, opportunistic maintenance, single-component system, degradation paths

Abstract

This master thesis describes a research project that is carried out at Océ-Technologies Venlo on condition based maintenance. The thesis is part of a bigger project within Océ to implement a predictive maintenance program in the total organization. This thesis focuses on the optimal maintenance policy for individual components. A method to decide between three different policies was developed and a case study on a part of an Océ machine was conducted. The method includes a decision tree and mathematical model. The model makes use of both unscheduled and scheduled downs as maintenance opportunities, where it is possible that not all tasks can be conducted during an unscheduled down. Data is gathered for a selected part of the machine and a dummy case is introduced to run the condition based maintenance model. Furthermore a sensitivity analysis is performed to illustrate the trade-off the model makes between cycle length between two consecutive replacements and maintenance costs.

Note: company data in this report has been censored and/or replaced by fictitious data

Executive summary

The project in this master thesis was conducted at Océ-Technologies in Venlo. Océ is part of the Canon Group and focuses on the business market in printing services. This project was executed at the Service & Support department for the VPi300 machine.

Problem Statement

Until now, Océ has functioned like a so called 'break and fix' organization. In case something breaks down, one goes there as fast as possible in order to fix the problem. The goal is to transfer to a 'sense and respond' organization. In other words, Océ should be able to detect an upcoming failure and thus plan the upcoming visit in advance. To reach this, it is desired to implement a maintenance program that consists of a mixture of maintenance policies, with the purpose to minimize the total amount of unscheduled downs against the lowest possible costs. The newly implemented remote data access on the VPi300 yields a great deal of information on actual machine status and can help to implement the desired maintenance program. However, implementing such a maintenance program requires a lot of work on many aspects. This project focuses on how to decide upon the optimal maintenance policy per component.

Research Approach

To decide upon the optimal maintenance policy per component, it was first defined which policies are possible within Océ. This yielded three policies: corrective, usage based and condition based maintenance. The first two are currently used within Océ, the last one is new and it has to be investigated whether this is a feasible option. A theoretical framework and mathematical model are developed to decide between the three maintenance policies. The thesis of Q. Zhu (2015) is used as a starting point for the mathematical model because it makes use of both scheduled and unscheduled downs as maintenance opportunities. An extra variable was added to include the probability a customer does not agree to the performance of additional tasks during an opportunity. After this, a case study is performed on the inkhandling function of the VPi300 machine. Since the research is conducted on a relatively new machine, there is not much failure data available. If possible a distribution is fitted to available data, otherwise an estimation is made in collaboration with manufactures and function specialists. A dummy case was developed for the condition based situation, because it was not yet possible to spot trends in the remote data on the inkhandling function. A random coefficient model is used to describe the degradation state of the dummy case.

The developed model calculates for all three maintenance policies the costs per time unit by dividing the expected cycle costs by the expected cycle length. The corrective maintenance policy is quite straightforward to compute: costs of the visit and component divided by the Mean Time To Failure. For the usage and condition based policy the model is more complex. The model assumes there are a fixed amount of scheduled downs during a year and an amount of unscheduled downs that arrive according an exponential process. All downs are considered as maintenance opportunities and offer the possibility to carry out several maintenance actions. During a scheduled down all actions are allowed and there are no restrictions, however for an unscheduled down it is possible an action cannot be conducted due to several reasons. For both policies a threshold is set after which all occurring downs are considered as opportunities and the first possible one is used to carry out maintenance. For the usage based policy this threshold is a time limit set at a fixed point before the planned maintenance visit. If for example a component get's replaced every 52 weeks, the time limit can be set at 50 weeks. The condition based policy has a stochastic limit; if the degradation path of a component crosses a certain state (the warning threshold) a sign is triggered and the next possible opportunity is taken. This degradation path can follow any distribution. Working with the opportunities leads to several possible visits, depending on the lifetime of the component and the occurrence of opportunities. The probabilities of all visits with the corresponding cycle lengths and costs are computed to calculate the costs per time unit in the end.

Results

The case study was performed on the inkfilters, which currently have a usage based maintenance policy. The model shows the expected lifetime is of such length that replacing after a year shortens the cycle so much that corrective maintenance is the best strategy, as long there is no condition based alternative or no changes are made in the expected lifetime. When one of these two happens, the optimal policy might change. Furthermore a sensitivity analysis was conducted on all policies. The following overall results were obtained:

- A change in costs has a linear influence on the cost per time unit if the probabilities do not change. The change per euro can be calculated for all policies to see if there will be a point in time where the lines cross and another policy becomes optimal;
- The customer acceptance of an opportunity has around the same influence as the arrival rate of unscheduled downs because they both say something about the number of possibilities that can be taken in a certain time interval;
- The cycle length has a big influence on the costs per time unit; meaning the costs per kind of visit don't differ to such extent that they can outweigh the benefits of a longer cycle length. Note this only holds for the values as entered for Océ, if the difference between the costs per visit increases, the cycle length may become less important.

Recommendations for Océ

The first recommendation is to use the framework to reconsider the maintenance policies used for components. To start, the framework can be applied to a subset of components that are expected to have a major share in maintenance. The case study on the ink filters showed it is important to think it through and not just make an assumption based on a 'gut feeling' because selecting the right policy can lead to large decrease of costs. Applying the framework is related to the second recommendation: creating more awareness and ground for lifetime estimations. When deciding upon a maintenance policy, it is crucial to know how a component will behave over time. Without knowledge on the failure behavior, it is very hard to apply the model and tell something about the optimal policy.

Additionally to the awareness on lifetime estimations comes the awareness of the benefits of predictive maintenance. Implementing condition based maintenance is time-consuming and some may wonder whether it is worth all the trouble. To make a strong case in demonstrating the benefits, it is recommended to first show for a small subset of components what can be won by implementing predictive maintenance.

As a next step on the road to predictive maintenance it is recommended to start clustering maintenance actions. The model in this research is limited to be single-component. Although other components are taken into account by the use of maintenance opportunities, this is only to a certain extent. It should be investigated how all the different actions can be best combined to minimize downtime. Additionally it is recommended to keep looking for ways to handle the data in the most convenient way. The availability of a huge amount of data holds as many opportunities as it is challenging. It is easy to get lost in the piles of data logging that are generated every day but it also offers a great deal of valuable information; it is worth the investment to use it to its fullest.

Academic Relevance

Zhu(2015) presents a recent research in the field of maintenance engineering which it is not much tested in the field yet. So far Zhu was the only model in literature that makes use of both scheduled and unscheduled downs as maintenance opportunities and implements condition based maintenance with these opportunities. This thesis aims at contributing to the topic of maintenance opportunities and condition based maintenance. It does so by implementing the model of Zhu in a company environment and adding the probability not all maintenance opportunities can be used. The model was solved analytically, eliminating simulation and therefore making the model generically applicable. It also shows a case study on the practical application and some more ideas for implementation. Furthermore some future research directions to make the model better applicable are stated.

Preface

This report not only concludes my master thesis project developed at Océ and the TU/e, but is also the final stage of more than five incredible years as a student.

The completion of this report would not have been possible without the help of others. First of all, Simme Douwe Flapper, my first supervisor. I really appreciated the great amount of feedback and the fast responses whenever I got stuck with a question. His experience and background knowledge in the field always provided an anecdote or example to go with an explanation, giving an extra touch to the story. I also really liked the non-content related chats and discussions on what to do after graduation. Then my second supervisor, Rob Basten. I would also like to thank him for the support during the project, especially when I got lost in the practical application of the model and we discussed possible implementations. I wish you all the best with the rest of the ProSeLo project.

Next, my supervisor from Océ, Mark. Thank you for the opportunity to conduct this thesis at Océ. From day one you where closely involved with the project and also supported me on bringing in my own ideas. Also the rest of the department, thank you all for your help and the good time I had during these past seven months. I am looking forward to work on the next project with you all the coming months.

My days as a student in Eindhoven wouldn't have been the same without my fellow students who provided me an amazing time. A special thanks to the board of UniPartners Eindhoven '13-'14, like they said: the level of retardedness is positively correlated to the revenue. Moreover, my friends from my hometown, the tappers in general, 'Q', my awesome roommates and without a doubt, the crew '12-'13 of the Villa; it was my pleasure. And lastly, Loek, thank you for your support, even all the way from Taiwan.

Finally I would like to thank my parents and brother. Bart, thank you for being such an awesome brother and the Tuesday-music nights we spent together. I hope we keep on jamming in the future. Dad, thank you for your feedback and our good conversations during 'jogging' in our pointless attempt to tire the dog. And mom, thank you for all your support, our little trips and of course, the infinite amount of delicious cakes you baked me.

Lonneke Teeuwsen

Table of Contents

List of figures

List of tables

List of definitions

Term	Explanation
Automated maintenance	Maintenance conducted by the machine itself, without human intervention
Black box data analysis	Big data analysis without prior knowledge or background information. All conclusions are based on correlation between data
Clicks	Measurement used to standardize all jobs to the same level to be able to compare them. One click resembles an A4 print and all jobs are counted in number of clicks
Condition based maintenance	Preventive maintenance carried out after a certain threshold is reached based on the state of a component. The measurements can be collected by continuous monitoring or by periodic checks
Contracted Service Hours	Hours per day Océ provides maintenance as agreed upon with the customer in the contract
Corrective maintenance	Maintenance carried out after the breakdown of a component to restore a failed system or component to its required performance level
Downtime	All the time a machine is unavailable for production due to unplanned maintenance visits
Expendables	An expendable is a service part that is physical part of hardware products and has a pre defined lifetime (expected yield = how many times will the part be used for maintenance per machine/year) and has considerable impact on running service costs of the hardware.
Failure distribution	See *lifetime distribution*
Key Operator Maintenance	An action that is performed by the operator of the customer at location
Lifetime distribution	This distribution represents the expected lifetime of the component and how the breakdowns are distributed over time.
Machine lifetime	For service (extern) the lifetime is set at 60 months or 120 million clicks, after this period the contract is prolonged or terminated. For R&D (intern) the machine lifetime is set on 300 million clicks so the design is made to survive extreme circumstances.
Machine Recoverable Error	An error the machine should be able to fix itself, if the error keeps occurring after initializing several times, it is converted in a permanent error and the Service department is informed
Maintenance	The combination of all technical and associated administrative action intended to retain an item in, or restore it to, a state in which it can perform its required function (Glossary of maintenance management, 1984)
Maintenance cycle	Interval between two consecutive maintenance actions (Zhu, 2015)
Mean Clicks Between Failure	Expected amount of clicks between a fix and the next failure. It is calculated on machine level by taken the total production volume per year and dividing this by the total amount of expected corrective visits per year
Operator Recoverable Error	Error that can be fixed by the customer himself. E.g. a small paper jam
Preventive maintenance	Maintenance carried out before the actual breakdown of a component. It can be divided into usage based and condition based
Remote data	All data collected via a remote connection with a machine
Sentry	A sheet rejected by the printer based on the results of the altimeter
Service tool	A service tool is a service part that is used to maintain or repair hard- or software, but is not a physical part of the hard- and software
Spare parts	A service part that is a physical part of hardware that can fail, but is not defined as an expendable or tool
Threshold	The limit that must be exceeded to elicit a certain response
Uptime	All the production time plus idle time and downtime due to planned maintenance of a machine. Unplanned maintenance is not counted as uptime. (as defined by Océ)

Usage based maintenance	Preventive maintenance carried out after a certain threshold is reached based on usage count or age, disregarding the actual state of the component.
White box data analysis	Data analysis performed with background information and technical knowledge. Data is used to assist with problem solving

List of abbreviations

BPR	Back Pressure Reservoir
CFR	Constant Failure Rate
CBM	Condition Based Maintenance
CM	Corrective Maintenance
DFR	Decreasing Failure Rate
ECC	Expected Cycle Costs
ECL	Expected Cycle Length
FST	Field Service Technician
IFR	Increasing Failure Rate
KOM	Key Operator Maintenance
MCBF	Mean Copies Between Failure
MTTF	Mean Time To Failure
MRE	Machine Recoverable Error
NSO	National Sales Organization
ORE	Operator Recoverable Error
PM	Preventive Maintenance
RSHQ	Regional Sales Headquarters
SD	Scheduled Down
UBM	Usage Based Maintenance
USD	Unscheduled Down

List of variables

τ	Moment of scheduled down
λ	Arrival rate of USD (Poisson process)
λ_t	Arrival rate of USD (Poisson process) in time interval t
ξ	The deviation of the starting point of a new maintenance cycle from SD
A	Age limit of the age of the ABM component
c^{USD}	Cost of an unscheduled maintenance visit
$c^{USD-CBM}$	PM cost of the replacement of the CBM component at an USD
c^{USD-PM}	Cost of the replacement of an ABM component at an USD
c^{SD}	Preventive maintenance cost of the component at a SD
c^{CBM}	Cost of the CBM action without other maintenance opportunity
c^{COM}	Cost of the component
$f(u)$	P.d.f. of the lifetime distribution of the ABM component
$g(s)$	P.d.f. of the Exponential distribution with parameter λ
H	Breakdown threshold on the degradation level
$K(A)$	Expected cycle cost of the ABM component
$K(W)$	Expected cycle cost of the CBM component
$L(A)$	Expected cycle length of the ABM component
$L(W)$	Expected cycle length of the CBM component
$MTTF$	Mean Time To Failure of the lifetime distribution of the component
$n\tau$	Moment of planned maintenance on a component
$P(Y)$	Probability of taking the opportunity when an USD occurs between W and H
or	when $t \geq A$
q	probability a maintenance cycle ends with an SD
SEV	Costs for severe consequences of breakdown
T_H	Occurrence time of breakdown threshold H
T_W	Occurrence time of warning threshold W
u	Moment of breakdown of component
v	Time of T_H
w	Time of T_W
W	Warning limit on the degradation level
$X(t)$	Degradation of the CBM component over time t
$z(s)$	P.d.f.of the Erlang distribution with parameters λ_t and k
$Z(A)$	Average cost rate of the ABM component
Z_{cor}	Cost per time unit for the corrective maintenance policy
$Z(W)$	Average cost rate of the CBM component

1 Introduction

In 2011 the development of a new product started at Océ Venlo: the high-tech VPi300 printer. A team formed of people from different departments was assigned the development task. The team provided a market entrance within four years, which is considered fast for this kind of product. Approximately four more years are planned to implement a high-end maintenance program. To provide this, the Service & Support and Research & Development department are collaborating. The research presented in this report took place at the Service department and will contribute to the setup of the desired maintenance program. This chapter starts with the research environment, after which the problem statement is given. Lastly the research proposal is presented.

To be clear in terminology as used throughout the rapport, the terms used to define maintenance are explained first. The term maintenance program is the mixture of all different strategies or policies used per component and aims at the maintenance of the total machine. The terms 'policy' and 'strategy' on the other hand are used interchangeably and are used to clarify what kind of maintenance is performed per component. So when the term 'program' is used, this refers to the total machine and 'policy' and 'strategy' to single components. Since this report elaborates on different maintenance policies and the literature uses the definitions on maintenance ambiguous, the definitions of the policies as meant in this report are listed below:

- **Corrective maintenance** Maintenance carried out after the breakdown of a component to restore a failed system or component to its required performance level.
- **Preventive maintenance** Maintenance carried out before the actual breakdown of a component. It can be divided into usage based and condition based.
  - **Usage based maintenance** Preventive maintenance carried out after a certain threshold is reached based on usage count or age, disregarding the actual state of the component.
  - **Condition based maintenance** Preventive maintenance carried out after a certain threshold is reached based on the state of a component. The measurements on the state of the component can be collected by continuous monitoring or by periodic checks.

The different maintenance policies are considered below. The dark blue ones are already implemented by Océ. For the light blue (condition based) ones it has to be investigated whether they are profitable and implementable. How maintenance is currently conducted within Océ is explained in paragraph 1.1.2. Both the figure and the definitions are based on the reader of Arts (2015). The distinction between the two basic classes (corrective and preventive) is taken from Tinga (2010).

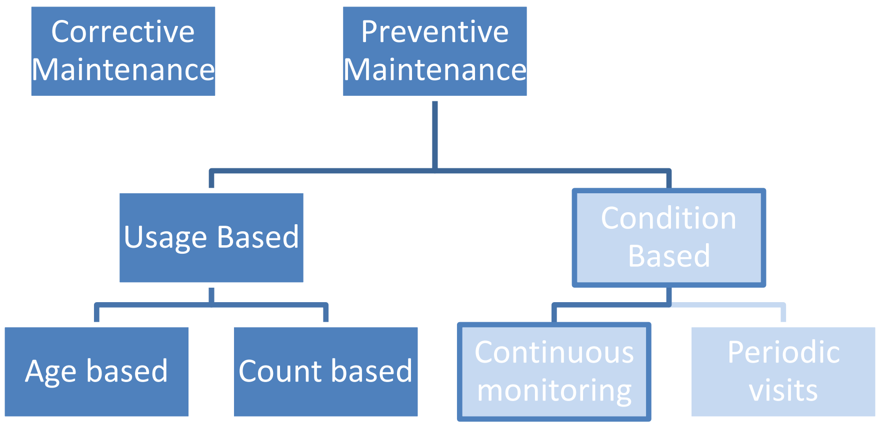


Figure 1 Overview of maintenance policies. Redrawn from Arts (2015)

1.1 Research Environment

1.1.1 **Company background**

Océ Technologies B.V. was founded in 1877 and is part of the CANON Group since 2011. This group is internationally active to become the number one company in printing(-services) on both the consumer- and business market. Océ focuses on the business market, for Canon one of the reasons for the take-over since Canon itself mainly focused on the consumer market.

Océ produces five product families which offer average speed, office size products. Besides those five, twelve other families with high-speed printing solutions are produced.
Globally Océ has approximately 3.600 employees, 2.400 are located in Venlo. Research and Development and Service employ respectively 7% and 21% of these 3.600 employees.

Until now Océ is the only active player in the new entered, sheet fed inkjet printing market. Being the first player on a new market brings great opportunities for Océ, but also implies a lot of uncertainties and use of new material. Some experience is known from the Océ location in Poing, Germany for they developed a machine comparable to the VPi300, but with continuous feed instead of sheet fed. Since no sign of a comparable machine by competitors (like HP, Xerox and Ricoh) is seen yet, the market share of the VPi300 is expected to grow in the coming years. Until now it is the only sheet-fed machine that can print with a speed of 300p/m where competitors stay behind at 220p/m.

1.1.2 **Maintenance on the VPi300**

Since this research aims at the maintenance of the VPi300, a short introduction is given about the current maintenance at this machine. Two policies are currently used: corrective and usage based maintenance. Components will be referred to as UBM (preventive usage based) or CM (corrective) components further on.

The presently used system to categorize a component for preventive or corrective maintenance is relatively easy: if a component is expected to survive the machine lifetime it is maintained correctively, otherwise preventively. The VPi300 is divided in different ‘functions’ which are parts of the machine that together fulfill a certain part of a print job. For example ink handling or the printhead. The expected lifetime is determined per function based on lab tests and past experiences. Furthermore Océ uses ‘maintenance opportunities’; if a Field Service Technician (FST) is already at location to solve a breakdown of another component, it is immediately checked if there are upcoming preventive actions that can already be conducted. This ‘check’ is performed by an application that calculates if a UBM component is expected to survive until the second next maintenance moment, based on the amount of clicks[1] the machine made since the former replacement of the component. If not, an FST gets a signal to conduct this extra maintenance task. The component thus get’s replaced before the planned moment. At this time (April 2016), around 75 components are listed as PM for the VPi300 and there are four moments of planned maintenance per year.

Besides the preventive and corrective actions, Océ defines so called KOM-actions. A KOM (Key Operator Maintenance) action is an action that is performed by the operator of the customer at location. This may for example be the placing of new ink cans or replacement of the wet tissue wipes. The wipes clean the printheads after every job and need to be replaced when the roll of wipes is used up.

Océ intends to use the data that is collected on the VPi300 to provide a better maintenance strategy, therefore an overview of all the collected data is given.

1.1.3 Available data

For the VPi300 there are two ways of collecting data: remote data collecting (machine data) and the reports FSTs fill out after every visit (visit report data). The remote data collecting is a new way of collecting data for Océ and generates a huge amount of data (8 GB per machine per day). So far Océ is still looking for a way to optimally make use of all the possibilities this data offers.

Since Océ became a part of Canon a couple of years ago the company consists of different management levels. This influences the accessibility of visit report data: the different countries report to the Region and the Region reports to the Océ headquarters (HQ), located in Venlo. Before the takeover, Océ was directly in touch with the countries and it was easier to get access to data.

1.1.3.1 Visit report data

At each visit, either planned or unplanned, the FST fills out a service report in either the STAR of ADAM application. Both are applications for a FST to fill out all information about a visit, where the ADAM is the new tool that is especially developed for the VPi300.

When an FST arrives at the customer his laptop is linked to the machine to retrieve the up-to-date status of the machine. Also, the reports of the seven former visits are shared, showing the failures and status of the machine at those times. The FST can manually supplement the information with customer complaints and observations. A work list shows all the tasks the FST has to fulfill, divided in two categories: obligatory and optional. In case an optional task is not conducted, a reason has to be provided (e.g. not carrying the required material). Otherwise the task just has to be conducted and checked as ‘completed’.

This data is used to form the Business Warehouse Reporting. Once per month the data is retrieved and processed together with other data (like sales of consumables) to show trends. Things like downtime, number of errors (either FST or machine recoverable) and costs of consumables are depicted. These reports are at customer or population level.

[1] A measurement used to standardize all jobs to the same level to be able to compare them. One click resembles an A4 print and all jobs are counted in number of clicks

1.1.3.2 Machine data

The VPi300 is equipped with sensors to measure all kind of conditions of the machine, for example temperature and moist. In total an amount of 8 GB of data per day per machine is generated. It is not feasible to import all this data (due to the capacity of the server) for all machines and therefore the data are separated in two groups: data for problem analysis (4 GB) and regular data (4 GB). The regular data is imported on a daily basis, the data for problem analysis only when a problem occurs. The separation was made individually by function specialists and the intention is to reduce this data to 2 GB per day.

After being imported, the data is stored in the Data Warehouse in three databases: the service data, the functional log and the billing data. The service data collects the information about errors (e.g. their occurrence) and is used to plan corrective and preventive maintenance. The billing data is administrative information like the amount of clicks and production hours. The functional log is new for the VPi300 and tells the condition of the machine, like temperature, moist etc.. This data is supposed to make predictive maintenance possible.
Currently there are different tools and dashboards to analyze the data:

- KPI-dashboard for customers; This KPI dashboard is meant to be sold to the customer. At this moment it is still in the start-up phase and not yet implemented, but customers have said to be interested. Periodically data is imported to the general Océ-server. The dashboards are generated automatically. It shows things like uptime, efficiency, ink usage, waste costs and costs per print. The graphs are at machine level and show only customer specific information. The customer can use this to optimize his own production process and gain more insight in the printer usage.
- QA(Quality)-dashboard; This dashboard is used internally by Océ as a trigger; it does not have any analytical functions. Again, the dashboard is on machine level. It shows service and billing data like idle time, MRE’s (Machine Recoverable Errors), ORE’s (Operator Recoverable Errors), ink and tissue usage and printed sheets, both successful and unsuccessful. Also it shows the moving average over 5 days of different values in order to spot outliers. In case some strange pattern or any deviations occur, an employee can call a customer to find out what is happening and if further actions are required. Currently it is used by the R&D Quality team.
- Diagnostic Framework; For now, this framework works at machine level but it is intended to extent it to population level. The framework allows you to select a machine and run so called ‘recipes’ on the data. A recipe contains an extraction of data, the process script and the visualization in the end. Function specialists from the R&D department wrote the existing recipes. Collaboration between Service and R&D is necessary to optimize this structure: if service indicates which visualization it needs, R&D can help to develop the right recipe. The ‘expert mode’ gives the opportunity to construct a recipe yourself, which requires some knowledge about programming. Python is the language used to program the framework.

The goal is to develop a maintenance dashboard with the option to analyze a population of machines in order to detect trends and common failures to establish thresholds. After which the thresholds can be used to monitor a single machine to determine the need for maintenance.

1.1.4 The business model

For maintenance, the business model consists of three components:

1. Monthly Maintenance Charge; A fixed charge per month paid by the costumer and agreed upon within the contract. It covers the service labor and incidental parts costs. The price depends on the machine configuration and the Service Level Agreements (SLA’s). The SLA’s can for example be about the response time or having a resident service technician. If

the response time is very short, an FST has to be standby all the time. This causes a lot of idle time among FSTs and thus expensive labor;

2. User Charge; A click charge per printed volume. Also a fixed charge agreed upon within the contract but depending on the user volume. It covers the consumption of printheads and expendables[2];
3. Consumables; Sold separately when needed, mainly ink and some other customer replaceable parts (e.g. wet tissue wipes). Océ has developed its own ink and has its own factory. So far this part yields the most revenue for Océ.

1.2 Problem Statement

Until now, the organization has functioned like a so called ‘fire brigade’ organization. In case something breaks down, one goes there as fast as possible in order to fix the problem; the corrective maintenance policy. The goal is to transfer to a ‘sense and respond’ organization (“private communication”, 2015). The way to this kind of organization is called ‘the road to Predictive Maintenance’. Figure 2 shows the different steps on this road. So far, the first three steps have been considered and (partly) implemented, but with the introduction of the VPi300 and the remote data collection, condition based maintenance has become the next challenge. The last step, predictive maintenance, is a mixture of all former steps. It is a maintenance program consisting of different policies such that the maintenance on the total machine is optimized. This step also involves organizational changes. The remote data will be a key element of the predictive maintenance, serving a dual purpose:

1. For the R&D department the data will provide information about the behaviour of components in the field leading to the improvement of the design and thereby increasing intrinsic reliability of the corrective maintenance components.
2. For the Service department the data has to provide the thresholds for preventive maintenance and ability to monitor them. The goal is to be able to minimize unplanned downtime and therefore maximizing the uptime (according to the definition of uptime as included in appendix A).

In the end Océ intends to make money out of this program by asking higher maintenance charges from the customer. Also the decrease of unplanned visits should decrease the need for ‘standby’ technicians and thereby decrease idle time, hence labor costs.

[2] a service part that is physical part of hardware products and has a pre defined and considerable impact on running service costs of the hardware

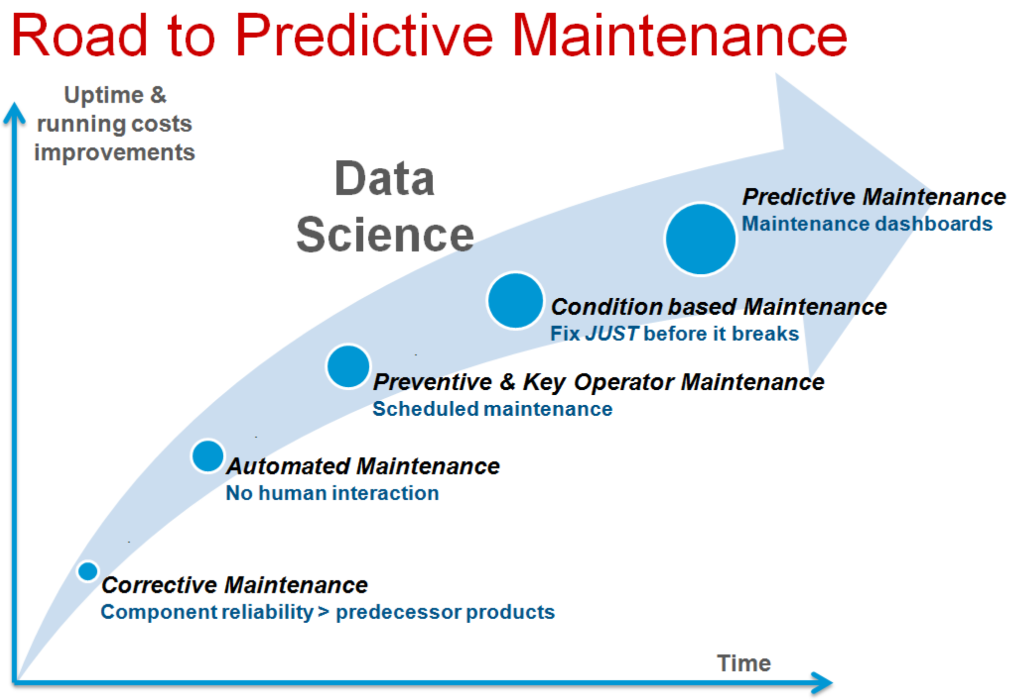


Figure 2 The Road to Predictive Maintenance, taken from "private communication" (2015)

To realize such a program in the long run, the following tasks are defined, categorized in four groups:

- **Use available data**: there is a lot of data available (functional logging and data dump of machine) but it has to be structured and analyzed. Most important: it has to be determined what data is important and will be used for further analysis. This data has to be logged in easy readable reports with the possibility to conduct customized analysis. The data can be analyzed both black and white box[3]. Also a connection between different ways of data collecting has to be made so they can complement each other;
- **Determine maintenance strategy per component**: the current policy per component has to be reconsidered since the remote data offers new insights in the failure behavior of the component. Therefore the breakdown thresholds and failure distributions have to be determined. Also the costs of the different policies have to be calculated. Furthermore Océ is interested what it would imply for both the customer and Océ when a certain strategy is implemented.
- **Cluster activities**: maintenance actions should be combined in order to minimize the number of visits. A trade-off should be made between the setup- versus the downtime costs (Zhu, 2015);
- **Implement in daily organization:** how does condition based maintenance influence planning of FSTs, time needed for maintenance and way of working on several departments.

This project will focus on the second part about the maintenance strategy per component and is further defined in chapter 1.3.

[3] Black box is big data analysis without prior knowledge or background information; white box is with background information and technical knowledge.

1.3 Research Proposal

1.3.1 **Research goal**

This master project focuses on the ‘condition based’ step of the ‘Road to Predictive Maintenance’. To implement this step, it has to be investigated when condition based maintenance would be possible and if this would be the most beneficial option. To decide whether condition based is the best option, it has to be compared to other possible policies (remember the policies presented in Figure 1). Therefore the goal of this research is to develop a framework to decide upon the maintenance policy per component. First corrective and usage based maintenance are considered, after that the condition based option is considered. Additionally the goal is to not only have a theoretical framework, but also a practical implementation. Hence a case study on the VPi300 machine is included. Furthermore the outcome of the research has to be generic, so it can easily be used on other machines or in case the circumstances for the VPi300 change.

1.3.2 **Research questions**

To reach the research goal, four research questions are formulated:

1. *‘How can be determined which maintenance policy is optimal: corrective or usage based?’*

At this moment components are considered CM if they are expected to survive the machine lifetime. However since it is desired to minimize the unplanned downtime[4] this division has to be reconsidered. According to the literature, only for products with a constant failure rate corrective maintenance is immediately advised. Components with an increasing failure rate[5] ask for a closer look (Arts, 2015). Therefore it is examined how this division between CM and UBM can be made so the most optimal way is found. This is reflected against the current method within Océ. Costs and failure distributions are taken into account. Also it is considered whether other factors influence this decision. This research question is answered in chapter 3.

2. *‘How can be determined if condition based maintenance is possible and if this is the optimal option?’*

.

Remote data gives the opportunity to closely monitor many functions in the machine and allows switching to CBM for a lot of components. However not for all components condition based is the best policy, therefore it has to be determined which components are suitable for condition based and if this is indeed a better option than CM or UBM. Hence, it is determined what factors need to be considered for condition based maintenance and a method is developed to compare this policy to other policies. Additionally it is checked how the remote data can be used for decision making. Chapter 4 elaborates on this research question.

3. *‘How can the framework be applied to an Océ machine?’*

[4] Downtime is defined as all the time a machine is unavailable for production due to unplanned maintenance visits. This definition is further explained in Appendix A.

[5] Appendix F further elaborates on the failure rate

To use the theoretical framework in practice, is has to be investigated how it can be used on an Océ machine. Since the focus is on the use of remote data, the VPi300 is used for a case study. The machine contains a lot of components and one function is selected to start the research. In cooperation with Océ, the inkhandling function is selected. Chapter 6 answers this research question.

> 4. *What would the implementation of condition based maintenance imply for the customers of Océ?*

Implementing condition based maintenance involves the use of remote data. This not only leads to changes within Océ, but also the customers get involved with the remote data. To add an extra part to the practical implementation, it is examined what condition based maintenance would imply for the customers and how this can be handled. This research question is answered in chapter 7.

1.4 Research Approach

The research approach will be explained per research question. Figure 3 shows the steps that are taken per research question. The first part (within the blue dotted line) is performed twice; once for research question 1 and once for question 2.

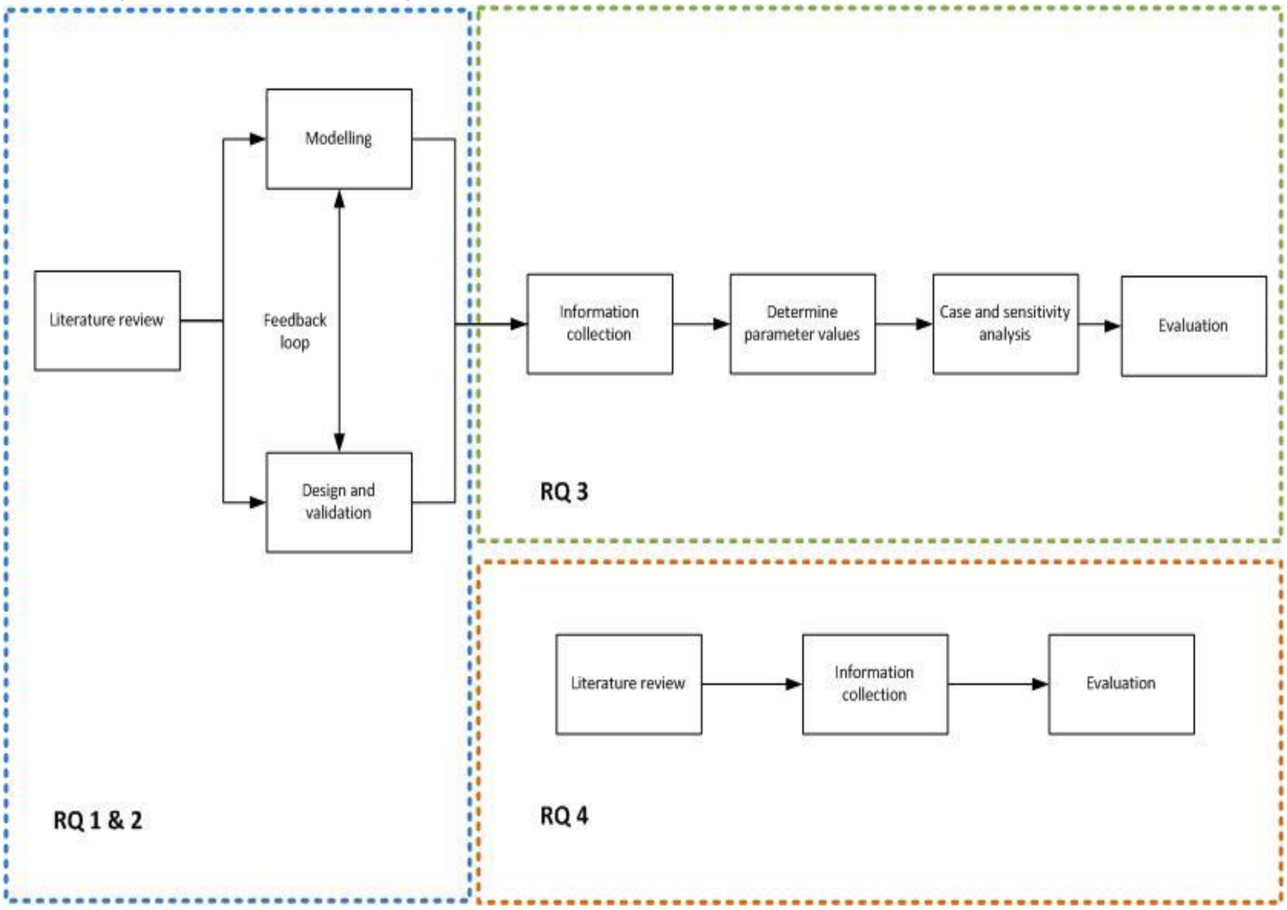


Figure 3 Steps per research question

RQ1 and 2. The first two questions are conducted in the same way and partly simultaneously. The first step is to review literature on this subject to support the mathematical modeling and theory behind maintenance policies. The literature is combined with the situation in the research environment to develop the framework to compare different policies and choose the optimal policy per component. After this the mathematical model is programmed in R and verified to check if the model works as it should be.

RQ3. This question starts with the collection of information on the inkhandling function. This is done by interviewing the people responsible for the selected function. Also some people of the Service & Support department are interviewed for a better idea about the methods used within Service & Support. Additionally the remote data is examined and the use of this data is discussed with function specialists. This information is used to determine the values of the parameters for the framework. Next to running the model with these parameters, a sensitivity analysis is performed. Not only to test the model, but also to provide an insight in what factors have a big influence on the total costs. The model is presented in a tool so the Service & Support department can easily recalculate things in the future.

RQ4. To answer this question, again literature is studied. Also Field Service Technicians are interviewed to see how they experience customer reactions on maintenance actions. The interviews with the Field Service technicians are evaluated with the literature and summarized in a discussion.

1.4.1 Research deliverables

This research should yield a calculation tool and decision tree to categorize service components as either CM or PM or CBM. For Océ it is important the tool is general in use since the input data may differ after the machine is operating for some time and more knowledge is available. Also they want to be able to use the framework on other machines. Per research question, different deliverables are determined. The first is the deliverable for question 1 and 2, Question 3 yields deliverable two till 3. The last deliverable is obtained by research question 4.

- ✓ A general tool and/or decision tree to decide upon a maintenance policy for future components or different input data;
- ✓ The parameter values for the selected function;
- ✓ A sensitivity analysis so the influence of different parameters in the model is clear;
- ✓ A discussion on consequences of CBM for customers

These deliverables can be used in future research on the ‘Road to Predictive Maintenance’. In the end of this research possible research directions are discussed.

2 Factors considered to compare maintenance policies

To compare the maintenance policies, a mathematical model is developed in chapter 3 and 4. However to first understand the differences and up- and downsides, the policies are discussed in this chapter. Understanding these up- and downsides is the first step in answering research question 1 and 2, respectively:

'How can be determined which maintenance policy is optimal: corrective or usage based?'

and

'How can be determined if condition based maintenance is possible and if this is the optimal option?'

First the policies are discussed and depicted in a matrix to give a rough idea of what policy is suitable in what situation. Next a decision tree is presented to make the first selection and to help on using the mathematical model.

2.1 Up- and downsides of the different maintenance policies

One of the factors considered is the usage of part lifetime. If a part is replaced preventively, there is a part of lifetime that is 'wasted'. When a component is expensive, this can be rather undesirable. With a corrective policy (CM), the lifetime of a part is used optimally; there are no unnecessary replacements. The condition based policy (CBM) is close to optimal; a part is replaced just before it breaks down. So some lifetime is wasted, but it is tried to keep this as little as possible by measuring the actual state of the component. Usage based (UBM) spills the most lifetime. A component is replaced after a fixed amount of time or clicks, regardless how long the component could have still been functioning. Figure 4 depicts this rang order.

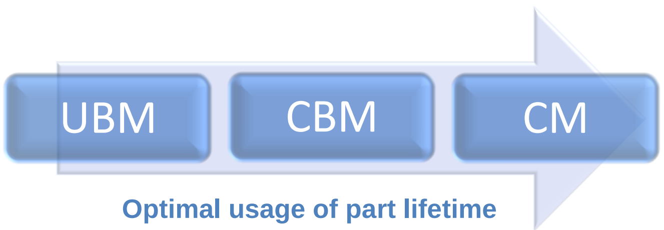


Figure 4 Usage of part lifetime per maintenance policy

Another factor that forms an up- or downside is the difference in costs between a planned and an unplanned maintenance visit; an unplanned visit is much more expensive than a planned one. This difference is mostly due to two reasons: firstly CM requires 24/7 standby FSTs to respond to calls, where SDs are planned in advance. Secondly during an SD several actions are combined and thus leading to lower set up cost per action. With CM only unplanned visits occur. UBM is a mixture and with CBM only planned visits happen. This rang order is depicted in Figure 5. The model balances the visit costs versus the wasted lifetime to see which policy is optimal.

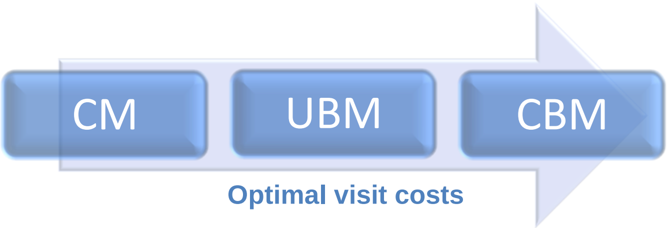


Figure 5 Relative visit costs per maintenance policy

All the up- and downsides of the policies are listed in Figure 6. The policies are placed in a matrix to give a fast idea of which policy is suitable for what kind of component. Note that the matrix is about components with an increasing failure rate only, for decreasing or constant failure rate CM is considered optimal (section 2.2 elaborates on this). The vertical axis shows part cost, the horizontal gives the cycle length. The cycle length is the time interval after which a component is replaced, this can thus be either due to breakdown or by preventive replacement.

As one can imagine, UBM is not desirable for a component with high part cost. The same is applicable for CM for a component with a short expected lifetime. CBM is cost wise the theoretical optimal strategy for almost all components. But the more practical downsides of CBM don't always make it possible to use this strategy; it can be very time consuming to find CBM thresholds or it might even be impossible to measure anything at all.

Where exactly the boundaries of the quadrants lie, is a consideration the model makes by the cost factors. Even though in reality it is not so trivial to place a component in a certain quadrant, the matrix gives an indication of the idea behind the policies and when they are best used. The down left quadrant has potential to become a KOM action; the low cost of component combined with the high frequency of appearance make it desirable to let the customer perform the maintenance action. Something that is not included in the matrix but may influence the chosen policy are the consequences of breakdown. When the breakdown of a component has severe consequences for other parts of the machine (e.g. damage to the printheads), it might be decided to follow a UBM or CBM policy no matter what to prevent breakdowns. This factor is included in the decision tree as presented in section 2.2.

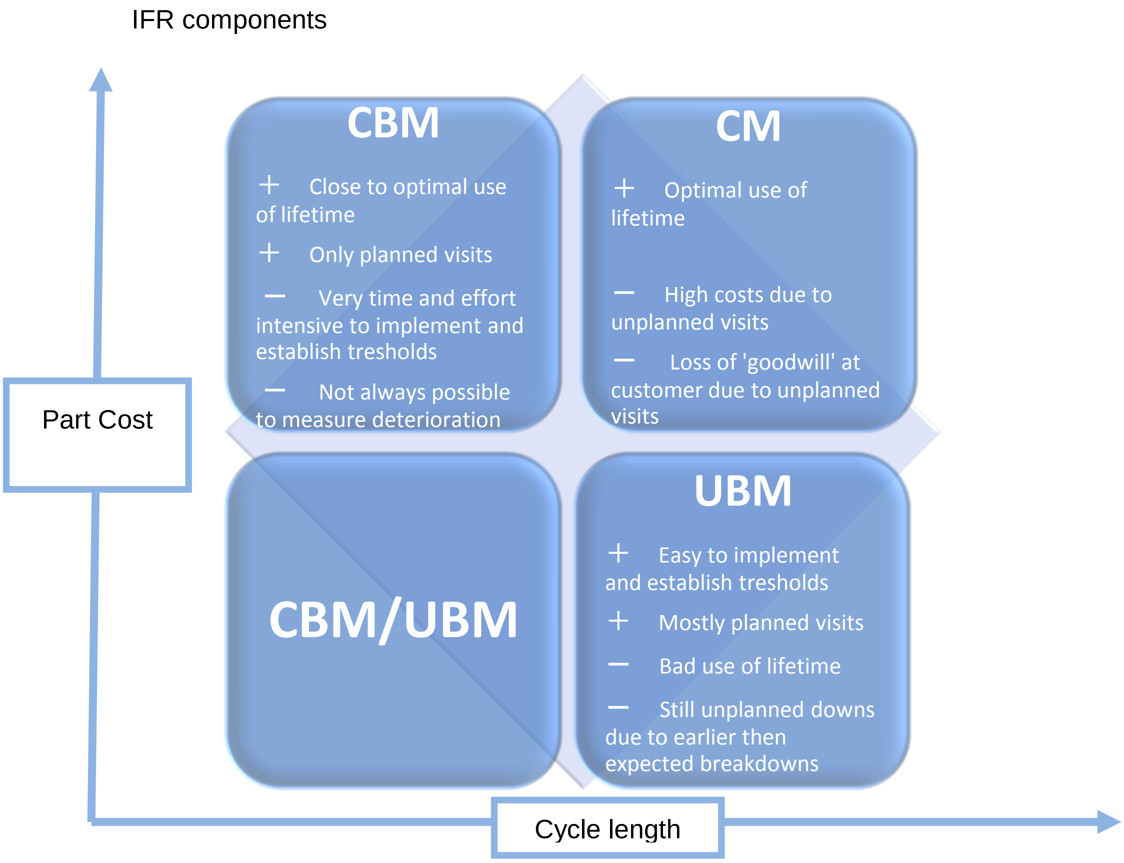


Figure 6 Matrix to categorize components and with the up- and downsides per maintenance policy

2.2 The decision tree

Before using a mathematical model to calculate costs, a rough selection can already be made. A decision tree is developed to make this first selection. Additionally the tree points out what part of the model to use and maybe add the extra option of 'severe' in case of large follow up damage. The tree is depicted below in Figure 7 and consists of the following questions:

1. *Does the component have an increasing failure rate*?; If a failure rate is not increasing, the component always has the same or less probability of breaking down. Hence it would not make sense to replace preventively at some time, because at that time the probability of break down is just as big as for example a month later (Arts, 2015). A corrective policy is the optimal policy for components with constant or decreasing failure rate. Therefore if the first question is answered with 'no', the corrective maintenance policy can be applied and no other policies have to be considered. This constant or decreasing rate is not a common failure rate for mechanical components though and is not likely to appear much in practice. However this question is included in case it does appear.

2. *Is it possible to measure the deterioration of the component*?; If it is technically not possible to measure the deterioration and determine the delay time, CBM is also not possible. In this case the 'CBM' option of the tool has to be overruled so the tool does not consider this option in the calculations. CM and UBM remain the only possible options. If this question can be answered with 'yes', all options have to be considered. Whether the deterioration will be measurable in time to plan a visit to fix the problem, is something that will be included in the mathematical model.

3. *Are there severe consequences at breakdown of the component*?; Furthermore it is important to consider the consequences of breakdown of the component; it might be the breakdown of a relatively simple component can have great consequences for the rest of the machine. This can also be referred to as ‘follow up damage’. For example the breakdown of an inkfilter; although it does not directly influence the functionality of the machine it can have great consequences if the printheads break down due to particles in the ink. The inkfilters are relatively cheap, but the printheads are an expensive part of the machine and thus the follow up damage is considered large. If a component is known to have great follow up damage, this can be put in the model to make CM more undesirable. Thus if this question is answered with ‘yes’, the model should be used with the extra ‘severe’ option.

4. *Is there no need to learn about failure behavior of the component*?; Then there is one last option to prefer corrective over preventive in case of increasing failure rate: to learn something about the behavior of the component. If a new part is developed and lab tests don’t yield sufficient knowledge about the failure behavior, it might be desirable to let it run until it breaks and afterwards examine the cause of breakdown. If ‘no’ is the answer, so there is the desire to learn more about the component, CM is advised, otherwise the tool should be used without the CBM option.

The green diamonds indicate a question, when answered with ‘yes’ the arrow to the right has to be followed. ‘No’ is given by the down warded arrow. The blue boxes tell whether to use the tool and with what settings or to use the corrective maintenance policy.

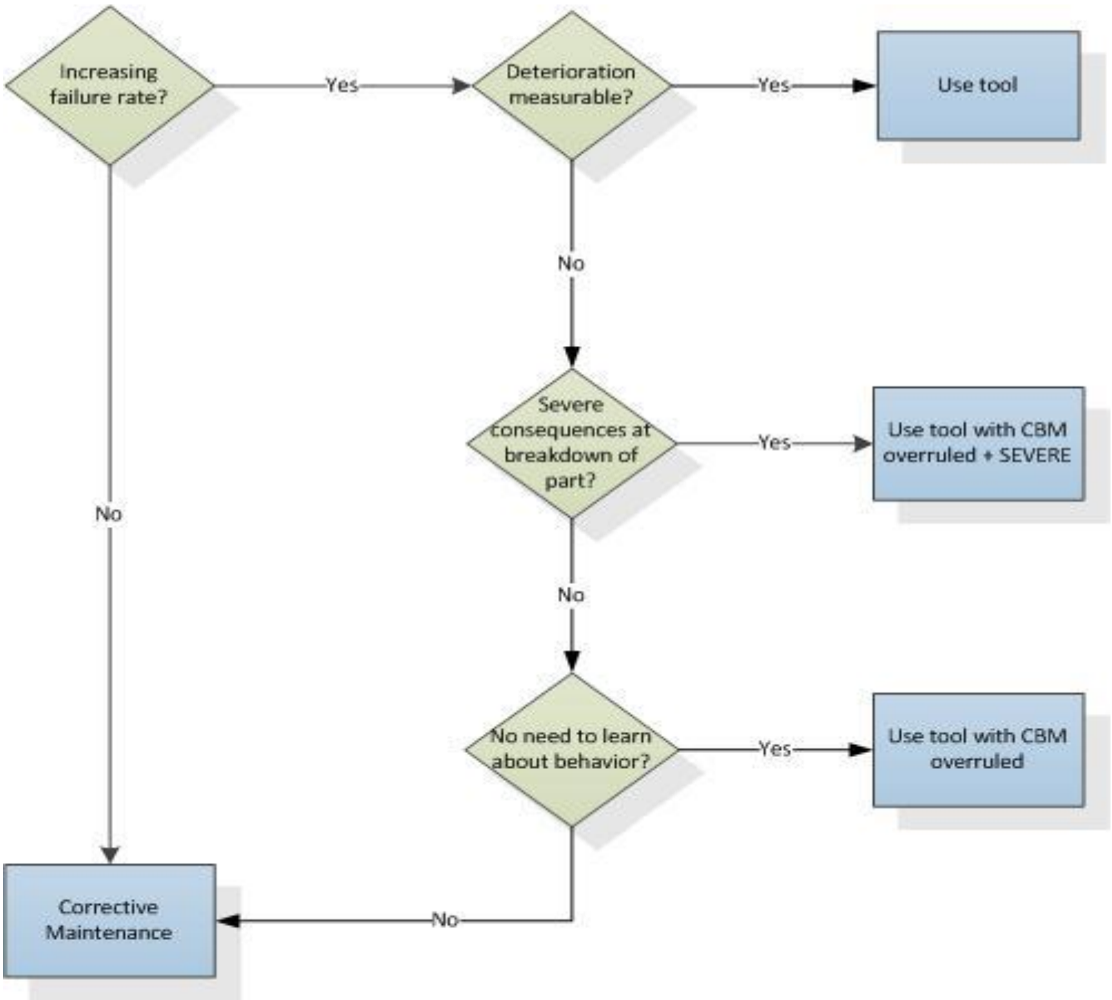


Figure 7 Decision tree for input for the mathematical tool

3 Corrective and Usage based maintenance

In this chapter, a mathematical model is developed to compare the corrective and usage based maintenance policies. The model is developed to answer research question 1:

'How can be determined which maintenance policy is optimal: corrective or usage based?'

The model calculates for both policies the costs per time unit by dividing the expected costs by the expected cycle length. A key element of both models is the lifetime distribution of a component. This distribution represents the expected lifetime of the component and how the breakdowns are distributed over time. It is needed to calculate the probability a component breaks down within a certain time period. Indirectly the failure rate is also taken into account by this, because the failure rate is derived from the lifetime distribution. Since the model is firstly developed to be applicable for Océ, the situation within Océ is used as starting point for the model.

3.1 Modeling the corrective maintenance policy

The idea behind a corrective policy is easy: just wait until a component breaks down and then go to the customer to fix it. However as stated before this leads to unscheduled downs and these kind of downs are usually the most disadvantageous. Theoretically this implies that no corrective policy at all is desired but in practice it turns out that for some components it is better to follow a corrective policy. The most important reason to select a corrective policy is if the failure rate is decreasing or constant. These features are mostly seen at electronics. However, even in case of an increasing failure rate, the corrective policy should be considered. If a component if very expensive, CM can be advisable too.

To calculate the costs per time unit, two things have to be obtained: the expected cycle costs (ECC) and the expected cycle length (ECL). In case of corrective maintenance there will only be unscheduled visits and the costs of an unscheduled down are incurred. Note that these costs also depends on the time it takes to conduct an action, longer downtime is a more expensive visit. In addition the cost of the component itself is considered as 'depreciation' cost to prevent waste of lifetime. The expected cycle length is equal to the expected time of breakdown. This is dependent on the lifetime distribution of the component and is referred to as 'mean time to failure' (MTTF). Dividing the expected cycle costs by the expected cycle length yields the costs per time unit.

The notation used:
$c^{USD}: cost\ of\ an\ unscheduled\ maintenance\ visit$
$c^{COM}: cost\ of\ the\ component$
$SEV: \ cost\ for\ severe\ consequences\ of\ breakdown$
$MTTF: mean\ time\ to\ failure\ of\ the\ component$
$Z_{cor}: cost\ per\ time\ unit\ for\ the\ corrective\ maintenance\ policy$
and:

$$Z_{cor} = \frac{c^{USD} + c^{COM} + SEV}{MTTF} \tag{3.1}$$

Formula 3.1 is subjected to the assumption that a maintenance action restores a component to an 'as good as new' situation or replaces a component entirely.

3.2 Modeling the usage based maintenance policy

Océ uses both scheduled and unscheduled downs as maintenance opportunities; therefore a model that uses both types of downs is developed. When studying the literature[6], only one model was encountered that used both types of downs. This is the model in chapter 4 of the thesis of Zhu (2015). The model can be explained with the help of a timeline:

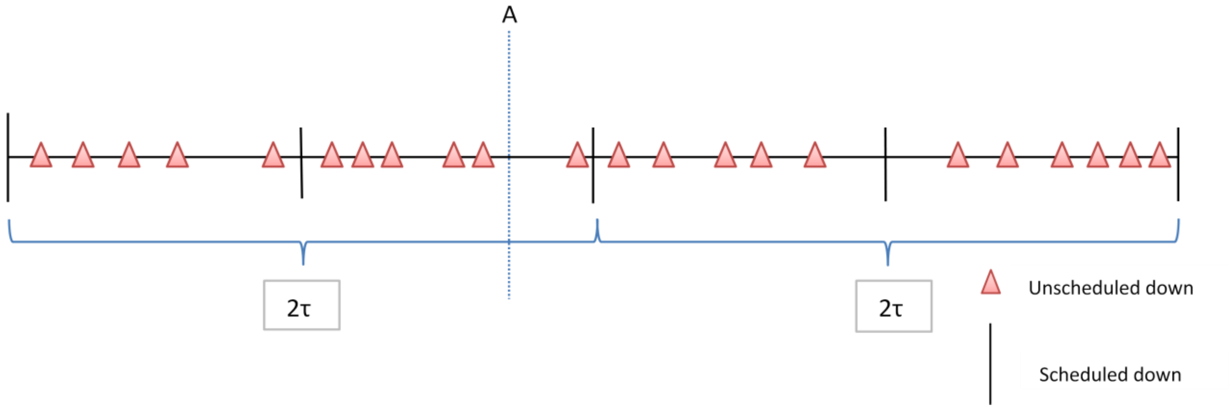


Figure 8 Timeline of an age-based maintenance policy with unscheduled and scheduled maintenance opportunities

For a certain component a moment is set after which the component will be preventively replaced (for the example on the timeline this is at time 2τ) The model then assumes there are a fixed amount of scheduled downs (the black bars) per year at time τ and a variable amount of unscheduled downs (the red triangles). The arrival of the unscheduled downs is presumed to follow an exponential distribution based on the Palm-Khintchine theorem: it states that even if the failures of some components do not follow an exponential distribution, the combination of a large amount of non-Poisson processes will still have Poisson properties (Ross, 1996). The age limit (A) is included as decision variable. After this point in time all the downs will be regarded as maintenance opportunities. Variable A lies at a certain point in time before the fixed replacement time 2τ. The model also assumes that the first occurring opportunity can be taken, regardless whether it is a scheduled or an unscheduled down.

However when looking at the situation of Océ, this last assumption is not true. In practice it is not always possible to conduct an extra maintenance task during an unscheduled down. This can be due to many reasons, e.g. not carrying the proper tools or materials or by lack of time, either from the customer or the FST. The most important reason is whether the customer agrees to it or not; an extra action implies longer (unplanned) downtime of the machine that might influence the production deadline of the customer. To include the possibility of not being able to take a maintenance opportunity, the model as presented by Zhu is extended with an extra variable: the probability a USD is accepted as a maintenance opportunity.

Some more side notes: there will be no limitations on the tasks that are carried out during a scheduled down because this was planned in advance so adequate time and material will be available. Lastly, like with corrective maintenance, the cost of the component has to be considered to prevent waste of life of expensive components. The cost of component was neither included in the model from Zhu (2015). To conclude: the model as developed by Zhu (2015), chapter 4 of his thesis, is used to model the usage based situation. Two variables are added: the cost of component and the probability an opportunity is accepted by the customer.

[6] the literature study is included in Appendix B

3.2.1 **Model description**

We consider an age-based maintenance policy for a single component in a multi-component system, making use of both scheduled (SD) and unscheduled downs (USD). The component is referred to as an UBM component (Usage Based Maintenance). Three kinds of actions can be conducted on this component:

1. Preventive maintenance at an USD ;
2. Preventive maintenance at a SD;
3. Corrective maintenance.

It is often cheaper to have scheduled downs instead of unscheduled downs, but it is also disadvantageous to replace too early because of wasted lifetime of a component. Hence, a decision has to be made whether to take the opportunity of joint maintenance actions or not (Zhu, 2015). The Age limit (A) is the main part of this decision. A is a limit set at a certain fixed point before the planned maintenance after which (un)scheduled downs are considered opportunities, so:

- If an opportunity at SD or USD appears at time $t < A$, do nothing at this opportunity;
- If an opportunity at USD appears at time $t \geq A$: take this opportunity if possible;
- If an opportunity at SD appears at time $t \geq A$: always take this opportunity to do preventive maintenance.

The interval between two consecutive maintenance actions is a maintenance cycle. For the UBM policy the moment of maintenance actions is a fixed moment and this moment does not get rescheduled when an action is performed earlier during an opportunity. To take this into account, the deviation of a SD is denoted with ξ. ξ indicates that the new maintenance cycle starts some time unit away from the previous SD and lies somewhere between 0 and $n\tau$. It follows a certain distribution and is used to approximate the behavior of the deviation.

The notation used is as follows:
τ : $moment\ of\ scheduled\ down$
λ : $arrival\ rate\ of\ USD\ (poisson\ process)$
λ_t : $arrival\ rate\ of\ USD\ (poisson\ process)\ in\ time\ interval\ t$
ξ : $the\ deviation\ from\ the\ SD$
A : $Age\ limit\ of\ the\ UBM\ component$
c^{USD-PM} : $cost\ of\ the\ replacement\ of\ an\ UBM\ component\ at\ an\ USD$
c^{SD}: $cost\ of\ the\ replacement\ of\ an\ UBM\ component\ at\ a\ SD$
c^{USD}: $cost\ for\ replacement\ of\ the\ UBM\ component\ at\ breakdown$
c^{COM}: $cost\ of\ the\ component$
$f(u)$: $p.d.f.\ of\ the\ lifetime\ distribution\ of\ the\ UBM\ component$
$g(s)$: $p.d.f.\ of\ the\ exponential\ distribution\ with\ parameter\ \lambda$
$K(A)$: $expected\ cycle\ cost\ of\ the\ UBM\ component$
$L(A)$: $expected\ cycle\ length\ of\ the\ UBM\ component$
$n\tau$: $moment\ of\ planned\ maintenance\ on\ a\ component$
$P(Y)$: $probability\ of\ taking\ the\ opportunity\ when\ t \geq A$
SEV : $costs\ for\ severe\ consequences\ of\ breakdown$
u : $moment\ of\ breakdown\ of\ component$
$Z(A)$: $Average\ cost\ rate\ of\ the\ UBM\ component$
$z(s)$: $p.d.f\ of\ the\ erlang\ distribution\ with\ parameters\ k\ and \lambda_t$

Subjected to four assumptions:

1. The lifetime of the UBM component is independent of SDs and USDs caused by other components in the system;
2. The time horizon is infinite;
3. Maintenance actions restore components to a state as good as new;
4. $c^{SD} \leq c^{USD-PM} < c^{USD}$.

As for the corrective policy, the expected cycle costs are divided by the expected cycle length to get the costs per time unit:

$$Z(A) = \frac{K(A)}{L(A)} \tag{3.2}$$

There are three types of visits that occur in several scenarios and the probability of occurrence is multiplied with the corresponding cost and cycle length. These are added together to yield the ECC and ECL. Also the cost of component is added again as a depreciation cost. Therefore the ECC is defined as:

$$K(A) = P_1 * (c^{USD} + SEV) + P_2 \ * c^{USD-PM} + P_3 * c^{SD} + c^{COM} \tag{3.3}$$

And $P_1 + P_2 + P_3 = 1$
P gives the probability a certain scenario will occur, together they have to be equal to one because something has to happen in the end.

The ECC and ECL are evaluated on the approximate distribution of ξ. ξ for the next maintenance cycle can be any possible value in $[0, n\tau)$. All the values have an equal probability of occurrence since the arrival of opportunities is assumed to follow an exponential distribution. Also the action is always performed at the SD if it is not performed earlier. Therefore ξ is equally distributed between 0 and $n\tau$ and is assumed to follow an uniform distribution:

$$H(\xi) = \begin{cases} 0 & if \ \xi < 0 \\ q + \frac{(1-q)\xi}{n\tau} & if \ 0 \le \xi < \tau \\ 1 & if \ \xi \ge \ \tau \end{cases} \tag{3.4}$$

q is the probability a maintenance cycle ends with an SD. To obtain q, the probabilities are first calculated exactly for a given ξ, then these conditional probabilities are multiplied with $f(\xi)$ tot get the unconditional probabilities:

$$P_1 = \dot{P}_1(0)q + \int_0^{n\tau} \frac{\dot{P}_1(\xi)(1-q)}{n\tau} d\xi \tag{3.5}$$

$$P_2 = \dot{P}_2(0)q + \int_0^{n\tau} \frac{\dot{P}_2(\xi)(1-q)}{n\tau} d\xi \tag{3.6}$$

$$P_3 = \dot{P}_3(0)q + \int_0^{n\tau} \frac{\dot{P}_3(\xi)(1-q)}{n\tau} d\xi \tag{3.7}$$

P_1, P_2 and P_3 are respectively the probability a CM action, an USD or SD are used. q can be obtained with an iterating procedure, starting with $\dot{P}_3(\xi)$, where $\dot{P}_3(\xi)$ is the probability an SD is used for the maintenance action (and $\xi = 0$). This procedure is described in Appendix D The ECL also is approximated with $f(\xi)$:

$$L(A) = \dot{L}(A|\xi = 0)q + \int_0^{n\tau} \frac{\dot{L}(A|\xi)(1-q)}{n\tau} d\xi \tag{3.8}$$

Where $\dot{L}(A|\xi)$ consist of all individual cycle lengths per probability:

$$\dot{L}(A|\xi) = \dot{L}(A|\xi, in\ 1.1)P_{[1.1]} + \dot{L}(A|\xi, in\ 2.1)P_{[2.1]} + \dot{L}(A|\xi, in\ 2.2)P_{[2.2]} + \dot{L}(A|\xi, in\ 3.1)P_{[3.1]} + \dot{L}(A|\xi, in\ 3.2)P_{[3.2]} \tag{3.9}$$

The cycle length consists of five parts. This is due to three possible scenarios (depending on the moment of breakdown) in which different maintenance possibilities can occur. The three scenarios:

1. $u \le A$ Breakdown occurs before the age limit is reached. Hence no visits were regarded as opportunities and a corrective maintenance action is performed;

2. $u > n\tau - \xi \ and \ u > A$ Breakdown occurs after the age limit and after the planned down. The maintenance action is either conducted during the planned down, or during an unscheduled down if an unscheduled opportunity that is accepted occurs;
3. $u \leq n\tau - \xi \ and \ u > A$ Breakdown occurs after the age limit but before the planned down. If no opportunity of an unscheduled down occurred that could be accepted, a corrective action is performed.

In total five probabilities are needed to calculate all possibilities, they are related to the type of down in the following way:

$$\dot{P}_1(\xi) = P_{[1.1]} + P_{[3.2]}$$
$$\dot{P}_2(\xi) = P_{[2.2]} + P_{[3.1]}$$
$$\dot{P}_3(\xi) = P_{[2.1]}$$

The probabilities and cycle length per scenario can be obtained by the equation 3.10 till A3.19. The derivation with the extra variable $P(Y)$ is included in Appendix E. An 'A' in front of an equation number indicates the derivation is included in the Appendix.

SCENARIO 1: $u \leq A$

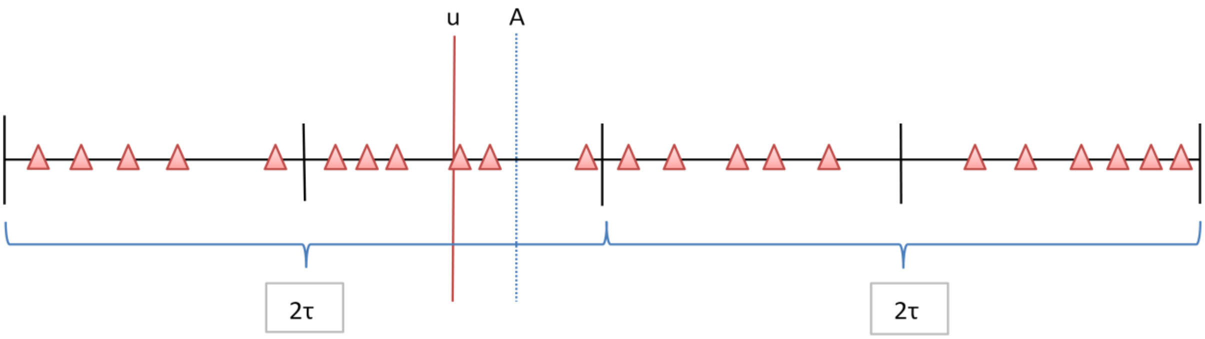


Figure 9 Timeline of an age-based policy with u before A

<u>Possibility 1.1</u>: a failure occurs at time $u \leq A$ so no opportunities are taken and a corrective maintenance action is performed. This happens with probability:

$$P_{[1.1]} = \Pr\{u < A\} = \int_{u=0}^{u=A} f(u)du \tag{3.10}$$

Contribution to expected cycle length:

$$\dot{L}(A|\xi, in\ 1.1)P_{[1.1]} = \int_{u=0}^{u=A} uf(u)du \tag{3.11}$$

SCENARIO 2: $u > n\tau \ and \ u > A$

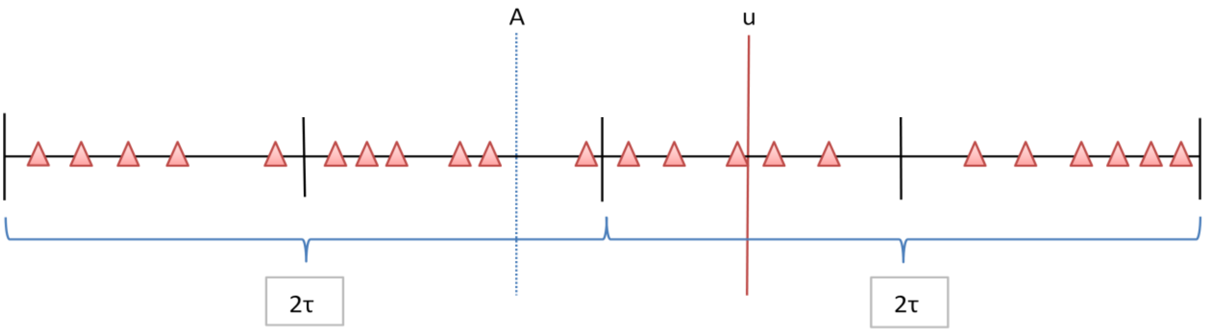


Figure 10 Timeline of an age-based policy with u after nτ

Possibility 2.1: the component doesn't fail before the SD ($n\tau$) and no USD that was accepted occurred after A. In this case the action is performed during a scheduled down.

$$P_{[2.1]} = \int_{u=n\tau-\xi}^{u=\infty} [\sum_{k=0}^{\infty} (1-P(Y))^k \frac{e^{-\lambda_t} {\lambda_t}^k}{k!}] f(u)du \tag{A3.12}$$

With $\lambda_t \ = \lambda(n\tau - A - \xi)$.
Since in this possibility the maintenance is performed at the scheduled down, the cycle length is $n\tau - \xi$. So the contribution to the expected cycle length:

$$\dot{L}(A|\xi \text{ , } in \text{ } 2.1) P_{[2.1]} = (n\tau - \xi) \int_{u=n\tau-\xi}^{u=\infty} [\sum_{k=0}^{\infty} (1-P(Y))^k \frac{e^{-\lambda_t} {\lambda_t}^k}{k!}] f(u)du \tag{A3.13}$$

Possibility 2.2: When an USD does occur before the SD and the opportunity is taken, the probability becomes:

$$P_{[2.2]} = \int_{u=n\tau-\xi}^{u=\infty} (P(Y) \sum_{k=1}^{\infty} [(1-P(Y))^{k-1} * \sum_{a=k}^{\infty} \frac{e^{-\lambda_t} {\lambda_t}^a}{a!}]) \ f(u)du \tag{A3.14}$$

With $\lambda_t \ = \lambda(n\tau - A - \xi)$
The contribution to the expected cycle length:

$$\dot{L}(A|\xi, in \text{ } 2.2) P_{[2.2]} = \int_{u=n\tau-\xi}^{u=\infty} [P(Y) \sum_{k=1}^{\infty} (1-P(Y))^{k-1} \int_{s=0}^{s=n\tau-A-\xi} (A+s) z_k(s) ds \sum_{a=k}^{\infty} \frac{e^{-\lambda_t} {\lambda_t}^a}{a!}] \ f(u)du \tag{A3.15}$$

with $z_k(s) = \frac{s^{k-1} \lambda_t^k e^{-\lambda s}}{(k-1)!}$ the density function of the Erlang distribution (see Appendix E for explanation on the Erlang distribution).

SCENARIO 3: $u \ \leq \ n\tau \ - \ \xi$ *and* $u \ > \ A$

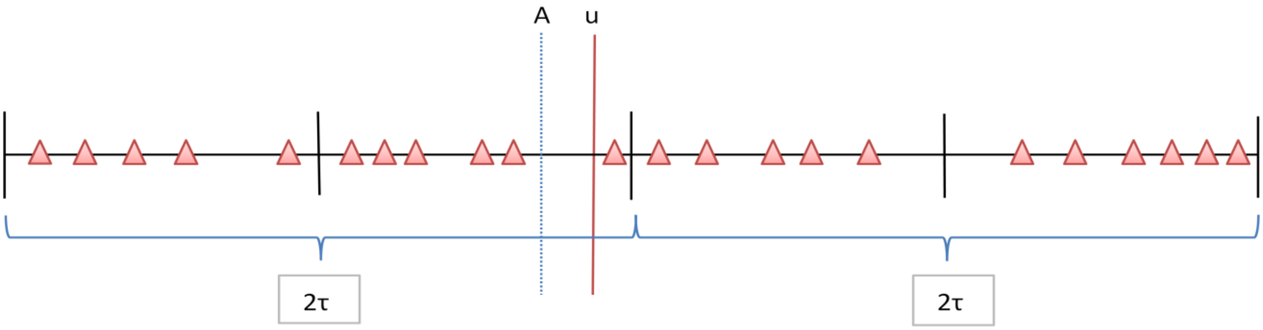


Figure 11 Timeline of an age-based policy with u between A and nτ

Possibility 3.1: when a failure occurs before a SD and an accepted USD occurs after A but before u, the action is conducted during this unscheduled down. Again, the formula is extended to include $P(Y)$:

$$P_{[3.1]} = P(Y) \int_{u=A}^{u=n\tau-\xi} \sum_{k=1}^{\infty} (1-P(Y))^{k-1} * \sum_{a=k}^{\infty} \frac{e^{-\lambda_t} {\lambda_t}^a}{a!} f(u)du \tag{A3.16}$$

With $\lambda_t = \lambda(u - A)$.
Contribution to cycle length:

$$\dot{L}(A|\xi, in \text{ } 3.1) P_{[3.1]} = \int_{u=A}^{u=n\tau-\xi} [P(Y) \sum_{k=1}^{\infty} ((1-P(Y))^{k-1} \int_{s=0}^{s=u-A} (A+s) z_k(s) ds \sum_{a=k}^{\infty} \frac{e^{-\lambda_t} {\lambda_t}^a}{a!})] \ f(u)du \tag{A3.17}$$

with $z_k(s) = \frac{s^{k-1}\lambda_t^k e^{-\lambda s}}{(k-1)!}$ the density function of the Erlang distribution

Possibility 3.2: when a failure occurs before a SD and no accepted USD occurs after A and before u, a corrective action happens. The corresponding probability is:

$$P_{[3.2]} = \int_{u=A}^{u=n\tau-\xi} \sum_{k=0}^{\infty} \left(1 - P(Y)\right)^k \frac{e^{-\lambda_t}\lambda_t{}^k}{k!}) f(u)du \qquad \text{(A3.18)}$$

With$\lambda_t = \lambda(u - A)$
Contribution to cycle length:

$$\dot{L}(A|\xi \text{ , } in \text{ } 3.2)P_{[3.2]} = \int_{u=A}^{u=n\tau-\xi} [\sum_{k=0}^{\infty} \left(1 - P(Y)\right)^k \frac{e^{-\lambda_t}\lambda_t{}^k}{k!}] u f(u)du \qquad \text{(A3.19)}$$

4 Condition based maintenance

This chapter presents a mathematical model to compute the costs per time unit for a condition based maintenance policy. Also it is described how condition based thresholds can be determined from data. Thereby this chapter contributes to the answer to research question 2:

'How can be determined if condition based maintenance is possible and if this is the optimal option?'

Usage based and condition based maintenance are both a way of preventive maintenance, but usage based is a more static way. The planned moment is based on average values and does not consider the actual state of a component and if replacement was really needed; the moment is static and is not adapted per case (Mann, Saxena, & Knapp, 1995). Condition based maintenance does regard the state of component and has no static replacement times. First the idea behind condition based is explained, after that the model is described and the obtaining of thresholds is explained.

4.1 Modeling the condition based maintenance policy

With condition based maintenance a certain feature of a component is measured that shows the degradation state of the component. This degradation state is used to establish two thresholds: a 'warning' threshold to indicate the breakdown is coming and the threshold when the component is considered to be broken down. The thresholds can be depicted as a Markovian[7] model with three states as shown in Figure 12:

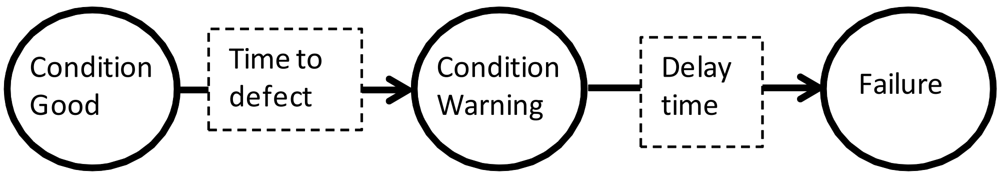


Figure 12 The delay time model as a Markovian process. Redrawn from (Arts, 2015)

The first state is a component in good condition, after some time the process enters the condition warning state and after some more time the failure state is reached. The time between warning and failure is called the delay time. The delay time model is a special case of a Markovian degradation process because it assumes that failing of a component consists of two stages: firstly it becomes recognizable as defective and then it fails after a certain time interval (Baker & Christer, 1994). Respectively these are the warning threshold and breakdown threshold. Note that the component has to be replaced somewhere between these thresholds.

The time between the two states can follow any distribution with a finite mean. Hence, there is always an uncertainty left when these distributions are not deterministic. The determining of the distributions is therefore necessary to distinguish the thresholds and their expected time of arrival.

Figure 13 and 14 give two examples of a delay time model. The first figure shows a condition that is slowly degrading, after some point the deterioration get's recognizable and it keeps degrading till it is broken down. The second one shows a situation where at first nothing is changing in the condition of the component. Then an 'event' happens after which the degradation starts and the deterioration is

[7] A Markovian process distinguishes sojourning degradation states and assumes a component moves through them sequentially (Arts, 2015)

measurable. This event can be all kinds of things, an example from Arts (2015): the axel rod of a train hardly degrades unless it is hit by a rock from the tracks (the event) and it gets a small crack. After that the growth of the crack can be predicted from material science until it breaks down (the delay time).

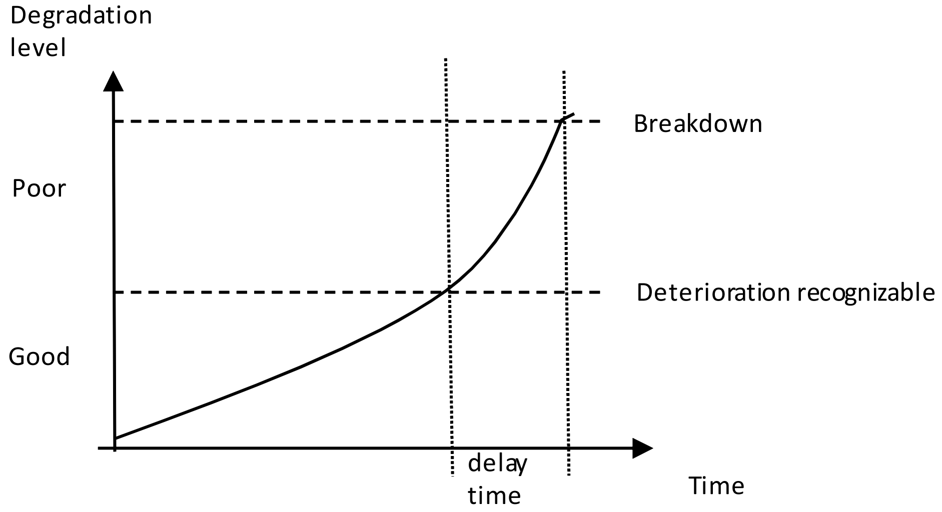


Figure 13 The two stages of breakdown in the delay time model in case of increasing failure rate. Redrawn from (Baker & Christer, 1994)

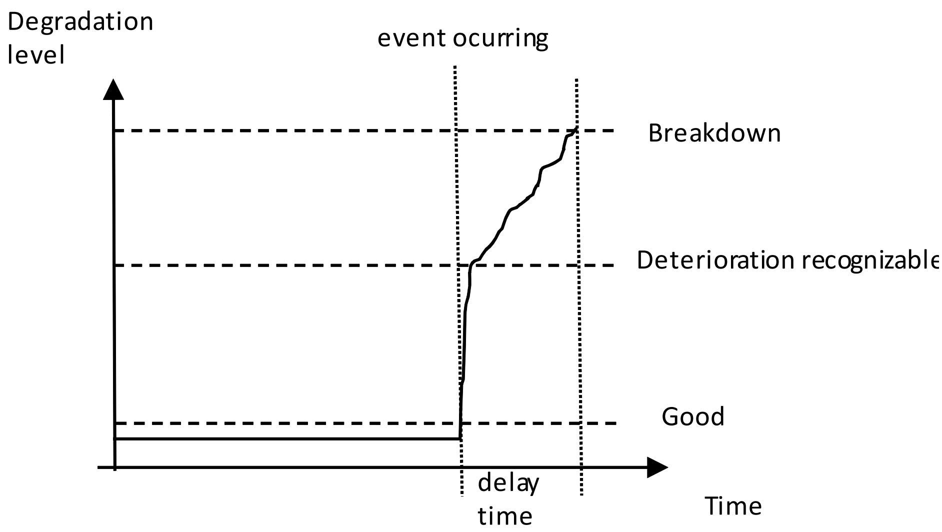


Figure 14 The two stages of breakdown in the delay time model in case of initial constant failure rate

Again the literature is studied[8] to find a model that combines condition based maintenance with opportunities of both unscheduled and scheduled downs. It turns out chapter 3 of the thesis of Zhu (2015) gives the best match. This model is altered the same way as the model of chapter 4 of Zhu (2015): the probability a customer does not accept an extra maintenance action during an unscheduled down is included. The model is explained with the timeline in Figure 15:

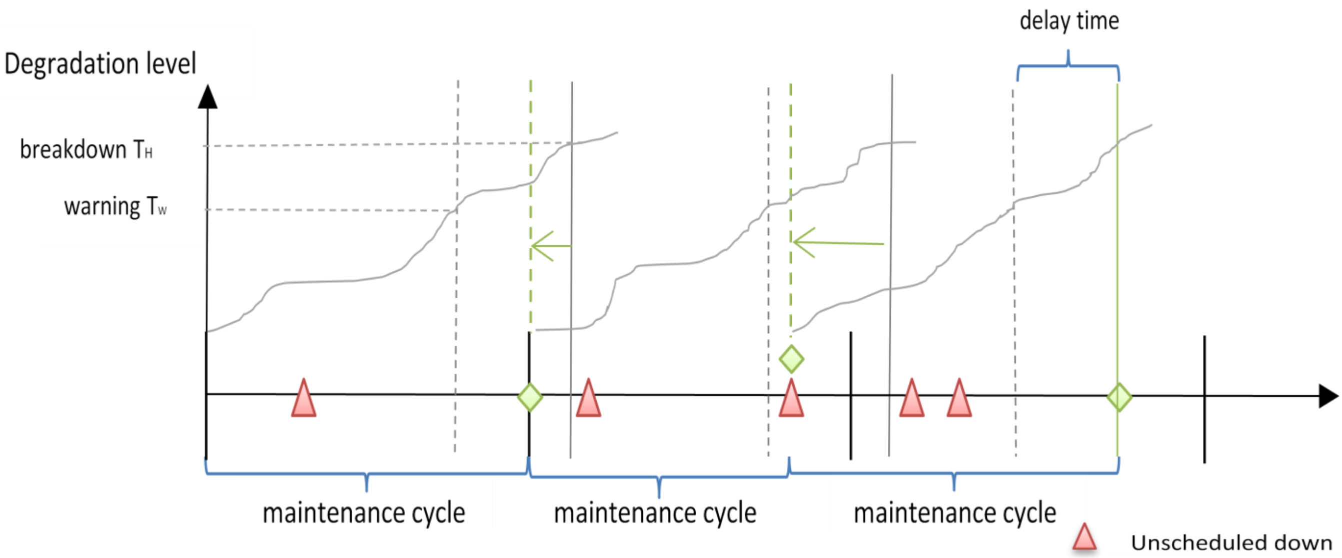
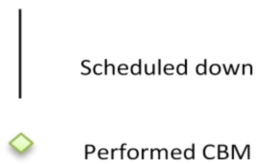


Figure 15 Timeline of a condition-based policy with scheduled and unscheduled maintenance opportunities



The grey, skewed lines represent the condition of the component. At some point in time the condition passes a certain warning threshold. After that point all downs are considered to be maintenance opportunities (the warning threshold can thus be compared to the age limit as used in chapter 3). The red triangles represent an unscheduled opportunity, the black bars a scheduled one. The green diamonds are the moment an action is actually performed. There are three options:

1. A scheduled opportunity occurs first or no occurring unscheduled ones could be accepted and the CBM component is maintained during a scheduled down. The first green diamond depicts this situation;
2. An unscheduled opportunity that is accepted occurs first and the CBM component is maintained during an unscheduled down. The second diamond shows this situation;
3. No opportunity occurred and the CBM component is maintained without using an opportunity. The last green diamond depicts this.

For this last option a new kind of visit is defined: the CBM visit. This is also a scheduled breakdown, only not scheduled a year in advance (like the PM visits that are 4 times per year in the example of the timeline) but a few weeks in advance, depending on the warning threshold. To be clear in terminology used: a CBM visit is the scheduled visit to perform a CBM action without using maintenance opportunities due to another component. A PM visit is one of the 4 yearly scheduled visits.

Although there are still unscheduled downs due to CM components, the ratio of scheduled/unscheduled is expected to change by implementing condition based components: more scheduled and less unscheduled ones.

[8] the study is included in Appendix B

4.2 Model description

This section describes the mathematical model. The model in chapter 3 of Zhu(2015) is used as starting point and is extended with two extra variables: : the cost of component and the probability an opportunity is accepted by the customer.

The system is about a condition based maintenance policy for a single component in a multi-component system, making use of both scheduled (SD) and unscheduled downs (USD). The component is referred to as a CBM component. Three kinds of actions can be conducted for maintenance of a CBM component:

1. CBM at an USD;
2. CBM at a SD;
3. CBM without other maintenance opportunities.

The notation used:

$\tau :$ *Interval of scheduled downs*
$\lambda :$ *arrival rate of USD (poisson process)*
$c^{USD-CBM}$: *PM cost of the CBM component at an USD*
c^{SD}: *PM cost of the CBM component at a SD*
c^{CBM}: *cost of the CBM action without other maintenance opportunity*
c^{COM}: *cost of the component*
$H :$ *breakdown threshold on the degradation level*
$K(W) :$ *expected cycle cost of the CBM component*
$L(W) :$ *expected cycle length of the CBM component*
$P(Y)$: *probability of taking the opportunity when an USD occurs between W and H*
$T_H :$ *occurrence time of breakdown threshold H*
$T_W :$ *occurrence time of warning threshold W*
$v :$ *time of* T_H
$W :$ *warning limit on the degradation level*
$w :$ *time of* T_W
$X(t) :$ *degradation of the CBM component over time t*
$z(s) :$ *p.d.f. of the erlang distribution with parameters* λ_t *and k*
$Z(W) :$ *Average cost rate of the CBM component*
$n \in \mathbb{N}$

Subjected to four assumptions:

1. The lifetime of the CBM component is independent of SDs and USDs caused by other components in the system;
2. The time horizon is infinite;
3. Maintenance actions restore components as new.
4. $c^{SD} < c^{CBM} \leq c^{USD-CBM}$

As for corrective and usage based maintenance, the cost per time unit is computed by dividing the expected cycle cost by the expected cycle length:

$$Z(W) = \frac{K(W)}{L(W)} \tag{4.1}$$

The ECC and ECL are obtained by calculating the probability a certain visit will occur and multiplying these with the corresponding costs and cycle length:

$$K(W) = P_1 * c^{CBM} + P_2 * c^{SD} + P_3 * c^{USD-CBM} + c^{COM} \tag{4.2}$$

$$L(W) = \sum_{n=1}^{\infty} \dot{L}(W, in\ 1.1)P_{[1.1]} + \dot{L}(W, in\ 1.2)P_{[1.2]} + \dot{L}(W, in\ 2.1)P_{[2.1]} + \dot{L}(W, in\ 2.2)P_{[2.2]} \quad (4.3)$$

With:

$$P_1 = \sum_{n=1}^{\infty} P_{[1.2]}$$

$$P_2 = \sum_{n=1}^{\infty} P_{[2.2]}$$

$$P_3 = \sum_{n=1}^{\infty} P_{[1.1]} + P_{[2.1]}$$

Subjected to $P_1 + P_2 + P_3 = 1$

P gives the probability a certain scenario will occur, together they have to be equal to one because something has to happen in the end.

The warning threshold always appears between two scheduled downs and the breakdown threshold can either appear before or after the next scheduled down. This yields two possible scenarios:

1. $(n-1)\tau \leq T_W \leq n\tau$ *and* $T_H < n\tau$ The breakdown threshold is reached before the next scheduled down, hence the component is maintained during the first unscheduled down that could be taken or nothing occurred and a CBM visit is performed;
2. $(n-1)\tau \leq T_W \leq n\tau$ *and* $T_H \geq n\tau$ The breakdown threshold is reached after the next scheduled down. Therefore the component is maintained during the first accepted unscheduled down or during the scheduled down when no other opportunities occurred or could be taken.

The time point of T_W is defined as *w*, T_H as *v*. Note that *v* depends on *w*. Therefore the probability of T_H is a conditional *p.d.f.*. The probabilities and cycle length per scenario can be obtained by formula A4.4 till A4.11. The derivation with the extra variable $P(Y)$ is included in Appendix E. Formulas with an A in front are derived in this appendix. The probabilities and cycle lengths per scenario are given below:

SCENARIO 1: $(n-1)\tau \leq T_W \leq n\tau$ *and* $T_H < n\tau$

Possibility 1.1: since the T_H appears before the PM visit, no opportunity for a scheduled down occurs. However if an unscheduled down occurs, this opportunity is taken with probability:

$$P_{[1.1]} = P(Y) \int_{w=(n-1)\tau}^{w=n\tau} \int_{v=w}^{v=n\tau} \left(\sum_{n=1}^{\infty} \left(1 - P(Y)\right)^{n-1} * \frac{e^{-\lambda_t} {\lambda_t}^n}{n!}\right) f_{T_H|T_W}(v|w)dv f_{T_W}(w)dw \quad \text{(A4.4)}$$

with $\lambda_t = \lambda(v - w)$ and contribution to the cycle length $L(W)$:

$\dot{L}(W, in\ 1.1)P_{[1.1]}$

$$= \int_{w=(n-1)\tau}^{w=n\tau} \int_{v=w}^{v=n\tau} [P(Y) \left(\sum_{k=1}^{\infty} \left(1 - P(Y)\right)^{k-1} * \int_{s=0}^{s=v-w} (w+s) z(s) ds \sum_{a=k}^{\infty} \frac{e^{-\lambda_t} {\lambda_t}^a}{a!}\right] f_{T_H|T_W}(v|w)dv f_{T_W}(w)dw \quad \text{(A4.5)}$$

with $z_k(s) = \frac{s^{k-1}\lambda_t^k e^{-\lambda s}}{(k-1)!}$ the density function of the Erlang distribution (see Appendix E for explanation on the Erlang distribution).

Possibility 1.2: if no unscheduled down appears or the opportunity could not be taken, a CBM action is performed. This happens with probability:

$$P_{[1.2]} = \int_{w=(n-1)\tau}^{w=n\tau} \int_{v=w}^{v=n\tau} \sum_{k=0}^{\infty} ((1 - P(Y))^k * \frac{e^{-\lambda_t} \lambda_t{}^k}{k!}) f_{T_H|T_W}(v|u) dv f_{T_W}(w) dw \qquad \text{(A4.6)}$$

With $\lambda_t = \lambda(v - w)$ and contribution to expected cycle length:

$$\dot{L}(W, in\ 1.2) P_{[1.2]} = n\tau \int_{w=(n-1)\tau}^{w=n\tau} \int_{v=w}^{v=n\tau} \sum_{k=0}^{\infty} (1 - P(Y))^k \frac{e^{-\lambda_t} \lambda_t{}^k}{k!}) f_{T_H|T_W}(v|w) dv f_{T_W}(w) dw \qquad \text{(A4.7)}$$

SCENARIO 2: $(n - 1)\tau \leq T_W \leq n\tau$ *and* $T_H \geq n\tau$

Possibility 2.1: T_H appears after the scheduled down, but if an accepted unscheduled opportunity is the first to occur, this is taken first. With probability:

$$P_{[2.1]} = P(Y) \int_{w=(n-1)\tau}^{w=n\tau} (\sum_{k=1}^{\infty} (1 - P(Y))^{k-1} * \sum_{a=k}^{\infty} \frac{e^{-\lambda_t} \lambda_t{}^a}{a!}) \int_{v=n\tau}^{v=\infty} f_{T_H|T_W}(v|w) dv f_{T_W}(w) dw \qquad \text{(A4.8)}$$

With $\lambda_t = \lambda(n\tau - w)$ and contribution to the expected cycle length:

$$\dot{L}(W, in\ 2.1) P_{[2.1]}$$
$$= \int_{w=(n-1)\tau}^{w=n\tau} \int_{v=n\tau}^{\infty} [P(Y) \sum_{k=1}^{\infty} (1 - P(Y))^{k-1} \int_{s=0}^{s=n\tau-w} (w$$
$$+ s) z(s) ds) \sum_{a=k}^{\infty} \frac{e^{-\lambda_t} \lambda_t{}^a}{a!}] f_{T_H|T_W}(v|w) dv f_{T_W}(w) dw$$

(A4.9)

with $z_k(s) = \frac{s^{k-1} \lambda_t^k e^{-\lambda s}}{(k-1)!}$ the density function of the Erlang distribution.

Possibility 2.2: when no unscheduled down occurred or it gets rejected based on $P(Y)$, the component is maintained during the PM visit. This happens with probability:

$$P_{[2.2]} = \int_{u=(n-1)\tau}^{u=n\tau} (\sum_{k=0}^{\infty} (1 - P(Y))^k * \frac{e^{-\lambda_t} \lambda_t{}^k}{k!}) \int_{v=n\tau}^{v=\infty} f_{T_H|T_W}(v|u) dv f_{T_W}(u) du \qquad \text{(A4.10)}$$

With$\lambda_t = \lambda(n\tau - u)$ and the contribution to expected cycle length:

$$\dot{L}(W, in\ 2.2) P_{[2.2]} = \int_{u=(n-1)\tau}^{u=n\tau} \left[\sum_{k=0}^{\infty} (1 - P(Y))^k P_k(t) \right) \int_{v=n\tau}^{v=\infty} v f_{T_H|T_W}(v|u) dv] f_{T_W}(u) du \qquad \text{(A4.11)}$$

4.3 Determining condition based thresholds

Whether condition based maintenance is possible or not, mostly depends on one thing: is it possible to measure the deterioration of a component? When it can be measured, a warning threshold and breakdown threshold have to be established. In the model in section 4.2, the deterioration of a component is modeled by a conditional probability; the occurrence of the moment of breakdown is dependent on the occurrence of the warning threshold. The time of occurrence of both can follow any distribution with a finite mean. The determining of these distributions is necessary to distinguish the thresholds and their expected time of arrival. Note that this not necessarily has to be equal to the lifetime distribution but is about the behavior of a certain feature of the component that indicates an upcoming failure. To obtain the degradation paths from data, there are two approaches:

1. **The black box approach**; with the black box approach no prior knowledge about the component is needed and pure data mining is used to detect correlation between events. For

example; ‘every time this component broke down, the pressure difference was this high’. Some skill in data mining is required and if this knowledge is not available, it might be considered to outsource the black box data mining to other companies or other external resources.

2. **The white box approach**; with a white box analysis technical knowledge of the component is used to make an assumption of what the data will show prior a breakdown and then analyze the data to see if this assumption is indeed true. The data has to provide the values for the thresholds and the trend line to go with the expectations.

   Of course the expectations can be checked with data from machines in the field, but it is also possible to run lab tests to confirm or reject an expectation. During the lab tests ‘artificial defects’ may be inflicted to a component to speed up the degradation process. This data has to be handled with care though; it is not always a good representation of the degradation due to working of the machine (Elwany, Gebraeel, & Maillart, 2011). However it can help to learn about certain degradation processes. ‘Normal’ lab tests (without artificial inflicted defects) with running on heavy workload and so on are possible as well.

The find the proper distributions to approximate the actual situation might be complicated. Some often used models are the Gamma process, Random Coefficient Model, Brownian Motion or Markov Process. Section 6.5 gives an example of a Random Coefficient Model with linear degradation paths. In case the degradation is not linear, a more generic form to handle conditional probabilities is given in formula 4.12:

$$f_{T_H|T_W}(v|w) = \frac{f(w)f(v)}{R(w)} = \frac{f(w)f(v)}{1-F(w)}, v \in [w, \infty) \tag{4.12}$$

This is a generic function and can be used for all distributions as long as the $p.d.f.$ remains the same after passing T_W.

5 Implementation and verification

Before using the model in practice, is has to be verified if it is working properly. Longo (2011) defined verification as the process of determining that a model implementation accurately represents the developer's conceptual description and specification. First the implementation is described, after that it is verified against the output of Zhu (2015).

5.1 Implementation

The model is implemented in the program R. R is an open source program that can easily be downloaded for free. The input parameters can be submitted in an excel file. The code itself consists of several R scripts and the script as used for the case study in chapter 6, is included in appendix J.

The model is meant to be generic, but it is not implemented for all possible distributions so some side notes have to be made: firstly the conditional probabilities are programmed according to equation 4.12. This formula only applies when the $p.d.f$ does not change after passing the warning threshold. Hence if a component requires two distributions or different parameters to model the degradation, the conditional probabilities have to be rewritten. This will depend on the kind of distribution and does not have a generic form. Secondly the program for UBM and CM is now set at a Weibull failure distribution. When other distributions are used, the distributions have to be adapted in the program.

5.2 Verification

The results from Zhu (2015) are used for the verification of the implementation of the model. When $P(Y)$ and c^{com} are set to respectively 1 and 0, the R program should yield the same results as chapter 3 and 4 from the thesis of Zhu. The numerical example with the parameter setting as presented in Table 1 is used for UBM.

Parameter	*Value*
c^{USD}	2
c^{SD}	10
c^{USD-PM}	1
c^{com}	0
$n\tau$	0.6
α	1.129
β	2.101
λ	2
$P(Y)$	1
A	0.4
q	1

Table 1 Parameter setting for verification of the UBM model

The R program yields $Z(A) = 5{,}08$, Zhu (2015) had a output of $Z(A) = 5{,}18$. This small deviation can be explained by the q that is set at 1 for the R program and is optimized in the implementation of Zhu.

The CBM implementation is tested against the random coefficient case as presented by Zhu (chapter 3 of this thesis). The parameters are set as follows:

Parameter	*Value*
c^{USD}	44500
c^{SD}	26500
c^{USD-PM}	28800
c^{com}	0
c^{CBM}	44500
α	0.159
β	3.73
λ	0.00886
τ	91
$P(Y)$	1
H	88
W	75.43

Table 2 Parameter setting for verification of the CBM model

Both yield $Z(W) = 45.09$. Thereby both implementations (UBM and CBM) are verified and it is concluded they are working correctly.

6 Case study on the inkhandling function of the VPi300

After developing the models for all three policies, it is time to test it in practice. Therefore a case study is conducted on the VPi300 machine of Océ. This chapter elaborates on research question 3:

'How can the framework be applied to an Océ machine?'

Since the VPi300 is a very large machine that consists of many components, it is decided to start with a part of the machine. Together with Océ it has been decided to focus on the inkhandling function. Inkhandling is located through a big part of the machine, from the supply cans to the printhead till the clean tray. Also the liquids to clean the system, AML and PML, are considered to be part of inkhandling. For this function it is investigated how thresholds are currently determined and if it is possible to measure component degradation with remote data. After this the parameter values are determined to be able to run the model. The inkfilter is selected to calculate the optimal policy and a sensitivity analysis is performed to show the influence of some parameters and to show their optimal value. Since no trends could be obtained from the remote data yet, a dummy case is presented to illustrate a CBM case. Finally the overall conclusions on the sensitivity analysis are stated together with suggestions how parameters could be optimized for Océ.

6.1 Thresholds and available (remote) data for the inkhandling function

The inkhandling function involves everything to get the ink from the supply cans to the printhead and the waste ink after printing. After leaving the supply cans, the ink is filtered with inkfilters to remove small particles. Additionally the ink gets degassed on the way to the printheads to prevent air bubbles of getting in the printheads. Then the ink enters the printhead module and is jetted on paper. The inkhandling function does not include the printheads and paper part, but it does include the handling of the waste ink after printing. The waste ink is collected in an ink tray and deposited in a waste can. The ink is moved through the machine by ink pumps and pressure differences. To provide under pressure, the inkhandling function contains an air pressure cabinet as well. This cabinet regulates the pressure differences and filters the air in the ink cabinet to keep it free from small particles.

Currently seven components of inkhandling are maintained with a preventive policy. According to function specialists and service specialists the replacement thresholds for these components are based on two things: experience from a similar component in other machines or an estimate made by the function specialists. The ink used in the VPi300 is a newly developed liquid, therefore a lot of the components are new or only known a bit from the Colorstream machine that was developed slightly before the VPi300 by an Océ location in Germany.

Next the remote data for the inkhandling function is examined. The machine is not out in the field long enough to provide enough data to spot trends. Or, one could say not enough components have failed during the time in the field. Due to this lack of data it is not yet possible to examine black box what trends indicate an upcoming failure. Therefore the approach was white box and the function specialists were asked what they expect to be indications of failures. This is not limited to the components that are currently maintained preventively, but the entire inkhandling function is examined. The following options are mentioned:

1. Pump activity; it is measured whether a pump is active or inactive. For each pump the time between activities and the duration of an activity can be subtracted from the data. If a pump has to turn longer or more often, this can indicate that either the pump is not working properly anymore, or the filters are getting stuffed and it takes longer to pass the

same amount of liquid. Pump activity may also increase due to increased printing activity, hence the pump activity should be measured relatively to the printing activity. The data has to be analyzed for trends to determine thresholds.

2. Micro filter pressure unit; the air pressure cabinet contains a micro filter that has to be replaced after two years. This filter is not manufactured at Océ, but bought from the company Festo. Although no remote data is measured by Océ, the manufacturer (Festo) implemented a way to measure pressure differences. When the differences get too high, an electrical signal is triggered and a red sign pops up to indicate the filter needs replacement. Currently this trigger is not used because the module is located inside the machine and cannot be seen without opening up. If a connection can be made between the signal and the remote data of the VPi300, this trigger can be used as a threshold for CBM.
3. Pressure differences; as with the micro filter in the pressure unit, a measurement of the pressure differences before and after the ink filter could tell something about the filter. However the pressure in not measured in the remote data and therefore this is not possible yet. It is advisable to consider this option and maybe implement a way to measure the pressure differences. The micro filter can be used as example of how to handle this.

As for the other components of inkhandling; it is expected that there are no condition based opportunities. However, black box data analysis may provide other options in the future.

6.2 Determining parameter values for the inkfilters

The ink filters are selected to run the model and perform the sensitivity analysis on. This because it is expected in the future there will be a condition based option and although there was no failure data available from the VPi300, there is data from another machine that uses the same filters. In this section all the parameters as needed for the model are presented.

6.2.1 **Lifetime distribution $f(u)$**

Océ expects the filters will break down due to clotting and not because of chemical reaction with the medium. The threshold is set at 12 months but this is much before the expected breakdown of the filter. The threshold is set so early because although a filter is a small and relatively cheap part of the total machine, a breakdown can have severe consequences for the rest of the machine. Right now it is not checked at replacement whether a filter is really clotted or not. Since there is not much known about the behavior of the filters, it is advisable to check this in order to make better predictions in the future.

The fit showed the data from the Colorstream follow a **Lognormal distribution** with **μ = 6,0275** and **σ = 1.2547**. The shape of this distribution is a bit similar to a Normal one; only the bell shape can be skewed and is not always symmetrical. The data is handled as right-handed suspended[9], grouped data. The data is suspended for two reasons:

1. Some filters are replaced preventively. So the ink filters are replaced before they really broke down and the actual failure time lies somewhere behind the point of replacement;
2. Not all filters have failed at the end of 2015. Weibull ++6 regards the last entered failure time as the end of the 'test period' and expects this period to end when all parts have failed. Since this is not the case, all the remaining components have to be marked as 'suspended' because their failure time lies behind the end of the test period. Ebeling (2010) refers to this as 'type I censoring'.

[9] 'suspended' is sometimes referred to as 'censored' in literature as well.

The data is grouped because multiple filters are replaced at the same time. The output of the fitting procedure is included in Appendix F. Appendix H includes a general explanation on data gathering and fitting to a distribution. Appendix G gives several distributions with the corresponding features and goodness-of-fit test.

6.2.2 Arrival rate λ and number of planned downs τ

For the model it is assumed the arrival rate will follow an Exponential distribution, based on the Palm-Khintchine theorem. It is expected this rule is applicable to the VPi300 as well. When applying this rule, one has to be sure there is not one component with significant large influence on the arrival of unscheduled downs that does not have an exponential lifetime distribution. Since for the VPi300 it is expected around 960 components will contribute to the arrival of unscheduled downs with none of them a contribution higher than 0.1 on a total of 22.4("private communication", 2014), the USD downs are expected to arrive according to a Poisson process. Unfortunately, no data for the VPi300 machine is available to fit a distribution to, so the estimations of the technicians are used. However appendix I includes a fit of failure data from the V600 machine to show how this can be done and that the assumption of exponential arrivals is suitable for other Océ machines. This appendix also includes an explanation about the exponential distribution and why it should be suitable for the arrival of unscheduled downs.

Because a data fit was not yet possible, λ is determined with the so called 'CM-rate' as defined by Océ. The CM-rate is defined per function based on the failure rates as expected by function specialists. It indicates how many times per year they expect the function will cause a CM-visit. It sums up to 22.4 expected CM-visits per year. Since everything will be calculated in weeks, the arrival rate has to be in weeks too. Additionally the arrival rate of all components, minus the inkfilters is needed. The inkfilters are expected to contribute 0.01 to the total CM-rate, hence the arrival rate per week[10]:

$$\lambda_{inkfilters} = \frac{22.39}{52}\ per\ week$$

The number of planned downs is fixed by Océ at four per year, hence one every 3 months or 13 weeks.

6.2.3 Costs[11]

The costs consist of three parts, depending on the kind of visit it is: setup costs, machine downtime costs and a penalty cost. First the setup costs are considered. The setup costs are only incurred when a FST has to go to the customer especially for that component. In case of a combined visit – so during a PM or corrective visit for another component - the setup costs are already incurred for that other component and are considered to be 'sunken cost'; they are made anyway, no matter if the extra action is conducted or not. The setup costs differ, depending on the kind of contract the customer has. There are 3 options:

1. € 112 for service window 1;
2. € 168 for service window 2;
3. € 224 for service window 3.

The setup cost for a scheduled down are always equal to the cheapest response contract.

[10] It is possible to divide by 52 because the exponential distribution is memory less and in every week a call has the same probability of arrival

[11] due to confidentiality reasons, the costs values are fake values

Next is the machine downtime cost. Océ suffers losses if the customer is unable to produce on a printer because less consumables are purchased at Océ. These losses are determined at €360. - per hour. In case of an unscheduled down these losses are raised with a penalty cost to include the customer preference in the model (customers prefer a planned down, so for Océ this is also preferred to improve customer satisfaction). This penalty cost is set in cooperation with Océ at 1/3 of the losses, so an additional €120.-.

Lastly an extra penalty cost is included for a corrective visit to put some extra 'weight' to these kinds of visits in the model. This cost is set at €200. - and is only incurred at a corrective visit when a component breaks down, not if a preventive action is performed during a corrective visit for another component.

So in total the following parts are obtained to compute the cost per kind of visit:

$$S = Setup\ cost = \begin{matrix} €112 \\ €168 \\ €224 \end{matrix}$$
$$c_{sys}^{U} = losses\ due\ to\ unscheduled\ system\ down\ time\ per\ hour = €480$$
$$c_{sys}^{S} = losses\ due\ to\ scheduled\ down\ time\ per\ hour = €360$$
$$P = penalty\ cost\ for\ corrective\ visit = €200$$

With the corresponding costs:

$$c^{PM-USD} = c^{CBM-USD} = c_{sys}^{U} = €480,-$$
$$c^{PM-SD} = c^{CBM-SD} = c_{sys}^{S} = €360,-$$
$$c^{CBM} = S + c_{sys}^{S} = €472$$
$$c^{CM} = S + c_{sys}^{U} + P = \begin{matrix} €812 \\ €848 \\ €904 \end{matrix}$$

The cost of component (c^{COM}) differs per component and is equal to the costs Océ incurs for this component, or the purchase costs. For the inkfilters this is equal to €76,-

6.2.4 Age limit A and planned moment $n\tau$

The inkfilters are planned to be replaced every year, so after 52 weeks. The age limit lies somewhere before these 52 weeks. Océ uses two times the Mean Copies Between Failure (MCBF) to determine whether a component gets preventively replaced or not. The MCBF depends on the total CM-rate because the time till the next expected visit is depended on the arrival rate of these visits. Since τ and λ are calculated in weeks, A is stated in weeks too. A lies two times the MCBF before the planned maintenance moment, located at $n\tau$. Hence:

$$A = n\tau - \left(2 * \frac{CM_{rate}}{52}\right) \qquad (6.1)$$

The inkfilters are replaced every two years, thus after 104 weeks. The age limit for the inkfilters becomes:$52 - \left(2 * \frac{CM_{rate}}{52}\right) = 51.14$ weeks. Note that this is the age limit according to the usual method within Océ, but does not have to be the optimal value. The sensitivity analysis can give some insight in the optimal value for A.

6.2.5 Probability of taking a maintenance opportunity $P(Y)$

This probability can be approached by a Bernoulli distribution, since it is either conducted or not and each case is independent of another. The estimation of this parameter is very hard though because it involves human behavior of both the customer and the FST. Unfortunately it is for the VPi300 not yet logged how many of the PM actions that passed the age-limit at a CM visit are really conducted or why they are not conducted. However for the VP6300[12] this is logged and this data is used to yield a probability. The FSTs fill out for each visit which PM actions they conducted and which ones they postponed. This data is collected for 11 machines over 2015 and the average over the percentage of accepted jobs is taken. On average 85.70% of the actions is accepted, so $\boldsymbol{P(Y) = 0.86}$

Machine	PM conducted	PM postponed	%
900120169	72	16	0.818182
700110357	135	31	0.813253
900230134	89	5	0.946809
900120171	54	3	0.947368
700110476	46	5	0.901961
700111159	40	3	0.930233
900230199	55	21	0.723684
700110385	74	0	1
700110279	131	34	0.793939
900120168	88	10	0.897959
900120124	32	17	0.653061
		average	**0.85695**

Table 3 percentage of PM actions postponed over 2015 per machine

Furthermore six FSTs were interviewed to hear their opinion on customer's reactions to extra maintenance actions during an unplanned visit. The FSTs were from different European countries (Scotland, Spain, Germany and Sweden) but all customer reactions are about the same. Whether a customer is willing to accept the extra maintenance action depends on his own production deadline. For example if a customer produces products that have to be mailed the same day, it is more likely an extra action is turned down then if the deadline is vaguer like 'somewhere at the end of the week'. Flexibility also depends on the daily production volume of the customer; a higher volume leaves less spare time for other actions. Lastly the duration of the replacement action is of influence; '10 minutes extra' is easier to sell then 2hours.

In addition the FSTs point out that a good relationship with a customer is important. Customers usually hold some kind of 'suspicion' towards a new FST. When a FST is familiar it is easier to communicate and come to agreements about when to conduct an action. Since this 'level of familiarity' is almost impossible to make quantitatively it is not implemented in the model. However it is advisable to try to send the same FSTs to the same customer as much as possible. Especially when it are high-volume customers.

6.3 Case study on the inkfilters

When using the model, one should start by using the decision tree. For the inkfilters the deterioration is not yet measurable. On to the next question: whether they have an increasing failure rate. Since the failures are distributed lognormal, the failure rate has no closed value but will start increasing and could change shape later. Since it starts increasing, the question is answered with 'yes'. As explained

[12] this machine is selected because it resembles the VPi300 best in printing volume per day. The FSTs pointed out volume is the most important factor for a customer to decline.

before, the breakdown of an inkfilter might have severe consequences for the printhead. This leads to the conclusion to use the model but with CBM overruled and a severe option. The overruling of CBM

just means ‘don’t run the CBM script’.

The parameters as determined in section 6.2 and are entered in the excel file as shown in Table 4. Note that severe is still set at 0. This because we first want to look what the model will do in a normal situation. The severe option is tested later in the sensitivity analysis. Furthermore the parameters for the lognormal distribution and the moment of planned maintenance (2 years) are set in weeks. Par1 and 2 refer to the parameters of the failure distribution, in this case the lognormal distribution.

	PY	Severe	CM_rate	nt	par1	par2	number of planned visits	duration	c_cbm	c_usd	c_usd_pm	c_sd	c_com	q	ξ
Value	0.86	0	22.4	52	6.0275	1.246	4	1/4	472	904	480	360	76	1	0

Table 4 Parameter values as entered in the model for the ink filter

Running the tool in this setting yields a cost of €0.54 per week in case of CM and €6.55 in case of UBM. Hence, CM would be the best option. Looking at the failure distribution this would make sense. The lognormal distribution with $\mu = 6.0275$ and $\sigma = 1.246$ has an expected value of $\exp(\mu + 0{,}5\sigma^2) = 901.22\ weeks$, or 17.33 year. So the expected cycle length using a CM strategy would be 17.33 against max. 1 at UBM. The big difference in cycle length outweighs the costal benefits of a scheduled down. Let’s take a look at the individual probabilities per component:

Scenario	*Probability of occurence*
$P_{[1.1]}$	0.046
$P_{[2.1]}$	0.691
$P_{[2.2]}$	0.260
$P_{[3.1]}$	0.0002
$P_{[3.2]}$	0.001
Total	=1

Table 5 Probabilities per scenario and possibility for the UBM policy on the ink filters

Scenario 2 has a probability of (0.691 + 0.260 =) 0.951 of appearing, which makes sense because this was the scenario that the actual breakdown of the component lies behind the planned replacement. Given the failure distribution this is the most likely scenario. A constraint of the model was the probabilities should sum up to 1, what they do.

6.4 Sensitivity analysis with the ink filter data

Table 6 gives an overview of the parameters that are varied in the sensitivity analysis and over what range. CM is only influenced by the option of ‘severe consequences’ because the costs of an USD get higher. These costs also influence UBM and are used to explain the influence of costs chances on the model. The variables are treated in order of the table.

Parameter	Values
Sev	1 till 500 euros
A	1 till 52 weeks
$n\tau$	1 till 52 weeks
λ	1 till 30 visits per year
$P(Y)$	0 till 1

Table 6 Parameter values used in the sensitivity analysis on CM and CBM

The first variables are the costs factors. Changing the costs only changes the numerator part of Z_{cor} and $Z(A)$. The probabilities and expected cycle lengths remain the same. Therefore a euro cost increase is equal to the corresponding probability divided by the expected cycle length:

$$Z_{cor}+ = \frac{1}{MTTF} \; per\ euro \tag{6.2}$$

$$Z(A)+ = \frac{P_i}{L(A)} \; per\ euro \quad i \in \{1, 2, 3\} \; or\ when\ c_{com}\ increases: Z(A)+ = \frac{1}{L(A)} \tag{6.3}$$

The costs for severe consequences of breakdown are used to show the linear increase. These costs are taken into account by adding a penalty cost for severe consequence of breakdown. This penalty cost is not an actual incurred cost, but is used to make an USD even more undesirable in the model. The penalty costs is varied between 1 to 500 euro's for now, but when running the model one could choose to set the penalty cost as the cost of the component that is likely to break down as follow up damage (e.g. in case of the degasser or inkfilters the price of the printheads can be used). Figure 16 shows the increase due to penalty costs is indeed linear. This is correct according to formula 6.2 and 6.3; the penalty cost adds an amount to the numerator of Z_{cor} and $Z(A)$ of $\frac{1}{901.22} = 0.00111$ and $\frac{0.047}{37.15} = 0.001265$ per euro respectively. The costs per time unit of UBM are increasing faster than of CM. Hence, CM is always preferred, no matter how high the penalty cost will get because the lines will never cross. If the estimation of a lifetime of 901.33 is correct, follow up damage is not an argument to use UBM and CM is recommended.

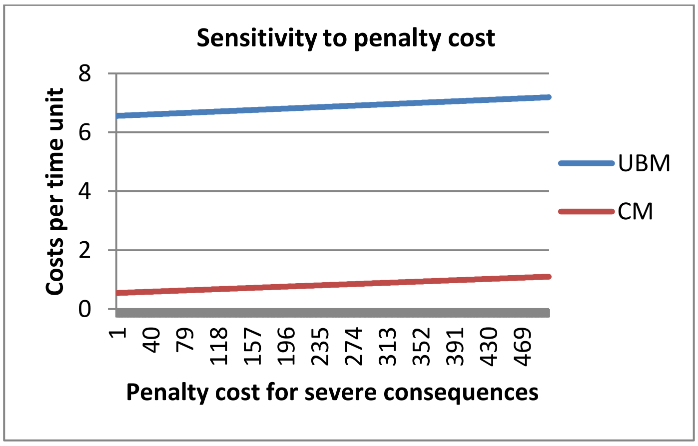


Figure 16 Sensitivity of CM and UBM to the penalty cost of severe consequences of breakdown.

Regarding the matrix presented in Figure 6 and Figure 4 about optimal use of lifetime; it should be UBM costs per time unit increase faster than CM. Let's see if this is correct according formula 6.2 and 6.3. Per euro increase of cost of component $Z_{cor} + = \frac{1}{901.22} = 0.00111$ and $Z(A)+ = \frac{1}{37.15} = 0.0269$, hence $Z(A)$ indeed increases faster.

Next is the age limit. The age limit defines the length of the period in which opportunities are considered. A is varied from 1 week till 52 weeks in advance of the planned maintenance moment. Thus in Figure 17 it means the horizontal axis indicates A is further away from $n\tau$ and it shows the costs per time unit increase when A lies further before $n\tau$. This can be easily explained for the inkfilters: if the time interval between A and $n\tau$ get's longer, there are more occurring opportunities and the maintenance action is likely to be performed far before $n\tau$. The cycle length (the enumerator) decreases and the cost per time unit increases. Furthermore the expected lifetime is so long that it is very unlikely the filter will breakdown before $n\tau$, so a shorter A does not lead to an increased probability of corrective breakdown.

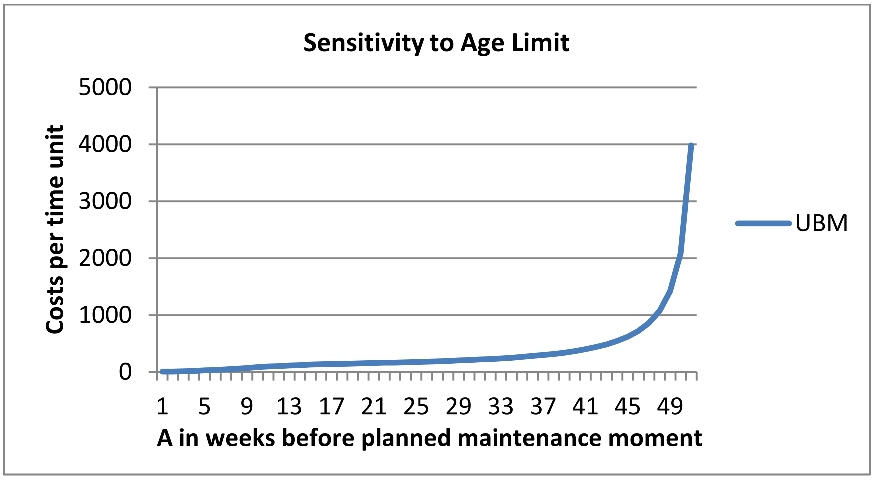


Figure 17 Sensitivity of UBM to the age limit

Then the moment of planned maintenance, that for the inkfilters is set at 52 weeks. Figure 18 shows the costs per time unit are only decreasing when $n\tau$ increases. This can again be related to the long expected lifetime; since CM is the most optimal policy and the formula's for UBM reduce to CM when $n\tau$ goes to infinity.

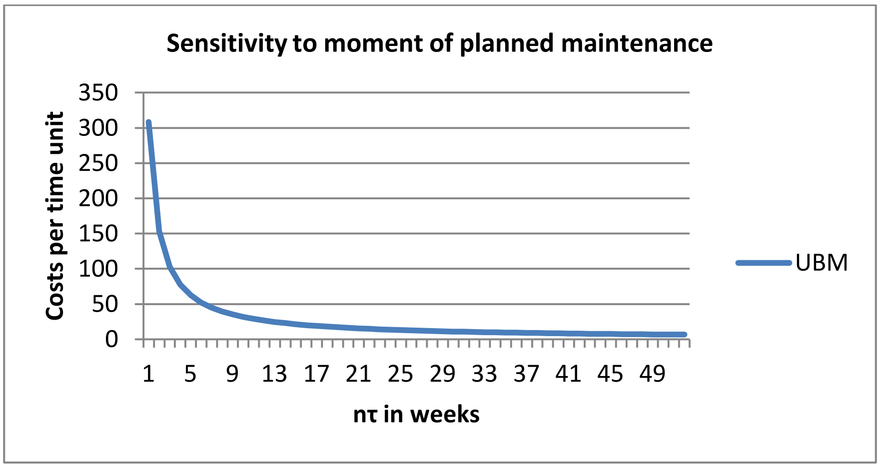
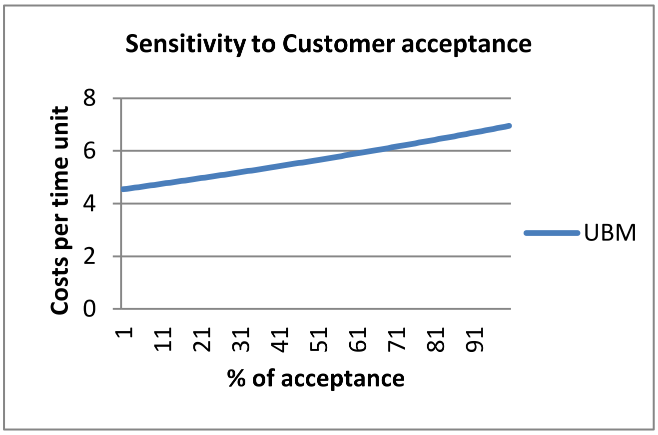


Figure 18 Sensitivity of UBM to the moment of planned maintenance

Lastly the customer acceptance $P(Y)$ and λ are examined. As can be seen in Figure 19, these parameters have the same influence on the cost rate. This makes sense because indirectly they both imply the same thing: it is better if the action is not performed during an USD. A higher acceptance percentage leads to more actions that are performed during an USD. A higher CM-rate means more occurring USDs and thus more actions during an USD. Since SD is the cheapest option and the probability of breakdown is significantly low, costs will increase when more actions are performed during an USD.



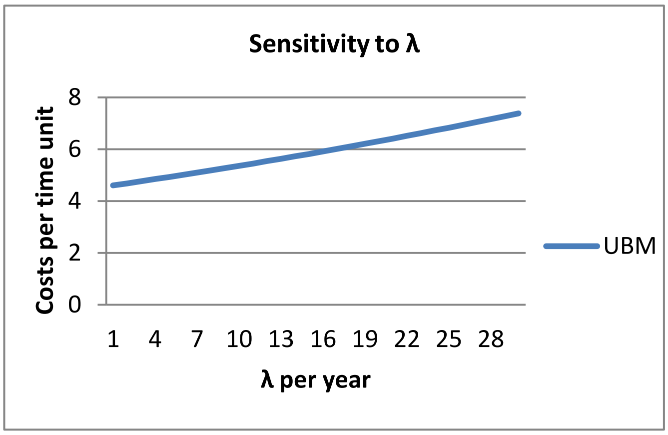


Figure 19 Sensitivity of UBM to customer acceptance and CM-rate per year

6.5 Condition based maintenance dummy case

6.5.1 The dummy parameters

As described in section 6.1 it is unfortunately not yet possible to detect trends in the data and obtain condition based thresholds. Therefore a 'dummy' case is created on the ink filters. All the values are fictional and not based on any real values from the inkhandling module. Hence the conclusion and interpretation of the outcomes are not applicable for Service purposes but are computed to show how the model works and can be used. This should be kept in mind when reading section 6.5.2.

Earlier it was explained the pump activity might indicate something about stuffing of the ink filters. Let's assume this is true and that the data showed a trend of increasing pump activity of the supply pump. This increase only will start after a certain amount of time, presumably after a year since no sign of increase is spotted so far. So the start of the increase lies after 52 weeks and this increase is linearly. Since the increase is linearly, a random coefficient model can be used to approximate the arrival times of the warning and breakdown threshold. A random coefficient model assumes the degradation path (X) of a certain type of component is linear, but this linear path may differ per machine, following a certain distribution. So the arrival of a degradation path at the warning threshold may differ per machine. Capturing this in a generic formula:

$$\chi(t) = a + \theta\hat{t}^b \tag{6.4}$$

The probability the warning thresholds is passed at time t can be written as:

$$\begin{aligned}\Pr\{T_\chi \leq \hat{t}\} &= \Pr\{\, a + \theta\hat{t}^b \geq \chi\} \\ &= Pr\left\{\theta \geq \frac{\chi - a}{\hat{t}^b}\right\} \\ &= 1 - F_\theta\left(\frac{\chi-a}{\hat{t}^b}\right)\end{aligned} \tag{6.5}$$

With t the time the warning threshold is passed and *a* and *b* constant parameters to shape the line. Θ is the slope that follows a certain distribution. Because no knowledge is available about this distribution, it is assumed to be distributed Weibull. The probability density function can then be written as:

$$f_{T_W}(u) = f_{T_\chi}(\hat{t}) = \frac{b\beta\alpha}{\chi - a}\left(\frac{\chi - a}{\alpha \widehat{t^b}}\right)\exp\left(-\left\{\frac{\chi - a}{\alpha \widehat{t^b}}\right\}^{\beta}\right) \tag{6.7}$$

Since the increase is assumed to be linearly, *b* is set to 1. To model that the start of the increase is not at point 0, but starts after some time, *a* is set at minus 20%. Figure 20 and 21 help to understand this. The first figure shows how the degradation path would theoretically behave, in the coefficient model this can be approached by continuing the line till it reaches the y-axis. For now the warning threshold is set at 80% and breakdown at 100%.

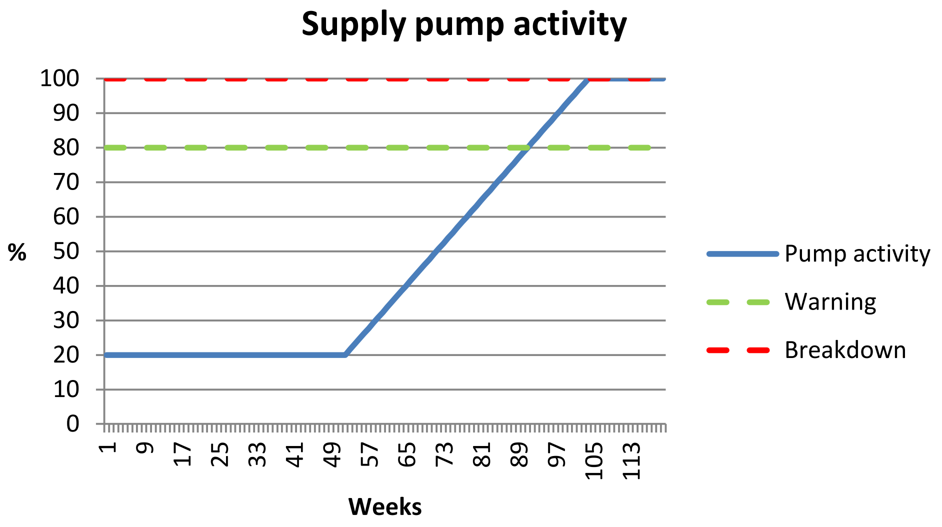


Figure 20 Dummy values to linear increasing supply pump activity

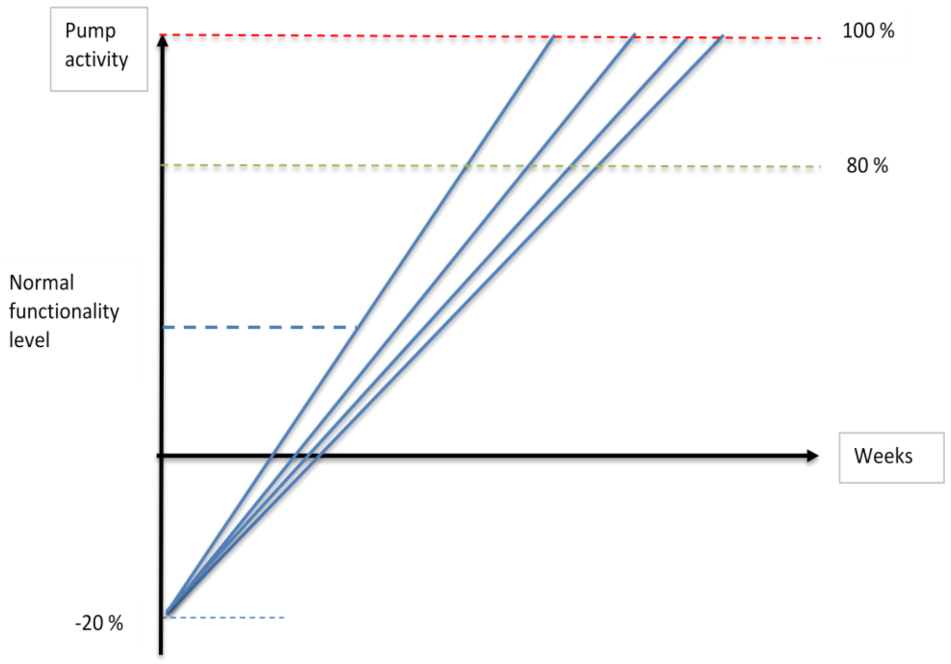


Figure 21 Degradations paths starting at a negative value to delay the start of the decay.

Under the assumption of linear the following holds; once the passing time (T_W) of the warning threshold is known, the exact time of the breakdown threshold can be calculated by $\frac{T_W*(H-a)}{W-a}$. For the calculation of the probabilities of the condition based scenario one only has to know whether T_H will appear before or after the moment of planned maintenance ($n\tau$). The conditional probability $f_{T_H|T_W}(v|u)dv$ thereby reduces to:

$$\int_{v=u}^{v=n\tau} f_{T_H|T_W}(v|u)dv = \begin{cases} 0 & if \ \frac{u*(H-a)}{W-a} > n\tau \\ 1 & if \ \frac{u*(H-a)}{W-a} \leq n\tau \end{cases} \tag{6.8}$$

For scenario 1 because this scenario involves the visits when the breakdown threshold lies before $n\tau$. and:

$$\int_{v=n\tau}^{v=\infty} f_{T_H|T_W}(v|u)dv = \begin{cases} 0 & if \ \frac{u*(H-a)}{W-a} \leq n\tau \\ 1 & if \ \frac{u*(H-a)}{(W-a)} > n\tau \end{cases} \tag{6.9}$$

For scenario 2 because this scenario involves the visits when the breakdown threshold lies after $n\tau$. Note that W is a variable that offers an opportunity for optimization, section 6.5.3 elaborates on this.

6.5.2 **Results of the dummy case**

The model as presented in chapter 4 is run with the values of the dummy case. The distribution of the slope is Weibull with shape parameter 1 and scale parameter 4. All other parameters are set the same as for the inkfilters. Table 7 shows the extra input for CBM as entered in excel.

	par1_war	par2_war	Warning	Breakdown
Value	1	4	0.80	1

Table 7 Extra parameter values as entered in the model for CBM

When entering all parameters, the following output is obtained:

Variable	*Value*
$P_{1.1}$	0.071
$P_{1.2}$	0.917
$P_{2.1}$	0.009
$P_{2.2}$	0.002
	= 1
K_W	504.206
L_W	1.83
$Z(W)$	= €275.30

Table 8 Output for the condition based dummy case

Scenario 1.2 has to highest probability of occurrence. This implies that the breakdown threshold appears before the planned down $n\tau$ and no opportunity arose or was accepted. Scenario 2 is very unlikely to happen; leading to the conclusion the degradation follows a path that is too steep to outlive $n\tau$. Scenario 1.2 is also the option with the highest cost of the CBM possibilities, the sensitivity analysis will show if the costs can be decreased be changing certain parameters.

6.5.3 Sensitivity analysis on the CBM dummy case

Table 9 gives an overview of the parameters that are varied in the sensitivity analysis and over what range. The variables are treated in order of the table, but first the influence of the costs is discussed (this is not included in the table).

Parameter	*Value*
λ	1 till 30 visits per year
$P(Y)$	0 till 1
τ	1 till 52 visits per year
Tw	0 till 0.99

Table 9 Parameter values used in the sensitivity analysis on CBM

As for CM and CBM the costs influence the cost per time unit in a linear way. Again only the numerator is changed, the probabilities and cycle lengths stay the same. The formula for cost increase per additional euro is therefore the same as formula 6.3:

$$Z(W)+ = \frac{P_i}{L(W)} per\ euro \quad i \in \{1,2,3\}\ or\ when\ c_{com}\ increases: Z(A)+ = \frac{1}{L(A)} \tag{6.10}$$

Next are $P(Y)$ and λ. As for UBM they have around the same influence on the costs only the other way around: it is better to perform a task during an occurring opportunity. This can be explained by the high probability of $P_{1.2}$; since the path is to steep to reach a SD, it is better if more USDs occur, else a CBM visit happens. The first is slightly cheaper than the latter; making it more beneficial if more opportunities occur or are more likely to be taken.

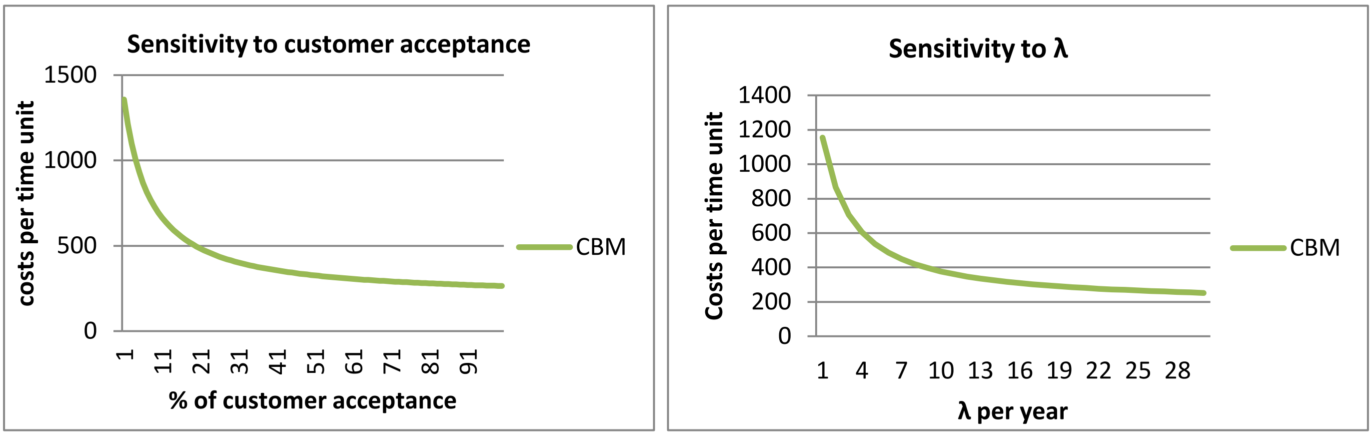


Figure 22 Sensitivity of CBM to customer acceptance and CM-rate per year

Next the sensitivity to the warning threshold is tested. The warning threshold influences both the cycle length as the costs. The cycle length is influenced because the interval that USDs are considered as opportunities changes with the threshold. The higher the threshold, the longer the cycle length. The costs are influenced by the changing of the probabilities. The higher the threshold, the more chance scenario 1 will occur. Figure 23 shows a clear turning point around 40%. When looking at the probabilities this is exactly the point where $P_{1.1}$ and $P_{1.2}$ are no longer zero and thus T_H falls within the interval to $n\tau$. This can be explained looking at formula 6.8 and 6.9. At 39% scenario 1 is till zero, so $* \frac{H-a}{W-a} > n\tau$. Let's see what happens to the fraction when W is 39 and 40: $\frac{120}{59} = 2{,}03$ and $\frac{120}{60} = 2$. τ is set at 13 and $(n-1)\tau \leq u \leq n\tau$, thus independent of n, u always has an interval of 13. If the fractions is equal or smaller than 2, is the first time $u * \frac{H-a}{W-a}$ can become smaller then $n\tau$ (namely for $n = 2$). If the fraction is bigger than 2, it will always be larger than $n\tau$, for every n. The costs increase fast after this point, indicating the visit costs outweigh the cycle length in this case.

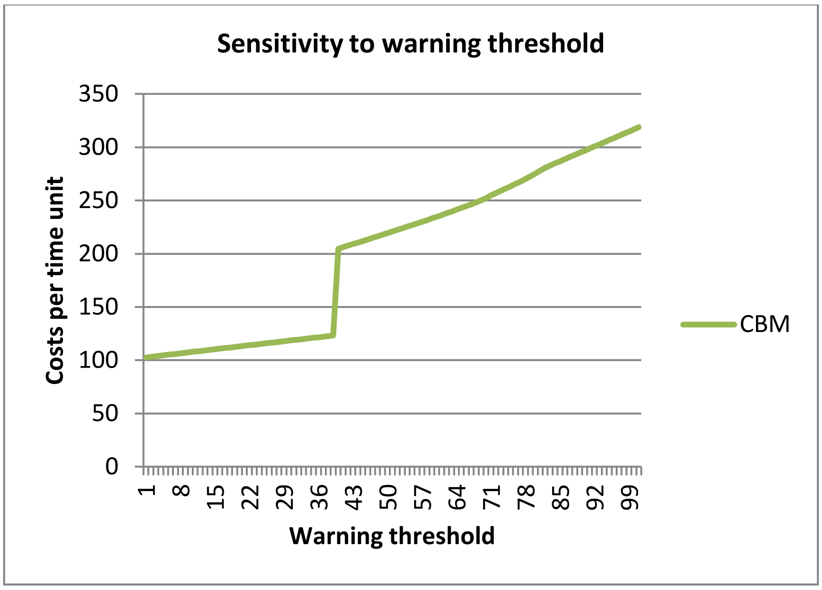


Figure 23 Sensitivity of CBM to the warning threshold

Lastly the sensitivity to the number of planned visits per year is checked. On one hand, more visits per year leads to shorter time between two visits, thus T_H will be bigger then $n\tau$ more often. Scenario 2 is in general cheaper then scenario 1, having a positive effect on the total costs. However on the other hand the cycle length get's significantly shorter when there are more planned visits, possibly causing the costs per time unit to increase. Figure 23 depicts that for the dummy case it is indeed more beneficial to have a longer cycle length and more expensive visits. The influence of the number of planned visits is large; the costs vary from $\pm$ 1300 till 200 Euros per time unit. Hence, this factor is an important one to consider when planning maintenance.

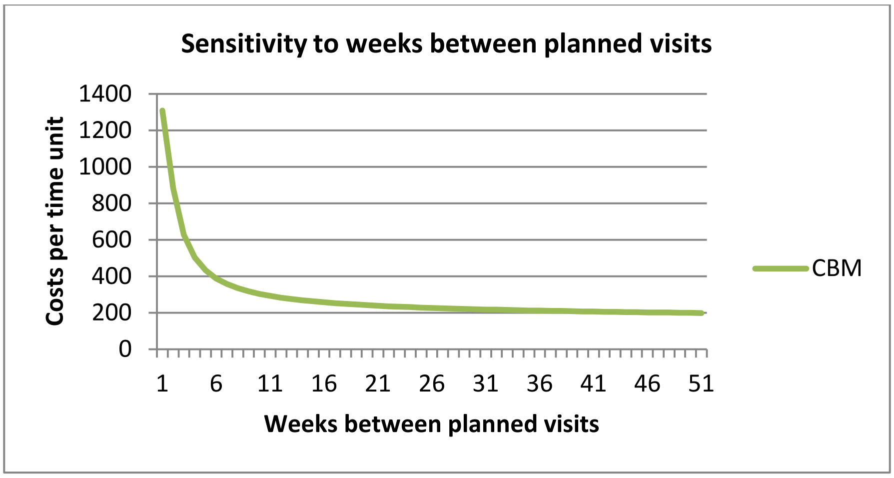


Figure 24 Sensitivity of CBM to the number of planned visit per year

Now, what if the parameters for the dummy case where a representation for a real degradation path to measure the function of the inkfilters? In that case, we can conclude CM would still be the optimal policy. The degradation path cannot be measured timely to response fast enough. The component will breakdown before the planned visit too often and the cycle length cannot become long enough to outweigh the visit costs.

6.6 Overall conclusions on the sensitivity analysis and optimization suggestions

Three general things can be stated after the sensitivity analysis:

- A change in costs has a linear influence on the cost per time unit if the probabilities do not change. The delta per euro can be calculated for all policies to see if there will be a point in time where the lines cross and another policy becomes optimal;
- The customer acceptance of an opportunity has around the same influence as the arrival rate of unscheduled downs because they both indicate the number of possibilities that can be taken in a certain time interval;
- The expected cycle length has a big influence on the cost rate; implying the costs per kind of visit don't differ to such extent that they can outweigh the benefits of a longer cycle length. Note this only accounts for the values as entered for Océ, if the difference between the costs per visit increases, the cycle length may become of less influence.

The sensitivity analysis gives insight on the influence of parameters on the output of the model. Some of the parameters can be influenced by Océ and thus offer an opportunity for optimization. First the age limit is discussed. This parameter currently lies two times the MCBF before the planned maintenance action($n\tau$). So when the $n\tau$ for the considered component is known, it is easy to compute the A. However two times the MCBF will lead to very early replacement and a lot of wasted lifetime. Let's take an example to show this. The VPi300 has an expected CM rate of 22 per year, thus two times the MCBF is ~4,5 weeks before the planned moment. However 22 per year is high in comparison to other Océ machines, 6 or 7 per year is more common. In a case of only 7 expected visits, two times the MCBF already becomes ~15 weeks in advance. So 15 weeks before $n\tau$, a component already gets replaced at the first opportunity. Of course one can argue that fewer opportunities will arise in these 15 weeks, but since the arrivals follow an exponential distribution every week has the same probability of an arrival. So a trade-off has to be made between a possibility of too early replacement and a higher probability of breakdown. The sensitivity analysis shows per component what would be the optimal moment and this can be used to reconsider the policy of two times the MCBF.

Then a parameter that is closely related to A: $n\tau$. This parameter can be optimized by using the sensitivity analysis. Another option is to calculate the optimal value if no maintenance opportunities are considered. The age-based model as presented by Mann, Saxena & Knapp (1995) and Arts (2015) can be used for this. These models also calculate the cost per time-unit and minimize this by varying the moment of scheduled down ($n\tau$). The idea of the age-based model is the same as for the more complex model as presented in chapter 3; the expected cycle costs are divided by the expected cycle length to obtain a cost per time unit ($Z(n\tau)$). However the simple model doesn't take other downs into account as possible maintenance opportunities, leading to only two possible visits; either the component is replaced at the planned moment, or it breaks down before this moment and has to be replaced earlier. Let u represent the lifetime of the component, then the expected cycle costs are given by:

$$Expected\ cycle\ costs = C^{USD} * \int_0^{n\tau} f(u)du + C^{SD} * \int_{n\tau}^{\infty} f(u)du \tag{6.10}$$

The expected cycle length is the mean value of the minimal of $n\tau$ and u. Given by:

$$Expected\ cycle\ length = \mathbb{E}[\min(u, n\tau)] = \int_0^{\infty} \min(u, n\tau)\, f(u)du = \int_0^{n\tau} uf(u)du + n\tau R(n\tau) \tag{6.11}$$

with $R(\tau) = Reliability\ function\ of\ the\ component = 1 - F(u)$.

Then $Z(n\tau)$ has to be minimized and solved for τ to find the optimal moment of replacement. This could be done with help of a mathematical program or manually by taking the derivative of $Z(n\tau)$ and setting this to zero:

$$\frac{Z(n\tau)}{dn\tau} = 0 \tag{6.12}$$

Lastly, the amount of planned downs per year can be influenced by Océ. For the VPi300 it is planned to keep this τ at once every three months. The sensitivity analysis can be used to see what would happen if this amount was about to change and what the optimal value is. However τ, is complicated to optimize with the tool, because the tool only looks at one component, while τ is applicable to the total machine. Therefore the model will yield different optimal τ per component, but only one can be applied. To really optimize this variable, clustering of the activities has to be considered. This is not within the scope of this research and will therefore not be taken into account but can be part of future research.

7 Discussion on consequences for the customer

Changing the maintenance policies not only implies changes for Océ internally, but also the customer has to adapt to different circumstances. In the literature there is not much information available yet about the implementation of Condition Based maintenance and the consequences of it for the people involved. However the article of Stefanie Paluch (2014) discusses customer expectations in the medical equipment industry. Although this is a whole different kind of industry, some things are applicable for other industries as well. Furthermore six FSTs from Océ are interviewed about their field experiences and the reactions of customers in certain circumstances. Table 11 lists the consequences and whether it is an up- or downside.

Consequence	*Upside or downside?*
Remote access to data	–
Less unplanned downs	+
FST has more prior knowledge of a machine when performing a maintenance action	+
New type of planned downs	+

Table 10 Up- and downsides for the customer when implementing condition based maintenance

The first thing that might be a major issue is the remote access of Océ to all the data of the machine. Although the remote access is only meant to deliver data about the machine, customers might be anxious Océ can retrieve company information in some way. Or, because it is an internet connection, a third party may be able to retrieve confidential information (Paluch, 2014). This perception of remote data being of 'high risk' can be changed by making agreements about the use of the data or, in extreme cases, give the customer the possibility to control the access to their system to some extent. Working on secure networks is also a good possibility when third parties are the suspected problem.

Another thing Paluch(2014) points out is that just the delivery of high-tech services isn't sufficient for a customer to adapt the new maintenance policy. Some more support by Océ is expected on a human interaction level. So clear explanations about the way the remote service will work and maybe a little demonstration if possible. The FSTs confirm that the relationship with the customer is very important. Because they often print confidential information, they are not keen on letting everybody near the machine and prefer a FST they know and trust. Accepting the remote access is associated with the understanding of the benefits of remote access and condition based maintenance. When the customer is fully aware of the advantages they will easier accept the remote access. The decrease of downtime is the major advantage for the customer. This decrease is achieved by minimizing the number of unplanned visits and at the same time minimizing the length of visits because a FST knows better in advance what the condition of the machine is.

Lastly the customer has to adjust to the new 'planned downs' for a condition based maintenance action. So instead of only the four planned maintenance moments and the corrective visits, there is a third kind of visit. However this is expected to be beneficial for the customer, because the amount of corrective visits is supposed to decrease and replaced by the condition based visits that are planned some time in advance. The customer is able to adapt his production planning to planned downs, for unplanned downs this is not possible. Hence, the condition based visits are beneficial. Again the relationship between customer and FST can be of great importance when it comes to plan the condition based visits. The FSTs point out it is easier to plan appointments with customers they are acquainting with.

Overall the implementation of condition based maintenance is also beneficial for the customer. But because it involves new technology, some suspicion may arise in the beginning. However with good communication and clear explanations about causes and purposes, these suspicions can be overcome.

8 Conclusions, limitations & recommendations

This is the last chapter and concludes the research. Section 8.1 answers the research questions as presented in chapter 1. In section 8.2 the recommendations for Océ are given. Lastly the limitations on the research together with future research directions are stated.

8.1 Answers to the research questions

Four research questions where defined and answered in the past chapters. Here the research is shortly summarized and the questions are answered.

1. 'How can be determined which maintenance policy is optimal for a component: corrective or usage based?'

To make the first rough selection, the following rule of thumb can be used: In case of decreasing or constant failure rate, stick to a corrective maintenance policy. Corrective maintenance has as only big advantage that there are no unnecessary replacements, for the rest the unplanned visits are mostly costly and unwanted by the customer. Therefore for all components with an increasing failure rate the trade-off has to be made between part cost and visit costs. Figure 6 shows a rough indication of when which policy is best. The mathematical model as developed in chapter 3 computes this trade-off by calculating the costs per time unit for both CM and UBM. Even though UBM might be cost wise the most beneficial option, CM can still be preferred. If it is desired to learn more about the behavior of the component in the field, CM is a good option. It is important to keep possible follow up damage in mind; if breakdown of one component can have severe consequences for the rest of the machine, CM can be very undesirable even if there is the desire to learn about the component. It is possible to add a cost of severe consequences in the model to see what this would imply for the costs per time unit.

2. 'How can be determined if condition based maintenance is possible and if this is the optimal option?'

If condition based maintenance is possible, is mostly dependent on whether it is possible or not to measure the deterioration. Finding possibilities can be done with a black- or white box approach. When it is possible to use condition based maintenance, the same trade-off between part cost and visits costs has to be made again. Chapter 4 presents a model to calculate the costs per time unit and optimize several parameters. The costs per time unit can be compared to the costs per time unit for the CM and UBM policy to find the cost wise optimal option. Again can be related to the matrix in Figure 6; CBM is expected to be best suitable for expensive components with a short expected life time because it minimizes the visit costs and uses the lifetime close to optimal. The mathematical model calculates where the boundaries are and in what case which policy is optimal. Additionally it is not only important if the deterioration can be measured at all, but also if it can be detected timely to response. The model includes this by using the distributions on the arrival time of both the warning and breakdown threshold and examining the occurring opportunities between the two.

3. 'How can the framework be applied to an Océ machine?'

To show how the framework can be applied to an Océ machine, a case study is conducted on the inkhandling function. The first step of applying the framework is to gather information on the components you want to apply it to. What is already known and what more information is needed to determine the parameter values? Especially the failure behavior asks special attention; it is the center of the framework and the more accurate the estimation, the more optimal the policy. With the information gathering also comes the investigation of condition based possibilities. The remote data and knowledge of function specialists can be combined to obtain condition based possibilities and thresholds.

After this the decision tree has to be ran through. It makes the first rough selection on CM components and shows in what settings to run the mathematical model. The case study on the inkfilters shows an example of how to use the decision tree. The filters are also used to show the next step: running the mathematical model. Due to very long expected lifetime, CM turns out to be the best policy. Another useful application of the framework is the sensitivity analysis. It shows insight in the influence of different parameters and can be used to optimize some of them.

Regrettably it was not possible to determine condition based thresholds for the inkhandling module, so a dummy case was introduced to show how the condition based part of the model works in practice. Again a sensitivity analysis was performed. However two options that might show trends in the future are pump activity and pressure differences. The first one can be used to measure the actual workload of the pumps and spot possible changes. The latter can be used to measure the clotting process of filters: the more they are clotted, the bigger the pressure difference. For the micro filter in the Festo this can already be done, for the other filters no data is available on pressure. When thresholds can be determined, the model can be used to calculate if implementing these thresholds is actually beneficial or another policy remains optimal.

4. 'What would the implementation of condition based maintenance imply for the customers of Océ?'

The literature study and interviews with FST's pointed out that although condition based maintenance is beneficial for the customers, they are likely to hold some suspicions. Especially in the beginning when the remote date connection is still new and has not proven its benefits yet. Customers may fear the remote data connection will lead to leakage of confidential information. To overcome this objection, it is important Océ not only delivers high-tech services, but supports customers on a human interaction level as well. Finally, the new way of planning with the extra condition based maintenance visit is something that has to be discussed with the customer. However the condition based maintenance visits are expected to lead to fewer unplanned downs and are thus beneficial for the customer.

8.2 Recommendations for Océ

This research was aimed at 'road to predictive maintenance' and recommendations are made for Océ to continue on this road.

The first recommendation is to use the framework to reconsider the maintenance policies used for components. To start, the framework can be applied to a subset of components that are expected to have a major share in maintenance. The case study on the ink filters showed it is important to think it through and not just make an assumptions based on a 'gut feeling'; the UBM and CM policy had a difference in costs of €6,- per week. Hence, selecting the right policy can lead to large decrease of costs. For the inkfilters it turns out that the expected lifetime is of such length that all other costs are negligible. A side note on this conclusion is that the expected lifetime came from a failure distribution that was fitted on failure data of the same sort of inkfilter, but that was used in another machine then the VPi300. It is also recommended to run the tool again when more is known on the failure behavior of the ink filters to see if this assumptions of long lifetime still holds. A decrease in expected lifetime or increase in costs difference can change the outcome.

This brings us to the second recommendation: creating more awareness and ground for lifetime estimations. When deciding upon a maintenance policy, it is crucial to know how a component will behave over time. Without knowledge on the failure behavior, it is very hard to apply the model and tell something about the optimal policy. Not only the model developed in this research depends on failure distributions, but most models in the literature do so. Analysis on lifetime behavior could be done to higher extent to optimize the maintenance strategy. This includes examination of components that are preventively replaced -to what extent was it necessary to replace them? - and of components that break down preliminary –what caused the preliminary breakdown?-. For example checking if the filters are really clotted when they are replaced or take back components that broke down to examine the cause of breakdown. But also at the developing phase, it is important to start thinking about what the component will do when it is in use.

Additionally to the awareness on lifetime estimations comes the awareness of the benefits of predictive maintenance. Implementing condition based maintenance is time-consuming and some may wonder whether it is worth all the trouble. To make a strong case in demonstrating the benefits, it is recommended to first show for a small subset of components what can be won by implementing predictive maintenance. Starting with a subset yields faster results and when results can be shown for some critical components, it is easier to prove the benefits for the total machine.

As a next step on the road to predictive maintenance it is recommended to start clustering maintenance actions. The model in this research is limited to be single-component. Although other components are taken into account by the use of maintenance opportunities, this is only to a certain extent. It should be investigated how all the different actions can be best combined to minimize downtime. When doing this, the method to define the age limit for UBM should be reconsidered. Using two times the MCBF causes the time between the limit and the actual planned maintenance moment to be rather long. Maintenance actions are advanced earlier, which is not always the best option. It is better to do this during clustering then single-component because it involves the combining of maintenance actions.

Based on the study of Paluch (2014) it is also recommended to not forget the human interaction with customers when continuing on the road to predictive maintenance. It takes some time to get accustomed to the new technologies and not just delivering these technologies, but keep on interacting on human level can have a positive effect on the adaption of remote data access.

Moreover, it is recommended to keep looking for ways to handle the data in the most convenient way. The availability of a huge amount of data holds as many opportunities as it is challenging. It is easy to get lost in the piles of data logging that are generated every day. Some things can help to handle the data and make it easier to draw conclusions from it:

- First of all it should be easier to examine data on population level. The diagnostic framework only allows to run an analysis at one machine at the time. Comparing machines and spotting special cases gets very time consuming if all data has to be retrieved manually per machine. To spot trends and outliers is it necessary both population and single machine data can be analyzed. Ideally this can be done using the same program for both and that is able to handle a huge amount of data. This is an important requirement since programs that are commonly used (like Excel or SPSS) are not suitable to handle so much data, thus another solution has to be found.
- Mostly raw data should be used for analysis, currently the moving average is popular for the interpreting of data. However, the moving average should be used with care. Although it can help soothing out the effect of ‘accidental’ outliers, it also might cause trends to go by unnoticed or are spotted too late. Especially when a change is implemented and one is interested to see the influence of this change, the moving average will give a distorted view since the effects of the change are averaged over past data.
- A special remark on the ADAM-tool: it only stores the information of the former seven visits and bases its internal calculations on these seven visits. With around 26 expected visits per year, this means only the information until 14 weeks back are stored. It might be considered to increase the amount of visits.

Lastly a remark on the micro filter: section 6.1 points out the manufacturer of the micro filter already implemented a way to measure the pressure difference and thereby indicate if a micro filter needs replacement. A connection between this measurement and the remote data could offer the first opportunity for condition based maintenance on the inkhandling function.

8.3 Limitations and future research directions

First of all, the practical use of the conditional probabilities from the condition based model is quite complex. How to make the translation from data on machine status to a threshold of when to conduct an action is something that needs further investigation. Therefore the first future research direction is about the establishing of condition based thresholds. This requires a collaboration of technical knowledge and statistical and data mining knowledge. Moreover, the model presented in this thesis and in the research of Zhu (2015) assume the degradation paths can be measured and use a distribution on these paths. But any inaccuracy of the estimations of these paths is left out of scope. How degradation paths can be accurately determined and measured, asks for more research in the future.

The second limitation has to do with the statistics in the model: the model is highly depending on statistics since it is all based on the failure distribution of a component. When nothing is known about the failure behavior, the outcome of the model becomes less trustworthy. Since a failure distribution is not something that is always available on every component and is not that easy to obtain, this is regarded to be a limitation of the model. In practice it is not very common to make a lot of use of failure distributions. This is considered to be a gap between academically research and company environments. Another future research direction is how the fill up this gap.

Bibliography

Arts, J. (2015, September 21). Maintenance Modeling and Optimization, lecture notes. Eindhoven: Technische Universiteit Eindhoven.

Baek, J.-G. (2007). An intelligent condition-based maintenance scheduling model. *International Journal of Quality & Reliability Management , 24* (3), 312-327.

Baker, R., & Christer, A. (1994). Review of delay-time OR modelling of engineering aspects of maintenance. *European Journal of Operational Research , 73*, 407-422.

Berkum, E. v., & Bucchianico, A. D. (2010). Statistical Compendium, reader. Eindhoven: Technische Universiteit Eindhoven.

Do, P., Barros, A., Bérenguer, C., Bouvard, K., & Brissaud, F. (2013). Dynamic grouping maintenance with time limited opportunities. *Reliability Engineering and System Safety , 120*, 51-59.

Ebeling, C. E. (2010). *An Introduction to Reliability and Maintainability Engineering.* Long Grove: Waveland Press, Inc.

Elwany, A., Gebraeel, N., & Maillart, L. (2011). Structured Replacement Policies for Components with Complex Degradation Processes and Dedicated Sensors. *Operations Research , 59* (3), 684-695.

Flapper, S. (2013, May). 1CM30 Condition Based Maintenance, lecture slides. Eindhoven: Technische Universiteit Eindhoven.

Longo, F. (2011). Supply Chain Management Based on Modelin Simulation: State of the Art and Application Examples in Inventory and Warehouse Management.

Mann, L., Saxena, A., & Knapp, G. (1995). Statistical-based or condition-based preventive maintenance. *Journal of Quality in Maintenance Engineering , 1* (1), 1355-2511.

McKinsey, G. I. (2011). *Big Data: The Next Frontier for Innovation, Competition and Productivity.* New York: McKinsey Global Institute.

Naidu, S., Amalesh, J., Rao, P., & Sawhney, R. (2009). An Empirical Model for Maintenance Strategy Selection based on Organizational Profit. *Industrial Engineering Research Conference* (pp. 1765-1770). Knoxville: University of Tennessee.

Paluch, S. (2014). Customer expectations of remote maintenance services in the medical equipment industry. *Journal of Service Management , 25* (5), 639-653.

Peng, H., & Basten, R. (2015, 7 20). Condition-Based Maintenance, lecture notes. Eindhoven: Technische Universiteit Eindhoven.

Pintelon, L., & Pinjala, S. (2006). Evaluating the effectiveness of maintenance strategies. *Journal of Quality in Maintenance Engineering , 12* (1), 7-20.

Ross, S. (1996). *Stochastic Processes, Second Edition.* John Wiley & Sons.

Tian, Z., Lin, D., & Wu, B. (2009). Condition based maintenance optimization considering multiple objectives. *J Intell Manufacturing , 23*, 333-340.

Tinga, T. (2010). Application of Physical failure models to enable usage and load based maintenance. *Reliability Engineering and System Safety , 95*, 1061-1075.

Vu, H., Do, P., Barros, A., & Bérenguer, C. (2014). Maintenance grouping strategy for multi-component systems with dynamic contexts. *Reliability Engineering and System Safety , 132*, 233-249.

Zhu, Q. (2015). *Maintenance Optimization for Multi-component Sytems under Condition Monitoring.* Eindhoven: Technische Universiteit Eindhoven.

Appendix A 'Uptime definition'

The definition of uptime can be explained with help of two figures, presented below. With the sales of a printer an agreement on service hours is made, referred to as Contracted Service Hours(see list of definitions). These hours can be divided in Uptime and Downtime, where Uptime is all the time the machine is available for production or is actually producing and the time that is scheduled for planned maintenance visits.

The downtime includes all the unplanned maintenance visits or breakdown of the machine due to component failure.

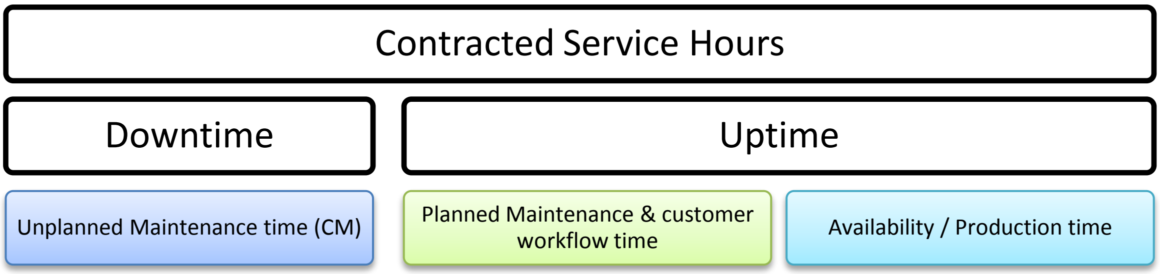


Figure 25 Division of the contracted service hours in downtime and uptime

So basically preventive maintenance should be uptime, but since it is often conducted during a corrective visit it is mostly counted as downtime.

	Regular target 3 months rolling average	
	8/5	24/7
$Uptime = \left(1 - \frac{\text{Unplanned Maintenance Time}}{\text{Contracted Service Hours}}\right) * 100\%$	*90%** *80% (excl. remote)*	*95%** *85% (excl. remote)*

*At LCP > 70%

Figure 26 Uptime calculation used by Océ

To calculate the targeted uptime a 3 months rolling average is used. 8/5 means 8 hours a day, 5 days a week and 24/7 is 24 hours, 7 days a week. Without remote control are the current numbers, with the implementation of remote control the targeted uptime goes up with 10%.

Appendix B ‘Literature review’

The literature was searched for different maintenance policies, both on mathematical models and human aspects and implementation. As it turns out, a lot of literature is available on age/usage based maintenance and many optimization models where found. The implementation part is less studied and most models are quite conceptual. Below the literature found on the different subjects are considered. First the corrective maintenance policy is examined. Then the (us)age based policy is stressed, followed by condition based. Lastly the implementation part is discussed.

Corrective maintenance
No literature was searched especially on this topic, for the calculations are relatively easy and there is not much to optimize when using this policy; only increasing lifetime is an option. (Arts, 2015) Describes a short section about how to calculate the costs, in other articles it is mostly used as a comparison to other policies. Since it is planned to use it for the same purpose, no separate literature was searched for.

(Us)age-based
Literature on this policy was studied more thoroughly. A lot of literature is available on both single-units as multi component systems. In most articles the total cost per time unit is calculated to make decisions upon a policy. Mann, Saxena and Knapp (1995) present a simple age-based policy without any restrictions or special circumstances. The costs per time-unit are calculated based on the probability a component survives till the next planned maintenance, this is the same way as in chapter 3.2.2 of Arts (2015). Both models are single-unit; they don’t take other components into account. Naidu, Amalesh, Sawhney & Rao (2009) don’t optimize within a policy but compare two policies by optimizing the organizational profit. Thereby they also take the inventory costs into account. They use simulation to estimate the parameters of their model but do not do any optimization on these parameters. This model is again single-unit. Arts(2015) introduces an age replacement policy with periodic maintenance opportunities and minimal repair. This model has an age-based policy as basis, but takes several other factors into account like the advanced performing of preventive actions due to a scheduled maintenance opportunity. If a component fails before an opportunity occurs, minimal repair is performed so it survives till the next opportunity. Zhu (2015) introduces a system without minimal repairs, but with unscheduled downs as new opportunities. Zhu does not consider any time restrictions or other limitations. Barros et al. (2013) take time limitations into account by first optimizing per component, but later perform grouping considering the kind of operation and duration of it. Also they optimize the maintenance intervals by using a penalty cost for downtime of the machine. In a later article Barros et al. (2014) present a grouping strategy with dynamic contexts, given the possibility to update a maintenance planning over a rolling horizon. The last four models are all multi-component because they take other components into account as well.

It is desired to model the current situation as veracious as possible, so a model is required that takes everything mentioned in chapter 3.3 into account. Table 11 gives an overview of the requirements and the models from the literature. An ‘x’ indicates the requirement is included in the model.

	Age Based	Opportunity of scheduled downs	Opportunity of unscheduled downs	No minimal repair	Cost of component	Able to conduct extra action	costs determination	No time limitations
Arts (2015)	x	x						x
Zhu(2015)	x	x	x	x				x
Mann, Saxena & Knapp (1995)	x			x				x
Vu, et al.(2014)	x	x		x			x	
Van et al. (2013)	x	x		x			x	

Table 11 Presence of requirements for modeling the usage based policy in studied literature

Condition based

Also for Condition Based several models are considered before picking one. First chapter 5 of Arts (2015) is considered. Arts uses delay time models to optimize the length of inspection intervals and Markovian degradation to find the degradation level to trigger maintenance. Again the total cost per time unit is used to compare or optimize. Also he presents two methods for the model solving: stochastic dynamic programming and linear programming. Maintenance opportunities are not included. Elwany, Gebraeel and Maillart (2010) present a similar Markovian model, but for continuous monitoring by sensors. The model is very specific for it is aimed at exponential degradation with use of Brownian error terms. Again, maintenance opportunities are not included. Zhu (2015) does include these opportunities, both scheduled and unscheduled downs. However this model does not give a method to determine the degradation states. Tian, Lin & Wu(2009) use a proportional hazards model to determine the degradation state and threshold. After that they optimize both costs and reliability with a physical programming model. Lastly the model of Baek (2006) is examined for he uses a decision-tree instead of a Markovian model. The idea of optimizing the costs as a vector-space depending on a decision taking at time t, is the same as in Arts (2015) and Elwany, Gebraeel & Maillart (2011). Dynamic programming is used to solve the tree. Mathematically this method does not yield the most optimal solution, but an experiment shows it does yield a good scheduling policy to use in practice (Baek, 2007). Mann, Saxena and Knapp (1995) model the condition based situation for a single-unit system in a very simple way: they do this by assuming only scheduled downs will occur when condition based is implemented. Leading to a simplification of the usage based model. Furthermore they give a qualitative review of condition versus usage based. Again a table is used to compare the different models, given below:

	Condition Based	Opportunity of scheduled downs	Opportunity of unscheduled downs	Solving method for degradation state	Continuous monitoring	No time limitations	General model
Arts (2015)	x			x		x	x
Zhu(2015)	x	x	x		x	x	x
Mann, Saxena & Knapp (1995)	x					x	
Tian, Lin & Wu (2009)	x			x			
Elwany, Gebraeel & Maillart (2010)	x			x	x		
Baek (2006)	x			x			

Table 12 Presence of requirements for condition based in studied literature

As for the degradations state modeling, some other articles are considered. (Baker & Christer, 1994) are studied to help understand the delay-time model. They stress the general use of the delay time model and what it implies. It is not directly linked to condition based maintenance, but gives a clear idea of the concept of delay time, which can be used for multiple purposes. The lecture notes of (Peng & Basten, 2015) about condition based maintenance give an example of how the random coefficient model can be used to model degradation states. They focus on single-unit systems, but the explanation of the random coefficient model is very clear and can be implemented in a multi-component system later on. The article of (Tinga, 2010) links physical failure models to condition based maintenance. He does this by giving an example on gas turbine blades and physical degradation. Additionally he elaborates on the pros and cons of several maintenance policies.

Human aspects and implementation

Non-mathematical literature on maintenance policies is a lot harder to find. The article of (Pintelon & Pinjala, 2006) uses he four-stage framework of Hayes and Wheelwright to evaluate the effectiveness of a maintenance policy. The main conclusion is a change of mind-set towards maintenance is the most important; it should no longer be regarded as just a secondary function. Case studies are used to show this. The article does not elaborate on how to accomplish this change in mindset. Lastly (Paluch, 2014) stresses customer responses to the implementation of condition based maintenance. It mostly focuses on the use of remote data connections and objections a customer can have against this connection. Paluch also offers solutions on how to handle these objections.

Appendix C 'The Failure rate'

The failure rate indicates how likely it is a component will fail at a certain point in time, given the component is already functioning for a certain amount of time. Sometimes this rate is referred to as hazard rate or mortality rate. When the lifetime distribution is known, it is easy to compute the failure rate:

$$h(t) = \frac{f_T(t)}{R(t)}$$

with $R(t) = 1 - F_T(t)$, the reliability function. And $f(t)$ and $F(t)$ respectively the probability density and cumulative density function of the lifetime distribution.

A component can have three kinds of failure rates: an increasing (IFR), decreasing (DFR) or constant failure rate (CFR). In case of a DFR, the component becomes more reliable over time. This is a common failure rate for electric components. Usually electronics are not subject to wear and breakdown due to manufacturing defects. The longer a component is running though, the less likely there is a manufacturing defect (Arts, 2015). An IFR implies the component gets less reliable over time. Most mechanical devices have this kind of failure rate. A CFR is a sort of special rate, since it can only occur in case of lack of memory of the failure distribution. The exponential distribution is a commonly used one with the lack of memory property. The conditions of parts over time can also be characterized as a combination of different failure rates. The bathtub curve as presented in Figure 27 is a well known example of this. The bathtub curve starts with a DFR to represent the infant mortality, followed by the useful life that is depicted by a CFR. In the end the wearout is modeled by an IFR.

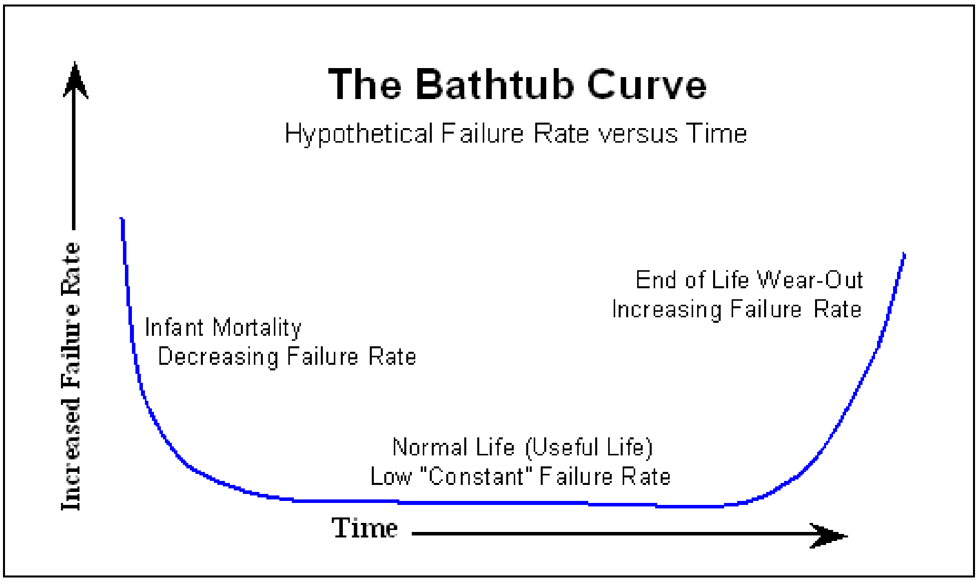


Figure 27 The bathtub curve

Appendix D 'Iteration algorithm to obtain q'

An iteration algorithm is used to find the value for q in equation (3.4). This algorithm is taken from Zhu (2015). It starts with an initial value for $q_0 = P_3(\xi = 0)$ and iterates k times till the difference between q_k and q_{k-1} becomes a very small positive value (e.g. $\epsilon = 10^{-8}$):

$$q_k - q_{k-1} < \epsilon$$

Table 13 summarizes the algorithm.

Initialize $q_0 = \dot{P}_3(\xi = 0)$

$k = 1$, $q_1 = q_0 \dot{P}_3(\xi = 0) + \int_0^{n\tau} \dot{P}_3(\xi) f(\xi) d\xi, \ where\ f(\xi) = \frac{1-q_0}{\tau}$

While $q_k - q_{k-1} < \epsilon$

$k = k + 1$

$q_k = q_{k-1} P_3(\xi = 0) + \int_0^{n\tau} P_3(\xi) f(\xi) d\xi, \ where\ f(\xi) = \frac{1-q_{k-1}}{\tau}$

End while

Obtain $q = q_k$

End

Table 13 Iteration algorithm as taken from Zhu (2015)

Appendix E 'Derivation with P(Y)'

P(Y) has to be included in both the formulas of chapter 3.3 as of chapter 3.4. Scenario 2 of chapter 3.3 is broadly explained, the derivation of the other scenario's can be done the same way only the boundaries and time intervals will change.

Scenario 2 chapter 3.3.2:

In the model on age based maintenance of Zhu every first occurring opportunity is taken, regardless the kind of opportunity it is. However in reality it is possible the customer declines a PM action during an unscheduled visit. This happens with probability $1 - P(Y)$, where $P(Y)$ is the probability that a customer accepts the extra PM action.
If the customer declines the action, two things can happen in scenario 2:

1. No other USD occurs and the SD at the end of the period is used;
2. Another USD occurs and again two options arise:
   a. the opportunity is taken with $P(Y)$;
   b. the opportunity is declined with $1 - P(Y)$.

In case of the last option, the same two things can happen again. This means on the interval 0 till $n\tau - A$ all occurring USDs have to be considered and summed (the interval from A to $n\tau$ can be regarded as 0 till $n\tau - A - \xi$ because the arrivals follow an exponential distribution. Therefore it doesn't matter were at the timeline you start as long as the interval is of the correct length). The interval considered is denoted with t $(= n\tau - A - \xi)$. The USD events follow an Exponential distribution with rate λ, therefore it is expected λ_t events will occur in $n\tau - A$. And $\lambda_t \ = \lambda(n\tau - A - \xi)$
Let $P_a(t)$ denote the probability exactly *a* events occur during $[0, t)$. Since the arrival rate is exponential, a Poisson distribution is used to calculate the probability of the number of events (X) being equal to *a*:

$$P_a(t) = P(X = a) = \frac{e^{-\lambda_t} {\lambda_t}^a}{a!} \quad \text{(A.1)}$$

Note that a PM action if either conducted at a certain USD, or at the planned visit when no USDs occur, or none of them is accepted. So only when an occurring USD is not accepted (with chance $1 - P(Y)$) the next occurring USD matters. On the other hand, even if the opportunity at an USD is taken, other USDs may occur. So all the $P_a(t)$ have to be taken into account to use the proper probabilities. A decision tree is used to visualize the possibilities:

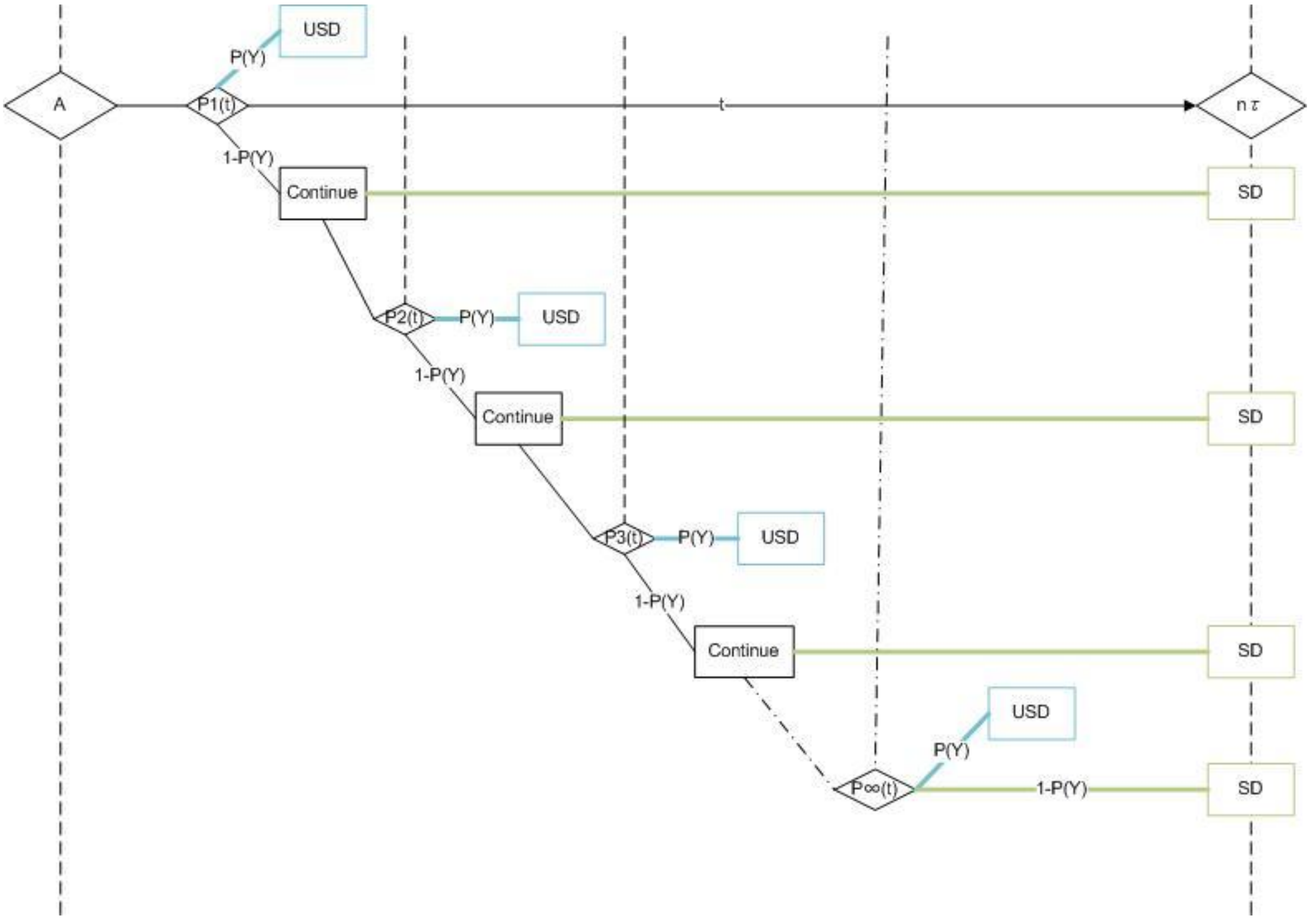


Figure 28 Visualization of possibilities during opportunities

From point A on the timeline till nτ shows the time the probability $P(Y)$ is relevant and needs to be implemented. The blue lines and boxes indicate a taken USD opportunity, the green ones a taken SD opportunity. 'Continue' means no opportunity could be taken yet and either an USD or a SD may occur first. If a SD is the first opportunity to occur, the model stops. If a USD occurs again $P(Y)$ is taken into account and the model may either stop or continue. All the different branches of the tree have to be summed to yield the opportunity of either an USD or SD action. The summation goes on until infinity because theoretically an infinite amount of USD opportunities may occur before the next SD.
So the probability that a component is replaced during a USD in period $n\tau - A - \xi$ is given by:

$$P_{USD}(t) = P(Y)(P_1(t) + P_2(t) + \cdots + P_\infty(t)) + (1 - P(Y))P(Y)(P_2(t) + P_3(t) + \cdots + P_\infty(t)) + (1 - P(Y))^2 P(Y)(P_3(t) + P_4(t) + \cdots + P_\infty(t)) + \cdots + (1 - P(Y))^{\infty - 1} P(Y) P_\infty(t)$$

Or more general:

$$P_{USD}(t) = P(Y)\sum_{k=1}^{\infty}(1 - P(Y))^{k-1}\sum_{a=k}^{\infty} P_a(t) \quad \text{(A.2)}$$

If no USD can be used, the action is performed during a SD:

$$P_{SD}(t) = P_0(t) + (1 - P(Y))P_1(t) + (1 - P(Y))^2 P_2(t) + (1 - P(Y))^3 P_3(t) + \cdots + (1 - P(Y))^\infty P_\infty(t)$$

$$P_{SD}(t) = \sum_{k=0}^{\infty}(1 - P(Y))^k P_k(t) \quad \text{(A.3)}$$

$P_0(t)$ is not included in the summation with $P(Y)$ for P_{USD} because this means no USD occurred and always a SD is used. Implementing these probabilities in the formulas for scenario 2 yields:

$$P_{[2.1]} = \int_{u=n\tau-\xi}^{u=\infty}[\sum_{k=0}^{\infty}(1 - P(Y))^k P_k(t)] f(u) du \quad \text{(A4)}$$

and:

$$P_{[2.2]} = \int_{u=n\tau-\xi}^{u=\infty}(P(Y)\sum_{k=1}^{\infty}[(1 - P(Y))^{k-1} * \sum_{a=k}^{\infty} P_a(t)]) \ f(u) du \quad \text{(A5)}$$

Scenario 3 chapter 3.3.2:

Basically this derivation is the same, only because now the period is not fixed (like from A till the SD), λ_t becomes dependent of u. Or, $\lambda_t = \lambda(u - A)$. With λ per month as used in the exponential distribution $g(s)$.

$$P_{[3.1]} = P(Y) \int_{u=A}^{u=n\tau-\xi} \sum_{k=1}^{\infty} \left(1 - P(Y)\right)^{k-1} * \sum_{a=k}^{\infty} P_a(t)\, f(u) du \tag{A6}$$

$$P_{[3.2]} = \int_{u=A}^{u=n\tau-\xi} \sum_{k=0}^{\infty} \left(1 - P(Y)\right)^{k} P_k(t)) f(u) du \tag{A7}$$

Chapter 3.4.2:

$P_{USD}(t)$ and $P_{SD}(t)$ can be derived the same way as for chapter 3.3.2. Only λ needs to be varied. This yields the following formulas:

$$P_{[1.1]} = P(Y) \int_{u=(n-1)\tau}^{u=n\tau} \int_{v=u}^{v=n\tau} (\sum_{k=1}^{\infty} \left(1 - P(Y)\right)^{k-1} * \sum_{a=k}^{\infty} P_a(t)) f_{T_H|T_W}(v|u) dv f_{T_W}(u) du \tag{A8}$$

and

$$P_{[1.2]} = \int_{u=(n-1)\tau}^{u=n\tau} \int_{v=u}^{v=n\tau} \sum_{k=0}^{\infty} \left(1 - P(Y)\right)^{k} P_k(t)) f_{T_H|T_W}(v|u) dv f_{T_W}(u) du \tag{A9}$$

with $\lambda_t = \lambda(v - u)$

For SCENARIO 2:

$$P_{[2.1]} = P(Y) \int_{u=(n-1)\tau}^{u=n\tau} (\sum_{k=1}^{\infty} \left(1 - P(Y)\right)^{k-1} * \sum_{a=k}^{\infty} P_a(t)) \int_{v=n\tau}^{v=\infty} f_{T_H|T_W}(v|u) dv f_{T_W}(u) du \tag{A10}$$

and

$$P_{[2.2]} = \int_{u=(n-1)\tau}^{u=n\tau} (\sum_{k=0}^{\infty} \left(1 - P(Y)\right)^{k} P_k(t)) \int_{v=n\tau}^{v=\infty} f_{T_H|T_W}(v|u) dv f_{T_W}(u) du \tag{A11}$$

with $\lambda_t = \lambda(n\tau - u)$

Expected Cycle Length:

The probabilities as mentioned above only take the chance of the arrival of an opportunity into account, but don't say anything about the time of arrival. The arrival time is needed to calculate the expected cycle length. For the scheduled downs, this is not so complicated because the downs are always at a fixed time $n\tau$. Therefore the formula for scenario 2, possibility 1 of chapter 3.3.2 becomes:

$$\dot{L}(A|\xi, in\ 2.1) P_{[2.1]} = (n\tau - \xi) \int_{u=n\tau-\xi}^{u=\infty} [\sum_{k=0}^{\infty} \left(1 - P(Y)\right)^{k} P_k(t)] f(u) du \tag{A12}$$

Also the formula for scenario 3.2 is not that complicated. Although the time is not fixed, it is independent of the arrival of the USDs and only depends on the failure time of the component.

$$\dot{L}(A|\xi, in\ 3.2) P_{[3.2]} = \int_{u=A}^{u=n\tau-\xi} [\sum_{k=0}^{\infty} \left(1 - P(Y)\right)^{k} P_k(t)] u f(u) du \tag{A13}$$

However for an USD the cycle length is not only dependent on the arrival of an USD and whether it is taken or not, but also at what time the USD arrives. The time until the *k*th event in a Poisson process can be measured with an Erlang distribution. Therefore the Erlang distribution is included in the summation and summed with A to yield the expected cycle length:

$$\dot{L}(A|\xi, in\ 2.2) P_{[2.2]} = \int_{u=n\tau-\xi}^{u=\infty} [P(Y) \sum_{k=1}^{\infty} \left(1 - P(Y)\right)^{k-1} \int_{s=0}^{s=n\tau-A-\xi} (A + s) z(s) ds) \sum_{a=k}^{\infty} P_a(t)] f(u) du \tag{A14}$$

with $z(s) = \frac{s^{k-1} \lambda_t^k e^{-\lambda s}}{(k-1)!}$ the density function of the Erlang distribution.

For scenario 3.1 the formula is of the same shape as A3.6, only λ_t is different and the boundaries of the integrals differ. The formula becomes:

$$\dot{L}(A|\xi, in\ 3.1) P_{[3.1]} = \int_{u=A}^{u=n\tau-\xi} [P(Y) \sum_{k=1}^{\infty} ((1 - P(Y))^{k-1} \int_{s=0}^{s=u-A} (A + s) z(s) ds \sum_{a=k}^{\infty} P_a(t))] f(u) du \tag{A15}$$

The idea for the cycle lengths of chapter 3.4 are the same as for 3.3, only there is in extra integral because of the distribution of the appearance of the warning threshold. The following cycle lengths are obtained:

SCENARIO 1:

$$\dot{L}(W, in\ 1.1)P_{[1.1]}$$
$$= \int_{u=(n-1)\tau}^{u=n\tau} \int_{v=u}^{v=n\tau} [P(Y)\ (\textstyle\sum_{k=1}^{\infty} \left(1-P(Y)\right)^{k-1} * \int_{s=0}^{s=v-u} (u+s)z(s)ds)\ \sum_{a=k}^{\infty} P_a(t))]\ f_{T_H|T_W}(v|u)dvf_{T_W}(u)du \tag{A16}$$

$$\dot{L}(W, in\ 1.2)P_{[1.2]} = n\tau \int_{u=(n-1)\tau}^{u=n\tau} \int_{v=u}^{v=n\tau} (\sum_{k=0}^{\infty} \left(1-P(Y)\right)^{k} P_k(t)) f_{T_H|T_W}(v|u)dvf_{T_W}(u)du \tag{A17}$$

SCENARIO 2:

$$\dot{L}(W, in\ 2.1)P_{[2.1]}$$
$$= \int_{u=(n-1)\tau}^{u=n\tau} \int_{v=n\tau}^{\infty} [P(Y) \sum_{k=1}^{\infty} \left(1-P(Y)\right)^{k-1} \int_{s=0}^{s=n\tau-u} (u+\ s)z(s)ds) \sum_{a=k}^{\infty} P_a(t)] f_{T_H|T_W}(v|u)dvf_{T_W}(u)du \tag{A18}$$

$$\dot{L}(W, in\ 2.2)P_{[2.2]} = \int_{u=(n-1)\tau}^{u=n\tau} [\sum_{k=0}^{\infty} \left(1-P(Y)\right)^{k} P_k(t) \int_{v=n\tau}^{v=\infty} v f_{T_H|T_W}\ (v|u)dv] f_{T_W}(u)du \tag{A19}$$

Appendix F ‘Weibull ++6 output of the distribution fit for the inkfilters’

Ink Filters

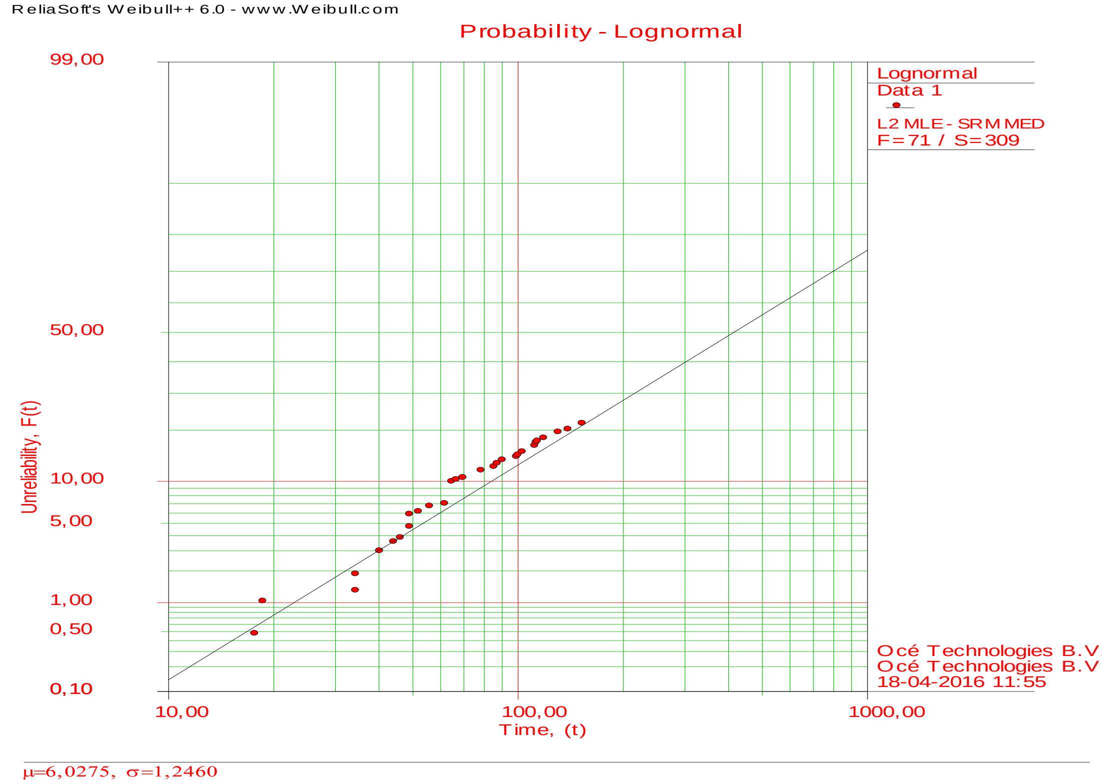


Figure 29 Scatterplot of input data versus the probability plot of the lognormal distribution

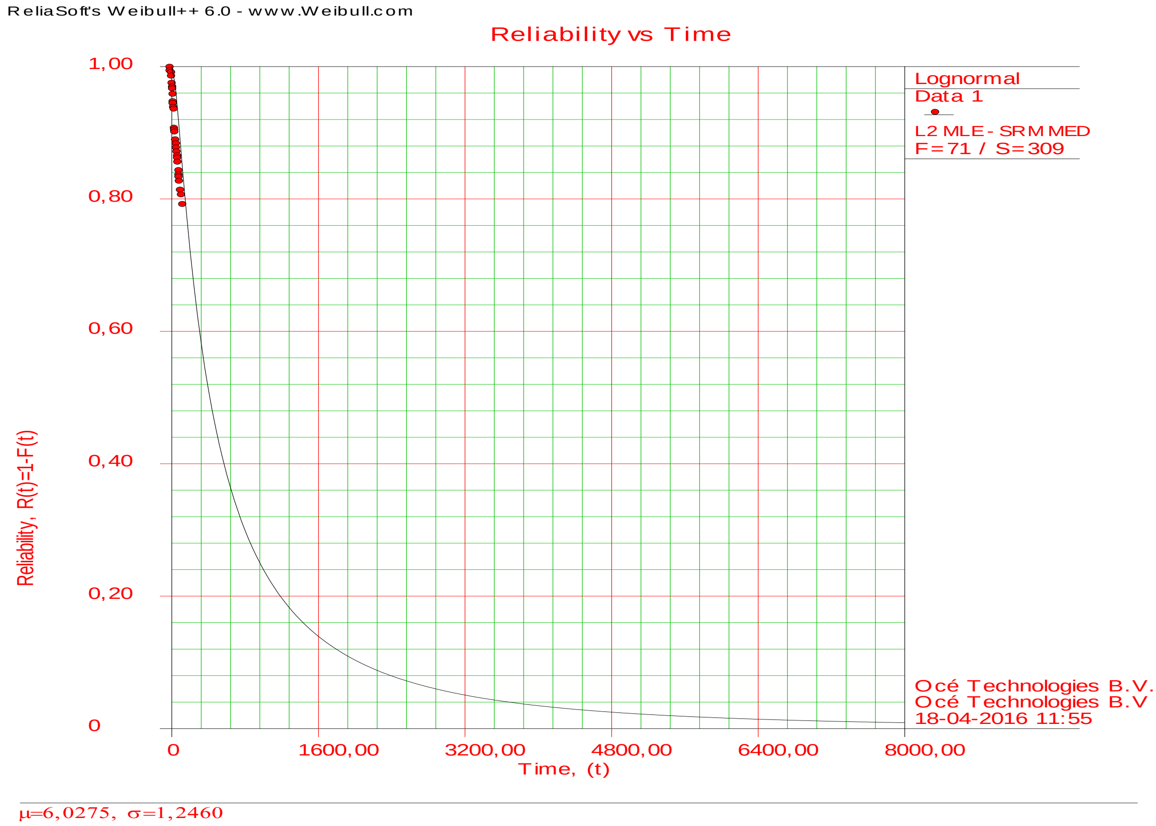


Figure 30 Scatterplot of input data versus the reliability function of the lognormal distribution

Appendix G ‘Fitting data to a distribution’

Data collection

In the ideal situation there is enough failure data available to fit a distribution to. Failure data is the data that shows after how long a component breaks down and how many of similar components are still operating at that time. So based on populations the estimate of the lifetime of a single component is made. This data does not always have to come from the field but can be obtained from lab tests as well. An example of field data is the list of used parts per month or week. It is important this is raw data so outliers can be detected. If an outlier is spotted, it should be examined to see if the cause of the outlier can be found. In that case the outlier can be deleted from the sample data. Some time is needed to gather this data though and sometimes not enough data is available, as was the situation for this report. More creative ways of determining a lifetime distribution have to be used in that case. There are several possibilities:

- If the component is not produced by Océ, the manufacturer can be asked for a lifetime distribution or test data;
- The distribution can be determined in collaboration with function specialists; this is a subjective way of collecting data. They know how the components work and can make an estimation of how components will behave over time. A histogram fit is a good method to use when the function specialists are not statistical-experts. With this method the function specialists have to indicate at what point in time how many of the components have failed and how many they expect to still be operating. A histogram of these probabilities can be constructed and fitted to a distribution;
- If a component is already used in other machines of Océ, data from this machine can be subtracted to apply a fit to. However other machines have other functionalities and components likely deteriorate differently per machine therefore data from the machine it is about is always preferred.

If possible, it is desirable to combine the above mentioned methods and compare the outcomes to come to the best estimation.

Fitting procedure

Before starting the explanation on fitting, a short introduction on lifetime distributions is given. Let u denote the time a component breaks down. The same types of components don’t break down at exactly the same point in time, but are distributed over time. A lifetime distribution reflects this and estimates at what time the component is expected to be functioning and when it is likely to break down. There are two main formulas to describe a distribution and other features (like expected value, variance and failure rate) can be derived from these:

1. The probability density function (p.d.f.); denoted with $f(x)$, gives the probability the lifetime is exactly ‘x’.
2. The cumulative density function (c.d.f.); denoted with $F(x)$, gives the probability the lifetime is equal or smaller then ‘x’.

$F_u(X) = P(u \leq X) = \int_0^X f_u(u)du$.[13] So F(x) is the primitive function of $f(x)$. What the $p.d.f.$ and $c.d.f.$ look like is dependent on the distribution and the parameter values. Next to the failure rate, the reliability function is an interesting feature for Service & Support. It gives the probability a component is defective or not. E.g. the probability a pump will work for at least 6 months is 95%. The corresponding function (the inverse of the cdf):

[13] Theoretically there are distributions that go from -∞ to ∞, but since a component cannot have a negative lifetime, a lifetime distribution should always start at 0.

$$R_u(X) = P_u(u \geq X) = 1 - F_u(X) = \int_X^\infty f(u)du$$

There are numerous different distributions and trying to find the best match by fitting all of them is time consuming. Therefore one should hypothesize a distribution, collect the data, apply a goodness-of-fit test and either reject or accept the null hypothesis. It is possible multiple distributions provide a fit with the data (e.g. Lognormal and Weibull distribution can take the same shape for certain parameter values) and the engineer has to select the best among the acceptable distributions (Ebeling, 2010). There are different goodness-of-fit tests and some are for specific distributions (respectively general and specific tests). Software packages often calculate different tests and give a ranking based on the computed statistics. Within Océ the software Weibull ++6 is available to perform a ranking calculation. The ranking calculation computes for six distributions[14] several goodness-of-fit tests and gives a ranking of which distribution has the best fit. It also provides the parameter values to go with the distribution. Another common used program is 'SPSS'. This program offers the possibility to do several statistical tests and analysis.

Next to this 'ranking' by software statistics, it is possible to assume some component will behave following a certain distribution and test this assumption. After removing outliers, the field data and 'data' as determined by the function specialists can be handled the same way. Although there are plenty of goodness-of-fit tests, the idea is all the same. First, two hypothesis are defined, one to assume the lifetime distribution is equal to the sample data and one that they are unequal. The hypothesis can be tested with several goodness-of-fit tests. Depending on the assumed distribution, different tests perform best. Some possible distributions with their characteristics and corresponding test are included in appendix I. Whether a hypothesis get's rejected or accepted depends on the output of the test and the desired significance level; the significance level indicates how much deviation of the sample data to the assumed distribution is allowed. A 5% or 1% significance level is common. When the hypothesis of equality gets rejected, a new distribution has to be hypothesized and tested again until a proper fit is found. The interested reader can find more on statistical testing and data collecting in 'An introduction to Reliability and Maintainability Engineering' from (Ebeling, 2010).

[14] Normal, Lognormal, two- and three parameter Exponential and two- and three parameter Weibull distribution

Appendix H 'Lifetime distributions and the corresponding goodness-of-fit test'

Distribution	*Failure Rate*	*Features*	*Goodness-of-fit test*
Exponential	Constant	memory less	Bartlett's test
Weibull	$= \begin{cases} 0 < \beta < 1, & decreasing \\ \beta > 1, & increasing \\ \beta = 1, & constant \end{cases}$	If the lifetime of a component depends on small subcomponents, it is often resembled by a Weibull distribution	Mann's test
Lognormal	no closed form	Has an failure rate that is initially increasing but may be decreasing later	Kolmogorov-Smirnov test
Normal	Increasing	Has a negative part if mean is close to zero and sigma is too large	Kolmogorov-Smirnov test

Table 14 Lifetime distributions with corresponding failure rate, feature and goodness-of-fit test, obtained from (Ebeling, 2010)

Appendix I ‘Fitting to the Exponential distribution’

To understand an exponential distribution, it can be compared to the process of throwing a dice. The same way it is explained in the memo of 1997 about the distribution of service calls in the time. When you roll a dice, there is a probability of 1/6 that you will roll a 6. This probability never changes; you always have the same chance of rolling a 6, no matter how many times you already rolled a 6 or not. So what is the probability of rolling a 6 after a few rolls? It is not 1/6+1/6+… etc. because this would imply you always throw 1x 6 when rolling six times, in practice this (almost)never happens. Therefore the complementary probabilities have to be considered, so the probability you do not roll a 6 (5/6). E.g. if you roll the dice three times the probability of not rolling a 6 is 5/6*5/6*5/6=125/216. The probability that you do roll a 6 is 1-125/216=91/216. Comparing this process to the arrival of service calls would imply that the probability of a call occurring is always the same; regardless the amount of calls already occurred for that machine. This is referred to as the memory less property of the failure distribution. The CM-rate is the mean value of the exponential distribution and 1/CM-rate is the parameter lambda, or the average arrival rate of calls. To determine the CM-rate, one has to consider the machines without calls as well; otherwise the CM-rate will be estimated too high. To make a good estimation, some time needs to pass by to get a proper idea. Again, this can be compared to the dices for a better understanding. If you start counting the times you roll 6 and divide this by the number of rolls, you should get 1/6. The more times you roll the dice, the closer you will get to this number. So for the machines; the more calls arrived, the better you can estimate the average arrival.

Fitting a data set to a distribution is partly based on mathematics, but partly on knowledge of characteristics as well. The knowledge of characteristics can be used to select some candidate distributions to perform a fit (Ebeling, 2010). The arrival of unscheduled downs is expected to follow an Exponential distribution due to the Palm-Khintchine theorem. Also the arrivals are independent of each other and, more important; the failure rate is constant, meaning that there always is the same probability of an error occurring, independent of what time at year it is. These are all characteristics of the exponential distribution, due to the memory less property. (When data or a process has less outstanding characteristics it is also possible to construct a histogram to compare the shape of the graph to the shape of the distribution curve.)

After selecting one (or more) candidate distribution(s) a fit can be performed manually or with use of statistical software. The least-squares method can be used for manual calculations. The method fits the parameters of a distribution by comparing the line of the distribution to the scatter plot of the data. The distance from each point to the curve should be minimized, so the total of all distances (D) should be minimized to give the best fit. Mathematically stated:

$$D^2 = \sum_{i=1}^{n} \left(F(t_i) - \hat{R}(t_i)\right)^2$$

With, in case of an exponential distribution:

$$F(t_i) = 1 - e^{-\lambda t_i}$$

To minimize this, the derivative of this function has to be set to zero and solved for the distribution parameters.

The fit of the failure data of the Océ VarioPrint 6250 serial number 0600100104 over 2015 is performed with the software ReliaSoft Weibull ++ version 6. But also the ‘distribution fitting’ app of Matlab can be used. Both yield the same distribution and parameter values. All the arrival dates of a visit are collected and the amount of days between each arrival is deducted from the dates. When Weibull++ is used, the data-type entered is time-failure, non-suspended, unique and exact. For Matlab this does not have to be specified. The fit yields a λ of 0.0986 per day. The reliability plot below shows how the data (the scatter plot) fits the exponential curve.

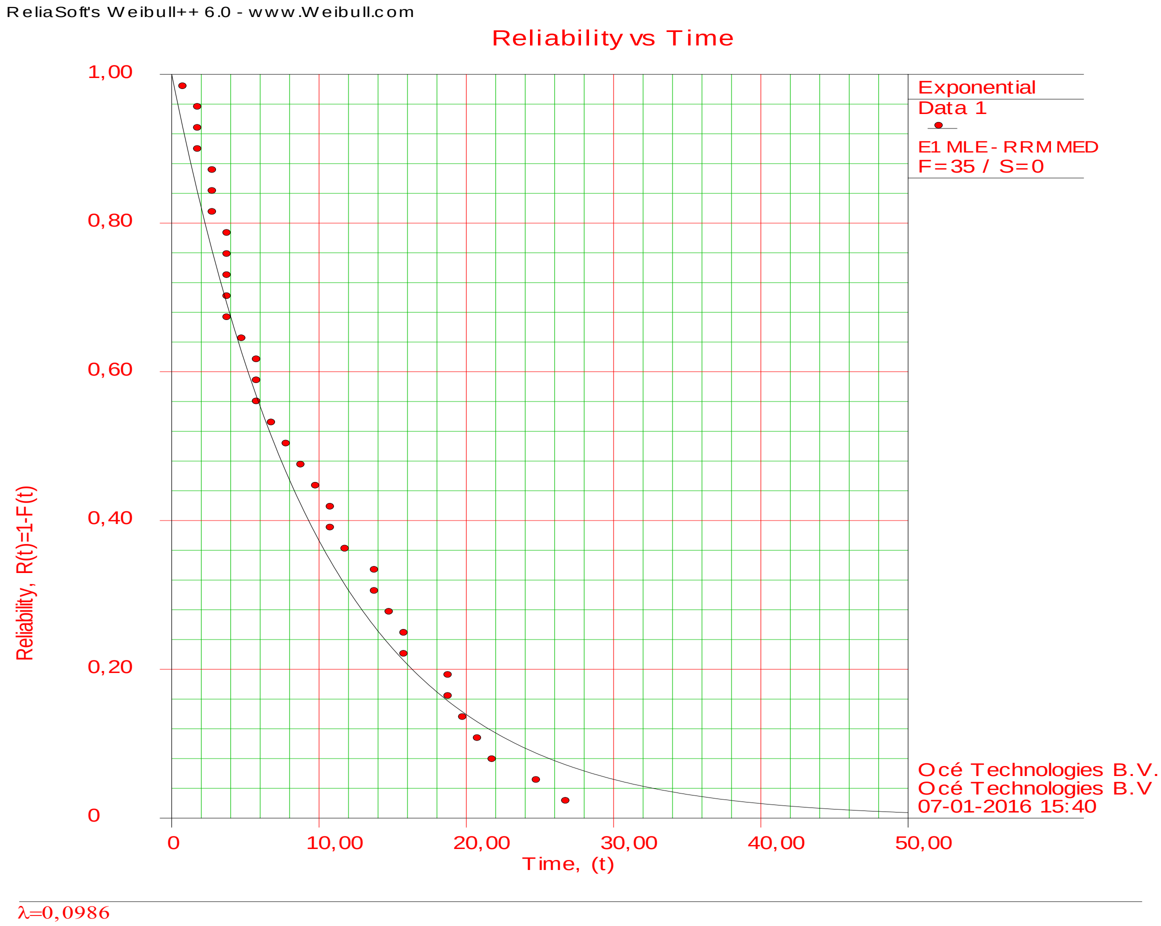


Figure 31 Reliability plot of Exponential data fit obtained by Weibull ++6

Appendix J ‘Code for case study and dummy case’

```
# define variables
install.packages("xlsx")
library(xlsx)
my_data <- read.xlsx("D:/Documents/Y_Afstuderen/dummy.xlsx", 1)
PY <- my_data[1,2]
CM_rate <- my_data[3,2]
CM <- my_data[3,2]/52
nt <- my_data[4,2]
par1 <- my_data[5,2]
par2 <- my_data[6,2]
c_cbm <- my_data[17,2]
c_usd <- my_data[8,2]
c_usd_pm <- my_data[9,2]
c_sd <- my_data[10,2]
c_com <- my_data[11,2]
A <- nt-(2*CM)
k <- 1:22
par1_war <- my_data[12,2]
par2_war <- my_data[13,2]
par3_war <- my_data[14,2]
t <- 52/my_data[16,2]

# Script UBM
# function P_USD
lambda1 <- CM*(nt-A)
multi <- NULL
for (f in 1:length(k)) {
  multi[f] <- (1-PY)^(f-1)*ppois(f-1, lambda1, FALSE)
  }
P_USD <- PY*sum(multi)

# function P_SD
SP2 <- matrix(data = (1-PY)^(k-1), nrow = (length(k)), ncol =1)
pois2 <- dpois(k-1, lambda1)
multi3 <- pois2 * SP2
datafr2 <- cbind(SP2, pois2, multi3)
P_SD <- sum(multi3)

#function P_1.1 & L_1.1
P_1.1 <- plnorm(A, par1, par2, TRUE)
LINT1.1 <- function(u){u*dlnorm(u, par1, par2)}
L_1.1 <- integrate(LINT1.1, 0, A)$value
# function P_2.1 & L_2.1
P_2.1 <- plnorm(nt, par1, par2, FALSE )*P_SD
L_2.1 <- P_2.1*nt

# function P_2.2 & L_2.2
P_2.2 <- plnorm(nt, par1, par2, FALSE)*P_USD
L_int_USD1 <- function(s){(A+s)*dgamma(s, z, lambda1)}
multi2 <- NULL
```

```
for (z in 1:length(k)){
  multi2[z] <- (integrate(L_int_USD1, 0, nt-A)$value*(1-PY)^(z-1)*ppois(z-1, lambda1, FALSE))
}
L_2.2 <- sum(multi2)*plnorm(nt, par2, par2, FALSE)*PY

#function P_3.1 & L_3.1
Ppart <- function(u){
  ((ppois(z-1, CM*(u), FALSE))*dlnorm(u+A, par1, par2))
}
Ppart2 <- NULL
for (z in 1:length(k)){
  Ppart2[z] <- ((1-PY)^(z-1)*integrate(Ppart, 0, nt-A)$value)
}
P_3.1 <- PY*sum(Ppart2)

erlang <- function(x, k, l = 1){
  dgamma(x, k, l)
}
L_int_P31 <- function(x,y){(A+x)*erlang(x, z, CM*(y-A))*dlnorm(y, par1, par2)*ppois(z-1, (CM*(y-A)),
FALSE)}
multi3 <- NULL
for (z in 1:length(k)){
 multi3[z] <- (integrate(function(y) {
   sapply(y, function(y) {
     integrate(function(x) L_int_P31(x,y), 0, y-A)$value
   })
 }, A, nt))$value*(1-PY)^(z-1)
}
L_3.1 <- sum(multi3)*PY

# Function P_3.2 & L_3.2
part_3.2 <- function(u){
  dpois(z-1, CM*(u-A))*dlnorm(u, par1, par2)
}
multi4 <- NULL
for (z in 1:length(k)){
  multi4[z] <- (((1-PY)^(z-1))*integrate(part_3.2, A, nt)$value)
}
P_3.2 <- sum(multi4)

part_L3.2 <- function(u){
  dpois(z-1, CM*(u-A))*dlnorm(u, par1, par2)*u
}
multi5 <- NULL
for (z in 1:length(k)){
  multi5[z] <- (((1-PY)^(z-1))*integrate(part_L3.2, A, nt)$value)
}
L_3.2 <- sum(multi5)

#calculation of Z(A)
K_A <- (P_1.1+P_3.2)*c_usd + (P_2.2+P_3.1)*c_usd_pm + P_2.1*c_sd+c_com
L_A <- L_1.1 + L_2.1 + L_2.2 + L_3.1 + L_3.2
```

```
K_A
L_A
Z_A <- K_A/L_A
Z_A

# test
1-(P_1.1+P_2.1+P_2.2+P_3.1+P_3.2)

# Script CM
 Z_cor <- (c_usd + c_com)/(exp(par1+0.5*par2^2))
Z_cor

# Script CBM dummy case
W <- my_data[14,2]
H <- my_data[15,2]
o <- -0.2
frac <- (H-o)/(W-o)
#Function for P_1.1CBM and L_1.1CBM
funWARN <- function(x){
  ppois(q-1, CM*((frac*x)-x), FALSE)*(((par1_war*par2_war)/(H-o))*(((H-
o)/(par2_war*x))^(par1_war+1))*exp(-((H-o)/(par2_war*x))^par1_war))*(if ( (frac*x) >= g*t){
    0
  } else {
    1
  })
}
funSUMM <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUMM[q, g] <- integrate(funWARN, (g-1)*t, g*t)$value*(1-PY)^(q-1)
  }
}
P_1.1CBM <- sum(funSUMM)*PY

funWARN_L <-  function(x, y){
  (y+x)*erlang(x, q, CM*((frac*y)-y))* ppois(q-1, CM*((frac*y)-y), FALSE)*(((par1_war*par2_war)/(H-
o))*(((H-o)/(par2_war*y))^(par1_war+1))*exp(-((H-o)/(par2_war*y))^par1_war))*(if ( (frac*y) >= g*t){
    0
  } else {
    1
  })
}
funSUMM_L <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUMM_L[q, g] <- (integrate(function(y) {
      sapply(y, function(y) {
        integrate(function(x) funWARN_L(x,y), 0, frac*y-y)$value
      })
    }, (g-1)*t, g*t))$value*(1-PY)^(q-1)
  }
}
```

```
L_1.1CBM <- sum(funSUMM_L)*PY

#Function for P_1.2CBM and L_1.2CBM
funWARN2 <- function(x){
  dpois(q-1, CM*((frac*x)-x))*(((par1_war*par2_war)/(H-o))*(((H-o)/(par2_war*x))^(par1_war+1))*exp(-
((H-o)/(par2_war*x))^par1_war))*(if ( (frac*x) >= g*t){
    0
  } else {
    1
  })
}
funSUMM2 <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUMM2[q, g] <- integrate(funWARN2, (g-1)*t, g*t)$value*(1-PY)^(q-1)
  }
}
P_1.2CBM <- sum(funSUMM2)

funWARN2_L <- function(x){
  (frac*y)*dpois(q-1, CM*(g*t-x))*(((par1_war*par2_war)/(H-o))*(((H-
o)/(par2_war*x))^(par1_war+1))*exp(-((H-o)/(par2_war*x))^par1_war))*(if ( (frac*x) >= g*t){
    0
  } else {
    1
  })
}
funSUMM2_L <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUM2_L[q, g] <- (integrate(funWARN2_L, (g-1)*t, g*t)$value)*(1-PY)^(q-1)
  }
}
L_1.2CBMW <- sum(funSUMM2_L)

#Function for P_2.1CBM and L_2.1CBM
funWAR <- function(x){
  ppois(q-1, CM*(g*t-x), FALSE)*(((par1_war*par2_war)/(H-o))*(((H-
o)/(par2_war*x))^(par1_war+1))*exp(-((H-o)/(par2_war*x))^par1_war))*(if ((frac*x) < g*t){
    0
  } else {
    1
  })
}
funSUM <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUM[q, g] <- (integrate(funWAR, (g-1)*t, g*t)$value)*(1-PY)^(q-1)
  }
}
P_2.1CBM <- sum(funSUM)*PY
```

```
funWAR_L <-  function(x, y){
  (y+x)*erlang(x, q, CM*(g*t-y))* ppois(q-1, CM*(g*t-y), FALSE)*(((par1_war*par2_war)/(H-o))*(((H-o)/(par2_war*y))^(par1_war+1))*exp(-((H-o)/(par2_war*y))^par1_war))*(if ( (frac*y) < g*t){
    0
  } else {
    1
  })
}
funSUM_L <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUM_L[q, g] <- (integrate(function(y) {
      sapply(y, function(y) {
        integrate(function(x) funWAR_L(x, y), 0, g*t-y)$value
      })
    }, (g-1)*t, g*t))$value*(1-PY)^(q-1)
  }
}
L_2.1CBM <- sum(funSUM_L)*PY

#Function for P_2.2CBM and L_2.2CBM
funWAR2 <- function(x){
  dpois(q-1, CM*(g*t-x))*(((par1_war*par2_war)/(H-o))*(((H-o)/(par2_war*x))^(par1_war+1))*exp(-((H-o)/(par2_war*x))^par1_war))*(if ( (frac*x) < g*t){
    0
  } else {
    1
  })
}
funSUM2 <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUM2[q, g] <- (integrate(funWAR2, (g-1)*t, g*t)$value)*(1-PY)^(q-1)
  }
}
P_2.2CBM <- sum(funSUM2)

funSUM2_L <- matrix(nrow = length(k), ncol = 500)
for (q in 1:length(k)){
  for (g in 1:500){
    funSUM2_L[q, g] <- integrate(funWAR2, (g-1)*t, g*t)$value*(1-PY)^(q-1)*g*t
  }
}
L_2.2CBMW <- sum(funSUM2_L)


#Calculation of Z(W)
P_1.1CBM
P_1.2CBM
P_2.1CBM
P_2.2CBM
L_1.1CBM
```

```
L_1.2CBM
L_2.1CBM
L_2.2CBM
K_W <- P_1.2CBM*c_cbm+P_2.2CBM*c_sd+(P_1.1+P_2.1)*c_usd_pm+c_com
L_W <- L_1.1CBM+L_1.2CBM+L_2.1CBM+L_2.2CBM
K_W
L_W
Z_W <- K_W/L_W
Z_W
#test
1-(P_1.1CBM+P_1.2CBM+P_2.1CBM+P_2.2CBM)

# Script CBM general for Weibull
#Function for P_1.1CBM and L_1.1CBM
funWARN <- function(x, y){
 dweibull(x, par1_war, par2_war)*ppois(q-1, CM*(x-y), FALSE)*((dweibull(y, par1_war, 
par2_war)))/(pweibull(y, par1_war, par2_war, FALSE))
}
funSUMM <- matrix(nrow = length(k), ncol = 100)
for (q in 1:length(k)){
 for (g in 1:100){
 funSUMM[q, g] <- (integrate(function(y) {
  sapply(y, function(y) {
   integrate(function(x) funWARN(x,y), y, g*t)$value
  })
 }, (g-1)*t, g*t))$value*(1-PY)^(q-1)
 }
}
P_1.1CBM <- sum(funSUMM)*PY

funWARN_L <-  function(x, y, z){
  (z+x)*erlang(x, q, CM*(y-z))*pweibull(y, par1_war, par2_war)*ppois(q-1, CM*(y-z), 
FALSE)*((dweibull(z, par1_war, par2_war)))/(pweibull(z, par1_war, par2_war, FALSE))
}
funSUMM_L <- matrix(nrow = length(k), ncol = 50)
for (q in 1:length(k)){
 for (g in 1:50){
  funSUMM_L[q, g] <- integrate(function(z) {
   sapply(z, function(z) {
    integrate(function(y){
     sapply(y, function(y){
      integrate(function(x) funWARN_L(x, y, z), 0, y-z)$value
     })
    }, z, g*t)$value
   })
  }, (g-1)*t, g*t)$value*(1-PY)^(q-1)
 }
}
L_1.1CBM <- sum(funSUMM_L)*PY

#Function for P_1.2CBM and L_1.2CBM
funWARN2 <- function(x, y){
```

```
  dweibull(x, par1_war, par2_war)*dpois(q-1, CM*(x-y))*((dweibull(y, par1_war,
par2_war)))/(pweibull(y, par1_war, par2_war, FALSE))
}
funSUMM2 <- matrix(nrow = length(k), ncol = 50)
for (q in 1:length(k)){
  for (g in 1:50){
    funSUMM2[q, g] <- (integrate(function(y) {
      sapply(y, function(y) {
        integrate(function(x) funWARN2(x,y), y, g*t)$value
      })
    }, (g-1)*t, g*t))$value*(1-PY)^(q-1)
  }
}
P_1.2CBM <- sum(funSUMM2)

funSUMM2L <- matrix(nrow = length(k), ncol = 50)
for (q in 1:length(k)){
  for (g in 1:50){
    funSUMM2L[q, g] <- (integrate(function(y) {
      sapply(y, function(y) {
        integrate(function(x) funWARN2(x,y), y, g*t)$value
      })
    }, (g-1)*t, g*t))$value*(1-PY)^(q-1)*g*t
  }
}
L_1.2CBM <- sum(funSUMM2L)

#Function for P_2.1CBM and L_2.1CBM
funWAR <- function(w){
  ppois(q-1, CM*(g*t-w), FALSE)*((dweibull(w, par1_war, par2_war)))/(pweibull(w, par1_war,
par2_war, FALSE))
}
funSUM <- matrix(nrow = length(k), ncol = 50)
for (q in 1:length(k)){
  for (g in 1:50){
    funSUM[q, g] <- (integrate(funWAR, (g-1)*t, g*t)$value)*(1-PY)^(q-1)*pweibull((g*t), par1_war,
par2_war, FALSE)
  }
}
P_2.1CBM <- sum(funSUM)*PY

funWAR_L <- function(x, y){
  (x+y)*erlang(x, q, CM*(g*t-y))*ppois(q-1, CM*(g*t-y), FALSE)*((dweibull(y, par1_war,
par2_war)))/(pweibull(y, par1_war, par2_war, FALSE))
}
funSUM_L <- matrix(nrow = length(k), ncol = 50)
for (q in 1:length(k)){
  for (g in 1:50){
    funSUM_L[q, g] <- (integrate(function(y) {
      sapply(y, function(y) {
        integrate(function(x) funWAR_L(x,y), 0, g*t-y)$value
      })
```

```
    }, (g-1)*t, g*t))$value*(1-PY)^(q-1)*pweibull((g*t), par1_war, par2_war, FALSE)
  }
}
L_2.1CBM <- sum(funSUM_L)*PY

#Function for P_2.2CBM and L_2.2CBM
funWAR2 <- function(w){
  dpois(q-1, CM*(g*t-w))*((dweibull(w, par1_war, par2_war)))/(pweibull(w, par1_war, par2_war,
FALSE))
}
funSUM2 <- matrix(nrow = length(k), ncol = 50)
for (q in 1:length(k)){
  for (g in 1:50)
  funSUM2[q, g] <- (integrate(funWAR2, (g-1)*t, g*t)$value)*(1-PY)^(q-1)*pweibull((g*t), par1_war,
par2_war, FALSE)
}
P_2.2CBM <- sum(funSUM2)

funWAR_L2 <- function(x){
  dpois(q-1, CM*(g*t-x))*((dweibull(x, par1_war, par2_war)))/(pweibull(x, par1_war, par2_war, FALSE))
}
funWAR_l2 <- function(u){
  u*dweibull(u, par1_war, par2_war)
}
funSUM_L2 <- matrix(nrow = length(k), ncol = 50)
for (q in 1:length(k)){
  for (g in 1:50){
    funSUM_L2[q, g] <- (integrate(funWAR_L2, (g-1)*t, g*t)$value)*(1-PY)^(q-1)*integrate(funWAR_l2,
g*t, Inf)$value
  }
}
L_2.2CBM <- sum(funSUM_L2)

#Calculation of Z(W)
K_W <- P_1.2CBM*c_cbm+P_2.2CBM*c_sd+(P_1.1+P_2.1)*c_usd_pm+c_com
L_W <- L_1.1CBM+L_1.2CBM+L_2.1CBM+L_2.2CBM
K_W
L_W
Z_W <- K_W/L_W
Z_W

#test
1-(P_1.1CBM+P_1.2CBM+P_2.1CBM+P_2.2CBM)
```