MASTER

Design of a decision support tool that calculates the availability and life cycle costs based on design and maintenance decisions

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Award date:
2014

Eindhoven, August 2014

Design of a decision support tool that calculates the availability and life cycle costs based on design and maintenance decisions

by

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In partial fulfilment of the requirements for the degree of

Master of Science
in Operations Management and Logistics

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

Subject headings: Availability, Life cycle costs, Maintenance Policies, Design

It should be noted that all the numbers used in this master thesis are fictitious

I. Abstract

In this master thesis, a mathematical is developed to determine the availability and life cycle costs for one customer based on the maintenance policy and design. Both failure based maintenance policy, and preventive block replacement policy are considered in the model. Design decisions can be made on the selection of the component and its reliability configuration. The serial configuration and the cold standby configuration are modelled. In the literature, limited articles are available about such models. Furthermore the model is implemented in a decision support tool which makes it possible to apply the model to different scenarios. In additions to the model and the tool, a case study for determining the availability and life cycle cost for different designs in different situations is provided.

II. Preface

This master thesis is the result of the final phase in the master Operations Management and Logistics at the Eindhoven University of Technology. In the last seven months I have executed this interesting project at Philips Healthcare.

First of all, I would like to thank my first supervisor, S.D.P. Flapper, for his guidance during my project. I appreciate the time and effort he put into my project. He was always available to answer my questions, even in the weekends. I enjoyed our, often long, meetings where he provided me his critical but always constructive feedback. In addition, I would like to thank. H. Peng for her questions and remarks during the meetings of my project proposal and conceptual report.

Next, I would like to express my gratitude to A. Zephat and T. Ketting Olivier, for giving me the opportunity to perform the project at Philips Healthcare and their support during my project. In particular, I want to thank them for providing me all the practical and technical knowledge about the medical scanner. This helped me to develop a tool which can be put into practice. Furthermore, I would like to thank many other colleagues who helped me during the project.

Last but not least, I would like to thank my family and friends for their interest and support. In particular, I want to thank my parents for giving me the opportunity to study for the last six years. Special thanks to my girlfriend, Michelle, for her encouragement during my entire master study. I also thank my fellow students for having an amazing time during the lectures and projects in the master program.

III. Management summary

This master thesis is the result of the Master program Operation Management and Logistics at the University of Eindhoven. This project has been executed by Philips Healthcare at the location Best.

Introduction

Philips sells different designs of the medical scanners to medical institutes all over the world. Keeping these systems working (available) in the medical institutes is crucial since operations interruption leads to significant costs for the customers. In order to prevent the customer for these significant losses, Philips sells service contracts with different guaranteed availability levels, where the maintenance of the medical scanner is performed by Philips. In order to maintain the systems, Philips applies a failure based maintenance policy with regular planned maintenance activities. Thereby, Philips considers applying the preventive maintenance policy to increase the availability of the medical scanners. Although Philips Healthcare guarantees a certain level of availability, Philips does not have a calculation model to obtain the expected availability of different systems designs, and maintenance policies. Previous research has shown that the amount of use of the system, the quality of the cooling in the medical institute, and the quality of the mains power are related to the availability of the system. Based on this, it is concluded that the availability of one system design varies along the customers. In addition to the availability, the life cycle costs of a system design are important to take decisions about the design and maintenance policy for one specific customer with typical local situation such as the amount of use of the system, quality of the cooling, and the quality of the mains power. Based on these statements, it is concluded that Philips is not able to take accurate decision about the design and maintenance policies for a specific customer with respect to availability and life cycle costs. This has led to the following research question:

What are the availability and life cycle costs of different system designs and maintenance policies for one specific customer?

In the project, two design decisions have been taken in to account: the selection of the components in the system design, and the reliability configuration of the system. Philips has two different configurations in the designs of the medical scanner, the serial reliability configuration and the cold standby configuration. Both configurations have been included in the model. Due to time limitation, only two maintenance policies have been incorporated in the model: the failure based maintenance policy with regular planned maintenance activities and the preventive block replacement policy. The preventive block replacement policy had been selected in addition to the current maintenance policy since block replacement is easier to implement than other preventive maintenance policies. This is due to the fact that the preventive maintenance actions are performed at a fixed time interval.

Research framework

The research framework of Mitroff et al. (1974) has been used as guideline along this project. This framework consists of four phases: the conceptualization, modelling, model solving, and implementation. In the conceptualisation phase, the life cycle cost elements have been determined according to the first level cost breakdown structure developed by Öner et al. (2007) with the use of the life cycle cost methodology developed by Woodward (1997). In addition to the life cycle costs, the holistic outline of the system availability elements developed by Smets, van Houtum, and Langerak

(2012) has been adapted to the case of the medical scanner. After the conceptualisation the mathematical model has been developed. The mathematical model has been implemented in a decision support tool which makes use of a Monte Carlo simulation. The decision support tool has been verified and validated. In the modelling solving phase the decision support tool has been applied to a case study for different designs of Subsystem Design 1. In the final phase, implementation, the tool and its manual were delivered and explained to the organisation during several workshops.

Results

During this project a decision support tool has been developed that is able to calculate the availability and life cycle costs of one scenario within 1 up to 12 minutes, depending on the scenario. This enables users to compare different scenarios relative quickly. The decision support tool consists of the User Interface, where the user can input the data for the simulation and read the output of the simulation: availability and lifecycle costs. Furthermore, an installation and user manual of the decision support tool have been made. In order to perform a case study, the data has been analysed. The steps that have been taken to estimate the input parameters of the case study, as accurate as possible, have been described. In addition to this description, an Excel Spreadsheet has been developed, which can estimate the time to failure and downtime distribution and the value of its parameters based on historical data.

The decision support tool has been applied to different Subsystem A designs, which can be used in System Design 1, for customers in Area A and Area B. The different designs of subsystem A consist of the current subsystem design A1 and the new subsystem design A2. The new design can be produced with or without a cold standby backup. The simulations of the different scenarios have shown that the life cycle costs of the subsystem A2 are considerable lower than the life cycle costs of subsystem A1. The biggest savings is due to the lower coolant costs. The drawback of the subsystem A2 is that the availability is lower compared to subsystem A1. However, by adding the backup to subsystem A2 the availability increases to more or less the same level as the availability of subsystem A1. The scenario results show that it depends on the values of the customer input parameters whether it is optimal to install the backup for the subsystem A2 with respect to the life cycle costs.

Conclusion and Recommendations

It is concluded that the decision support tool enables Philips to take decisions about design and maintenance policy based on availability and life cycle costs for individual customers. For this reason it is recommended to use the developed tool during the selling process of a new system to a specific customer. The tool supports the account manager to determine the optimal design for a specific customer. Furthermore, it is recommended to use this tool in determining the price of service contracts, since the tool can provide the expected cost for Philips during a service contract.

Academic Relevance

The developed model consists of the relation between availability and both the reliability configuration of the medical scanner design and the selection of the critical components. This contributes to a rather new research topic “Design for Availability”, which investigates the relation between the design of a capital good and the availability or downtime. Moreover, the developed model contains the relations between different maintenance policies and designs, and the availability and life cycle costs. This combination is rare in the literature. Furthermore, the model is applied to a practical case, where it is in most literature unclear how the model should be applied into practice. The model is not only useful for the medical scanner: it can also be applied to other capital goods.

Contents

Definitions

Term	Definition
Availability	The fraction of time that a system is in condition to perform its intended function during contract hours
Backup component	A component that is installed in the system which can perform the same function as the main component
Contract hours	The hours that the medical scanners is required by the customer to perform its intended function
Contracting lifetime	The period of time over where a service contract is sold by Philips
Corrective maintenance	Is a set of activities, which is performed with the intention of restoring the functionality of the item or system, after a failure
Critical component	A component that may cause system downtime at failure
Design	The process of defining the critical components and its architecture to satisfy the specified requirement
Downtime	The time that the system is not available to perform its intended function during contract hours
Failure	An event where the system or component is not able to perform its function according to its specifications
Life cycle costs	The costs that occur during the life time of the system for Philips
Limited functionality failure	A failure which does not cause system down time, it only disturbs the scanning process
Maintenance policy	The maintenance strategy that determines the type of maintenance at which event (e.g. failure, time passing)
Medical scanner	System that produces medical images of the human body
No functionality failure	A failure that causes system downtime, the critical component is not able to perform its intended function
Planned Maintenance	Pre-defined maintenance activities such as cleaning filters and checking wires
Preventive Maintenance	Replacing an operating component by an as good as new one to reduce the probability of a failure

Reliability	The probability that a component or system will perform without interruption a required function for a given period of time when used under stated operating conditions
Reliability configuration	The way critical components are related to one another with respect to reliability is indicated by the configuration (Ebeling, 2010)
Service contract	Agreement between Philips and the customer where Philips maintains the system of the customer and guarantees an availability service level for a fixed fee per year
Subsystems	Group of related components, which together perform one or more functions

Abbreviations

CBS	Cost Breakdown Structure
CC	Critical Component
CM	Corrective Maintenance
DT	Diagnostic time
DNA	Does not apply
FDV	Field Data View
FSE	Field Services Engineer
GDWH	Global Data Warehouse
IS	Imaging systems
LCC	Life Cycle Costs
MD	Maintenance delay per failure
MDT	Mean Downtime
N.A.	Nothing Available
PM	Preventive Maintenance
RPT	Replacement time
TTF	Time to failure

1. Introduction

This research project has been conducted at Philips Healthcare. This chapter gives the description of the research environment, problem statement, research design and the report outline.

1.1. Research Environment

1.1.1. Deliverables

At the start of this project two deliverables were assigned. First a decision support tool that is able to calculated the availability and life cycle cost for one specific customer based on maintenance policy and design of the system. This tool should help Philips in making decision about the system design and the maintenance policy for one specific customer with typical local situation. The second deliverable is a case study for specific scenarios based on pre-defined design alternatives.

1.1.2. Company background

Royal Philips Electronics is the Netherlands-based parent company of the Philips Group. It consists of three divisions: Philips healthcare, Consumer Lifestyle and Lightning. This research project is conducted in the Philips Healthcare division. Philips is present with manufacturing and sales offices in more than 100 countries and it employed 116,000 people in April 2013. Philips had a turnover of 24.8 billion Euros in 2012 (Philips NV, 2012). As shown in Figure 1, the Healthcare is the largest (41%) division in terms of sales in 2012. Furthermore, the Healthcare sales increased with 6.4% in 2012, which is considerably more than the Consumer Lifestyle and Lightning division with a sales growth of respectively 1.7% and 3.8%.

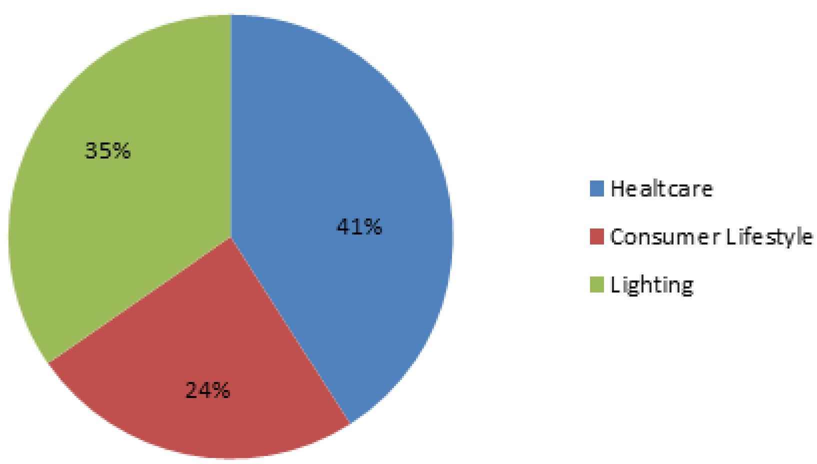

Figure 1: Philips NV sales 2012

The goal of the Philips Healthcare division is to develop innovative solutions to improve patients' outcome, provide better value and expand access to care. Over 37.000 employees are working in the Healthcare division of Philips and more than 450 products and services are offered in more than 100 countries. This study is done at location Best, Netherlands, which is European headquarter of Healthcare division with 3000 employees.

The Healthcare division consists of 4 businesses groups: Home Healthcare Solution, Imaging systems, Patient Care and Clinical Information, and Global Customer services. This research is done in the Imaging Systems (IS) group. In the Imaging Systems group, medical scanners are produced. In this research, the medical scanner is subject to investigation. More information about the medical scanner can be found in the next section.

1.1.3. Medical Scanner

Medical scanners are used to produce images of the human body. These images, which are called medical images, are used for medical diagnostic and treatments purposes. The first commercial medical scanner was developed in 1963. After the first medical scanner release, the technology evaluated rapidly. Nowadays, various types of medical scanners are available to produce medical images, which help doctors in diagnosing and treating diseases of patients. Medical scanners can be classified as capital goods since medical scanners are high technical systems which are used by medical institutes to deliver their service (van Houtum, 2010).

Philips is making different system designs of the medical scanner. Each system design can be broken down into subsystems, which consist of several components. The system breakdown is shown in Figure 2

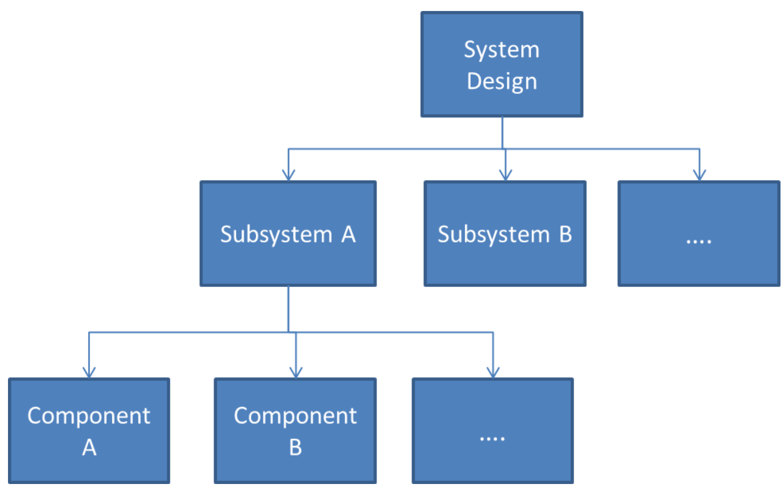

Figure 2 Medical Scanner breakdown structure

The components can be dived into critical and non-critical. The critical components of subsystems do cause system downtime and non-critical do not. Special attention in this project is on the critical components, since availability is considered. It should be noted that if a subsystem consists of at least one critical component, the subsystem is classified as critical subsystem.

1.1.4. Service contracts

Philips sells performance based service contracts, which is an agreement between Philips and a customer where Philips maintains the system of the customer and guarantees an availability service level for a fixed fee per year. Customers who bought a medical scanner can outsource part or all of their maintenance activities to Philips for a fixed fee per year.

Customers are not obligated to outsource the maintenance activities for the entire Medical scanner. The customer can decide to cover some specific components of the medical scanner in the contract instead of the entire system. The group of components of the system that is under service is called covered system and is denoted in the service contract. The majority of the service contracts cover the entire system.

The maintenance activities that can be outsourced by the customer to Philips are captured in three services: repair service, planned maintenance service, and software updates. The repair service consists of providing all replacement components, which may be refurbished and labour necessary to repair covered system. The second service is a schedule of planned maintenance activities for covered systems. During a planned maintenance activity Philips performs pre-defined maintenance activities such as cleaning filters and checking wires. Besides the repairs and replacements, Philips installs operating system software updates provided by the original equipment manufacturer for the covered system.

The key performance indicator incorporated in the service contract is the guaranteed availability (96%, 98% or 99%). In case the guaranteed availability is not met, Philips has to pay a penalty cost. The duration of a service contract is normally one year. After one year the customer could decide to buy another year. However, the majority of the customer buys service contracts year after year until the system is at the end of its lifetime (i.e. the period of time over which the product is developed, in operation by the customer and eventually disposed by the customer).

1.2. Problem Statement

Different designs of the medical scanners are sold to medical institutes all over the world. Keeping these systems working (available) in the medical institutes is crucial since operations interruption leads to significant costs for the customers. In order to prevent the customer for these significant losses, Philips sells service contracts with different guaranteed availability levels. When the achieved availability over the year is below the guaranteed availability of the service contract, Philips has to give a discount on the contract for the upcoming year. Although Philips Healthcare guarantees a certain level of availability, Philips does not have a calculation model to obtain the expected availability during a contract year. This means that Philips is not able to take accurate decisions about the design for a customer with respect to availability.

Moreover, the availability of the systems in the field is not measured systematically. Thus, it is not known whether the availability of the systems is above the guaranteed availability. In recent years, a few customers have claimed the penalty discount. Due to the increasing importance of the medical scanners availability, it is expected by the marketing department of Philips Healthcare that more customers may claim the discount in the future if the availability is too low. Moreover, the availability of the medical scanner tends to be more and more important during the selling process of medical scanners. Increasing number of customers only wants to buy a medical scanner if Philips guarantees a certain level of availability. In short, medical scanner availability has high priority.

Philips is looking for possibilities to increase the availability. First, Philips is making alternative designs including backups (i.e. one or more components that are installed in the system which can perform the same function as the main component) for critical components to increase the availability. These backups should take over the functionality of the critical component at a failure, which improves the availability of the system. In addition to the backups, Philips also considers to replace critical components preventively to improve the availability of the systems and decrease the maintenance costs and penalty costs. However, Philips does not have a model which is able to determine the effect of design decisions and maintenance policies on the availability and life cycle costs.

Previous research by Philips has shown that the amount of use of the medical scanner plays an important role in the availability of the system. From a customer questionnaire it is known that the quality of the medical institute cooling and the mains power are also related to the availability. However, Philips does not have a quantitative model that is able to determine the effect of the quality of the medical institutes' cooling and the mains power on the availability and life cycle costs of the medical scanner. In addition, it is known that the number of contract and scan hours, which are different per customer, are related to the availability and life cycle costs. However, these relations are not included in a quantitative model. Furthermore, the influence of the service contract type on the life cycle costs is not known. In the rest of this report, the quality of the medical institutes' cooling, mains power, service contract type and the amount of scan hours per year are defined as customer specific parameters.

From this section, it is concluded that Philips is not able to make accurate decisions about the design and maintenance policy with respect to availability and lifecycle costs for one customer with typical local situation.

1.3. Research Design

1.3.1. Research goal

Philips is looking for a quantitative tool to determine the availability and related life cycle cost of a system design for a specific customer. This should support Philips in making accurate decisions about the system design and preventive maintenance interval for specific customer based on availability and life cycle costs.

Moreover, a user of the tool should be able to quickly compare the availability and life cycle costs of different scenarios based on design, maintenance policies, and customer parameters. For this reason, it has been decided that the computational time of the decision support tool to determine the availability and life cycle costs for one system design, with one set of maintenance policies, and with one set of customer data should be less than 15 minutes.

This leads to the following research goal:

Design a decision support tool that is able to determine the availability and Life cycle costs for a specific customer based on the decision variables, design and maintenance policy, within restricted computational time.

1.3.2. Research Question

From the research goal of the previous section the research questions is derived:

What are the availability and life cycle costs of different system designs and maintenance policies for one specific customer?

In order to answer the main research question and to deliver both deliverables three sub questions (SQ) are formulated.

Sub Question 1

In order to take decisions about the design and maintenance policy with respect to life cycle costs and availability it should be known which cost elements occur for a medical scanner from a Philips perspective. Furthermore, the relation between the cost elements, availability, and decision variables should be defined. Some cost elements are sensitive to modifying the decision variables and some are not related to the decision variables.

What are the life cycle cost elements for a medical scanner and how are they related to system availability and the decision variables? (Chapter 2)

Sub Question 2

Once the life cycle cost elements and the relation between the life cycle cost elements, availability, and decision variables are identified, the relations should be translated into a mathematical model. In order to make the effect of different decisions visible without a lot of manual computation time, the mathematic model is implemented into a decision support tool which is able to obtain the availability and life cycle costs within restricted computational time.

How can the availability and life cycle costs of a system be determined for one customer within restricted computational time based on the system design and maintenance policy? (Chapter 3-4)

Sub Question 3

After the decision support tool is developed, the tool is applied to different design alternatives for different customers. In order to apply the tool to a practical case, it should be known how the values of the input parameters can be estimated.

How can the values of the input parameters be estimated based on the data available by Philips? (Chapter 5)

1.3.3. Research demarcation

Although, there are not many differences between the different designs of the medical scanner, it is essential to focus on one specific model due to time limitations. After discussion with Service experts, it is decided to choose the System Design 1 for the case study. The reason behind the selection of the System Design 1 is that the effect of the decision variables can be examined, since Philips is making new designs of subsystems used in System Design 1. Furthermore, sufficient data is available of System Design 1.

Currently, Philips is investigating a new design including backups to improve the availability of the system. Kumar et al. (2000) distinguished three standby systems: cold standby, warm standby, and hot standby. In case of a cold stand-by backup the backup component is switched on when the main component fails. In a warm standby configuration, the backup component shares a partial load along with the main component. When the backup component shares equal load with the main component it is called a hot-standby backup. The backups in the new designs of Philips can be classified as cold-standby backups. Due to technical reasons, it is expected by service experts that Philips is not going to design other backups than cold-standby in the future. For this reason it is decided to only take into account cold-standby backups in this research project.

Due to time limitation it is not possible to examine all different maintenance policies. Together with the service experts it is decided to only take into account the failure based maintenance policy with regular planned maintenance activities and the preventive block replacement policy. The argumentation behind this is the fact that a block replacement is easier to implement than other preventive maintenance policies, since the preventive maintenance actions are performed after a fixed time interval.

The life cycle costs of a system from a Philips perspective, which are taken into account in this project, are defined as all the costs that occur during the life time of the system. The development costs that occur to develop a new design are excluded in the life cycle costs since the tool should support Philips in making decisions about available designs.

1.3.4. Research Methodology

The research model developed by Mitroff et al. (1974) is used as a guideline along the project. The model is shown in Figure 3 . The operational research approach consists of four phases: (1) conceptualization, (2) modelling, (3) model solving and (4) implementation (Bertrand & Fransoo, 2002). In each phase several sub question are answered.

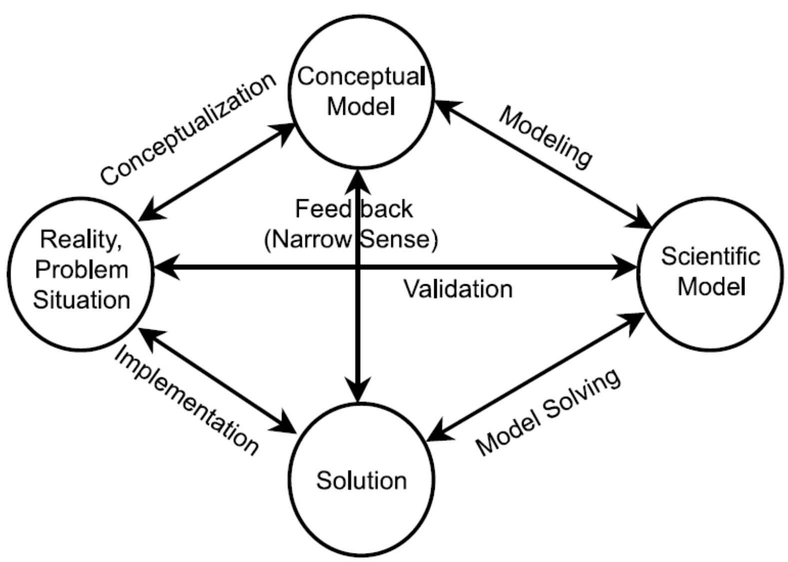

Figure 3: Research model developed by Mittrof et al. (1974)

Conceptualization

- *What are the life cycle cost elements for a medical scanner and how are they related to system availability and the decision variables?*

Conceptualization is the first phase of the research model developed by Mittrof et al (1974). In this phase a conceptual model of the problem is defined. This means that life cycle cost elements are determined. Moreover, the conceptual relation between these cost elements, availability, and decision variables are obtained. The conceptual phase is described in Chapter 2.

Modelling

- *How can the availability and life cycle costs of a system be determined for one customer within restricted computational time based on the system design and maintenance policy?*

In the second phase, the mathematical model is developed. The causal relations between the variables defined in the conceptualization phase are described in mathematical terms. This mathematical model is implemented in a decision support. The modelling phase is described in Chapter 3 and 4.

Model solving

- *How can the values of the input parameters be estimated based on the data available by Philips?*

In order to apply the mathematical model to a practical case, the methods to estimate the input parameters of the decision support tool are described. Furthermore, the decision support tool is tested and applied to different scenarios. These scenarios are compared for different customers in different areas. The model solving phase is described in chapter 5 and 6.

Implementation

The final phase of the research model is the implementation phase. In this phase, the implementation actions are explained. The implementation phase is described in chapter 7.

1.4. Report outline

This first chapter explains the research environment of this project with the research goal and research question. The second chapter provides a life cycle cost analysis and an overview of the availability elements. The relations between the life cycle costs and availability decision variables are also explained in chapter 2. The third chapter provides the mathematical relation between the decision variables, availability, and life cycle cost. Next, in chapter 4 the decision support tool is explained. The estimation approaches of the input variables of the decision support tool are explained in chapter 5. Then, the decision support tool has been applied in several scenarios, which is described in chapter six. Chapter 7 describes the implementation of the decision support tool. Finally, in chapter 8, the conclusions and recommendations are made.

A schematic overview of the report outline can be found In Figure 4

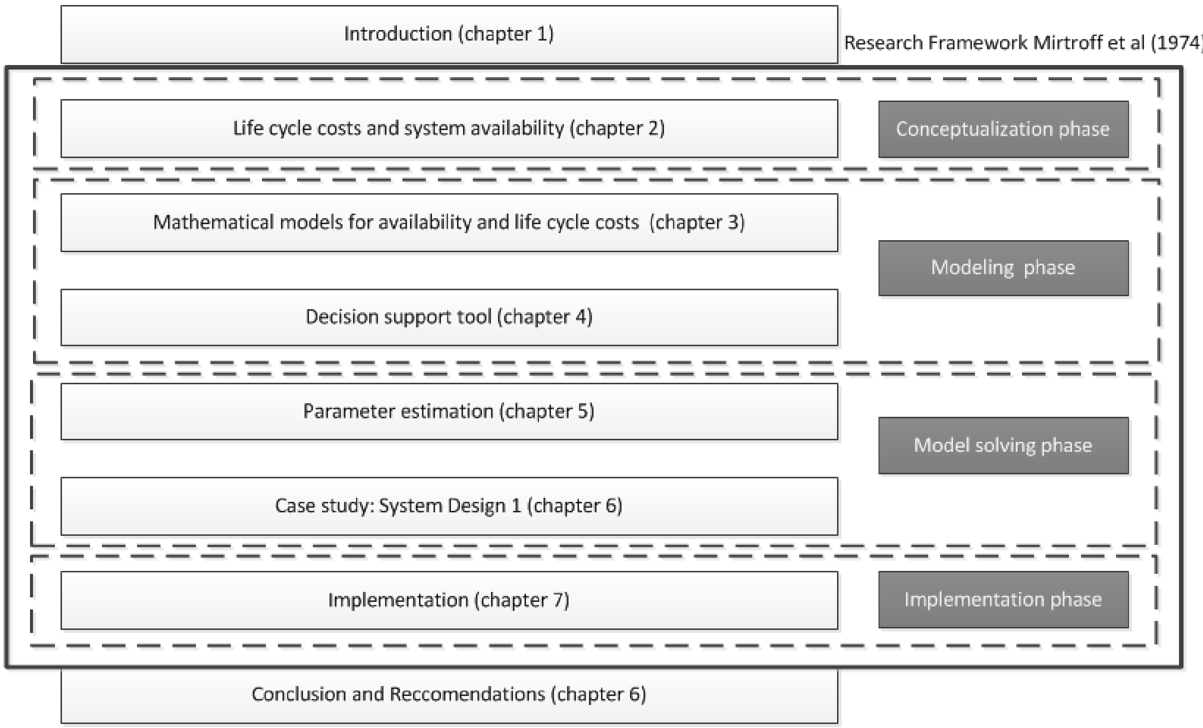

Figure 4: Report outline

2. Life cycle costs and system availability

2.1. LCC methodology

In the literature numerous Life Cycle Cost (LCC) methodologies are designed to produce LCC calculations. In 1997, Woodward has provided a LCC procedure consisting of four steps as shown in Figure 5. First, define the cost elements of interest from a customer or producer perspective. Second, define the cost structure which involves grouping costs to identify potential trade-offs. Third, establish the cost estimating relationship, a mathematical expression that describes, for estimating purposes, the costs of a system as a function of one or more independent variables. Fourth, develop a method to evaluate the potential trade-offs.

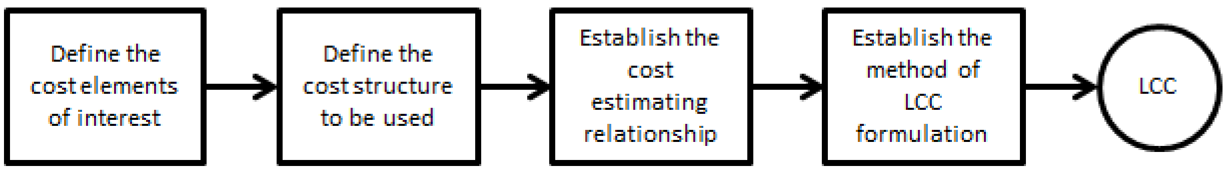

Figure 5: Woodward (1997) life cycle costing procedure

In relationship with the research framework, the first two steps are part of the conceptualization phase and the second two steps are part of the modelling phase.

Currently Philips does not have a detailed LCC calculation model for the entire medical scanners. Zephat (2009) made a life cycle costs model for one component of the medical scanner. The cost elements and structure have been identified and the cost estimating relationships have been described. However, some cost elements with respect to service contracts and the relation with availability are missing. In order to get a good overview of the LCC of the entire system, the four steps of Woodard (1997) have been performed. The cost elements and cost structure are defined in section 2.3 and step 3 and 4 of Figure 5 are described in chapter 3.

2.2. Cost elements from a Philips perspective.

According to Woodward (1997) the cost elements of interest are all the cash flows that occur during the life of the system. These costs should be grouped to identify potential trade-offs. Öner et al. (2007) propose that the cost can be grouped into sub collections called *cost elements* broken down level by level. The decomposition of this is called the cost breakdown structure (CBS) (Öner et al., 2007).

Öner et al. (2007) developed a first level cost breakdown structure for capital goods from a customer perspective. The first level CBS consist of acquisition costs, operating costs, maintenance costs, downtime costs and disposal costs as shown in Figure 6.

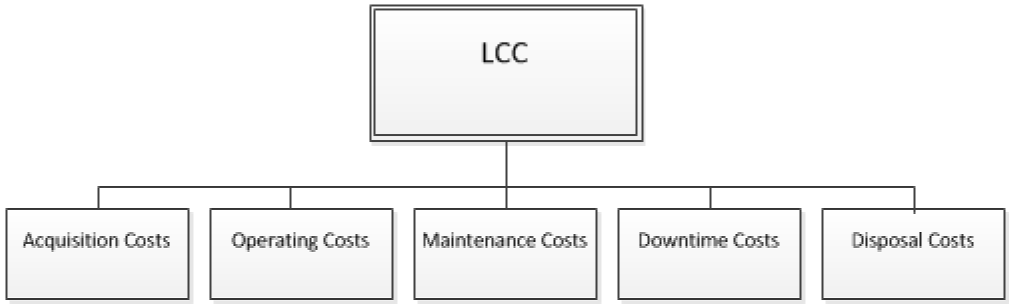

Figure 6: First level cost buckets (Öner et al., 2007)

In contrast to acquisition costs, maintenance costs and downtime costs, the operating costs and disposal costs do not occur for Philips. These costs are for the customer. The acquisition costs are all the cash flows that occur before the system is in use by the customer. For Philips, these costs consist of the purchasing prices of the components, assembly costs and shipment & installations costs. It should be noted that the development costs are excluded in this research. These costs are excluded since this project concerns designs which already exist.

Maintenance costs regarding medical scanners occur when the system is in use by the customer. However, maintenance costs are relevant to Philips as well since Philips offers warranty and sells service contracts. The costs for maintenance during the warranty period are called “Warranty costs” and during the service period are called “Maintenance service costs”. This distinction has been made since separate decision can be made with respect to warranty and service.

In adaption to the maintenance costs, Philips is penalized for a system under service that suffered too much downtime measured over one calendar year. These costs are called contract penalty costs.

To summarize, the Life Cycle Cost of medical scanners from a Philips perspective consists of the costs elements purchasing prices of the components, assembly costs, shipment and Installation costs, warranty costs, maintenance service costs and contract penalty costs as shown in Figure 7.

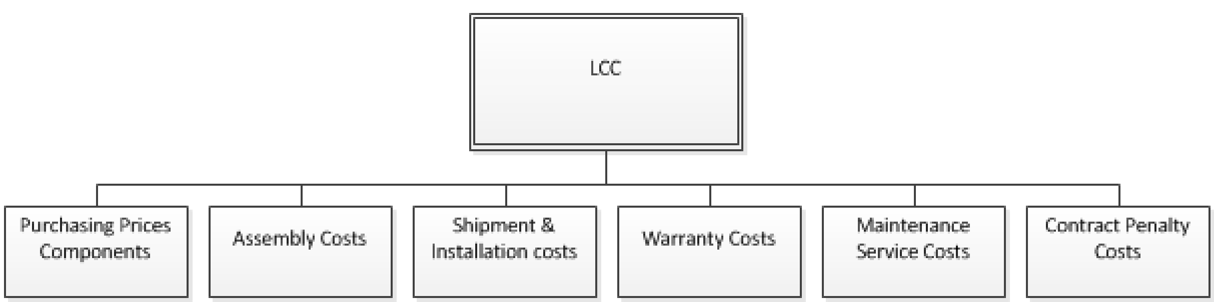

Figure 7: First level cost elements for a medical scanner,

Maintenance service costs and contract penalty costs do not occur for every customer. When a customer does not decide to outsource their maintenance activities to Philips, the maintenance service costs and contract penalty costs are not part of the life cycle cost of that specific medical scanner from a

Philips perspective. In the installed base data (i.e. Global Data Warehouse (GDWH)), it is shown that the majority of the customers buy a service contract after the warranty period.

Furthermore, the total amount of maintenance service costs and contract penalty costs are determined by the contracting lifetime of the service contracts. It is not valid to take the service contract length (i.e. one year) as the contracting lifetime since the majority of the customers prolongs the contract year after year. In order to get a good overview of maintenance service costs and contract penalty costs the contracting lifetime should be estimated per specific customer.

The first level cost breakdown structure as shown in Figure 7 should be broken down in a more detailed level for the medical scanner. This is done in section 0 after more insight is gathered in the conceptual relation between availability and LCC.

2.3. Availability

The system performance parameter availability is a contract requirement of the medical scanners' service contracts. Availability is defined as the percentage of time the medical scanner performs its intended function during contract hours over one year time period. In the literature, this type of performance measure is called interval availability (Ebeling, 2010). The yearly hours, that the medical scanners is desired by the customer to perform its intended function, are defined as contract hours. This does not refer to the hours that the system really works but the time span that the customer plans scans. For example, if the customer plans scans from 8 AM to 5 PM, Monday to Friday, and 50 weeks per year, then the contract hours of this customer are 2250 hours. During these contract hours the system should be available for the customer.

In order to show that downtime during non-contract hours does not affect the availability, a graphical example has been made, which is shown in Figure 8. In this figure, the total system downtime in calendar hours of the three situations is equal. However, the availability in the first situation is 75%, in the second situation 100%, and in the third situation 50%. This difference between these three situations with respect to availability is caused by the downtime that is not during contract hours.

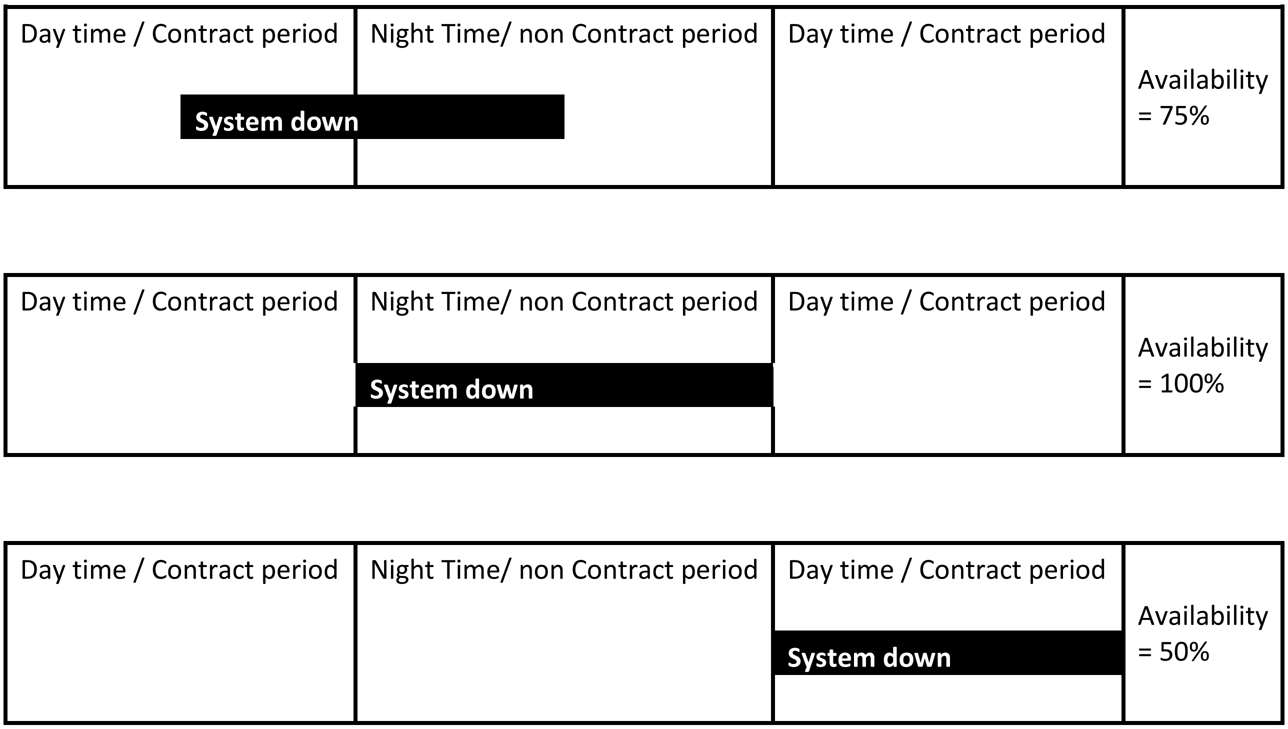

Figure 8: Examples of system down situation during contract and non-contract periods

In principle, preventive maintenance is performed outside contract hours. In case it is not possible to perform preventive maintenance outside contract hours (e.g. a system which performs 24 hours per day 365 days per year) the scheduled preventive maintenance hours during contract hours are deducted from total number of contract hours per year. This means that system downtime due to preventive maintenance action does not reduce the availability. Since the preventive maintenance actions are performed during non-contract hours the availability can be calculated with equation (1) (van Houtum, 2010):

$$Availability = 1 - \left(\frac{Downtime\ during\ contract\ hours\ per\ year}{Contract\ hours\ per\ year}\right) \qquad (1)$$

System downtime is caused by a failure of a critical component where the critical component has no functionality. At a failure, the component could have no functionality or limited functionality. When a component has limited functionality it can still perform its intended function, which means that there is no downtime. However, the scan may have inferior quality or the scan process is not optimal. For this reason, components are always replaced by an, as good as new, component at a failure. In the rest of this report a distinction has been made between “No functionality” failures and “Limited functionality” failures.

The availability of the system is determined by the availability of the critical components. The components of the medical scanner have different time intervals where it is operating. Some components are operating "24/7", some during contract hours, and others only when the system is scanning. Due to the fact that the contract hours and scan hours vary along systems, which are in use by different customers, the different time intervals are taken into account. Each critical component can be classified into one of three different classes with respect to operating hours:

1. Category (A): The components that operate the entire year (e.g. the medical institute cooling)
2. Category (B): The components that operate during contract hours(e.g. computer of the scanner)
3. Category (C): The components that operate when the system is scanning (e.g. scanning components)

The schematic representation of the relation between the calendar time interval and the operating time is given in Figure 9.

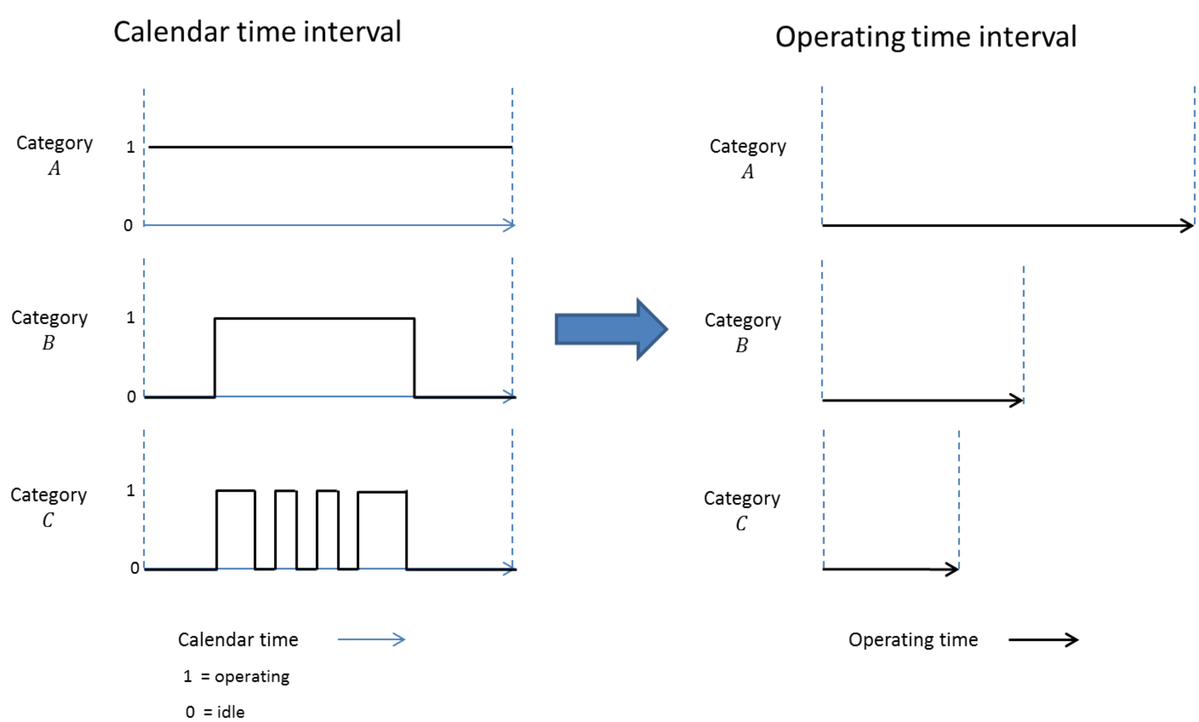

Figure 9: Relation between calendar time interval and operating time interval

Number 1 in the calendar time interval denotes that the component is operating, and number 0 denotes that the component is idle. In the operating time interval the time that the component is idle (number 0) is excluded from the interval. It should be noted that the calendar time interval of component in category A is equal to the operating time interval. Furthermore, a category C component installed in the same system as another category B component will always have a shorter operating time interval than that particular category B component.

According to Smets, van Houtum, and Langerak (2012) factors that are related to system availability can be sub divided in factors that increase the uptime and factors that reduce the downtime of a system.

Downtime can be dived in Maintenance Delay (MD) and Replacement Time (RPT) (van Houtum, 2010). Moreover, availability depends on the manufacturer's design activities (categorized under "**Design**") as well as on its after-sales activities when the system is already operational at the customer (categorized under "**Operations**"). The holistic outline of system availability elements of Smets, van Houtum, and Langerak (2012) is modified to the case of Medical scanners, which is shown in Figure 10.

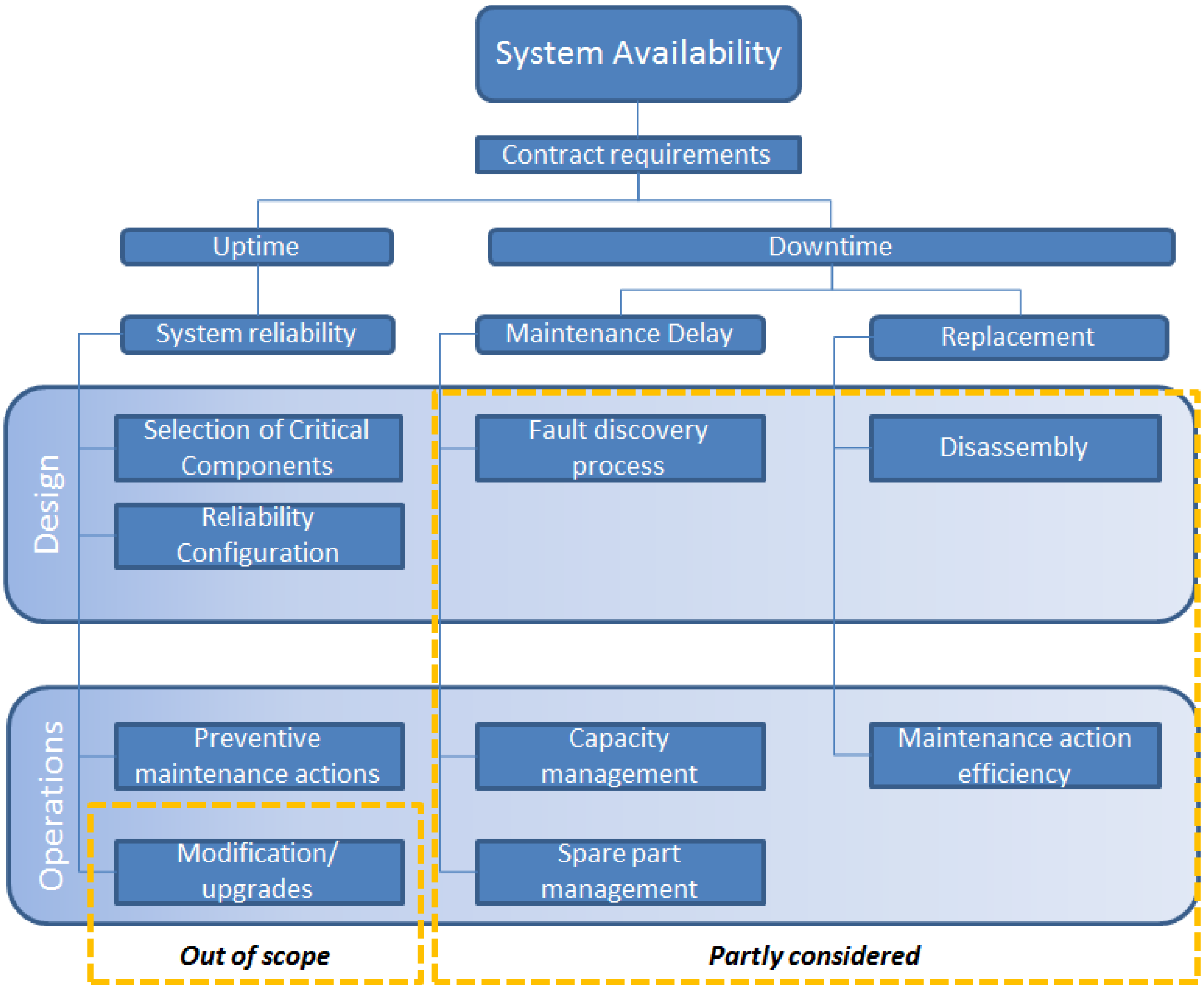

Figure 10: the holistic outline of system availability elements of the medical scanners (Smets, van Houtum, & Langerak, 2012)

Uptime

The time that a system is available to perform its intended function in a given period is defined as uptime. This time can be increased by decisions made on, selection of critical components, reliability configuration, preventive maintenance actions, and modification/upgrades.

<u>Selection of critical components</u>

For the medical scanner different critical components among alternatives can be selected. Each critical component has its own failure behaviour. Consequently, the reliability and corresponding availability differ per critical component. Decisions about the selection of critical components together with the reliability configuration determine a considerable part of the availability of the system. The selection of the critical components among alternatives is a decision variable in this research project.

Reliability configuration

The way critical components are related to one another with respect to reliability is indicated by the configuration (Ebeling, 2010). For example, in a serial configuration the system is always unable to perform its intended function if one of the critical components has no functionality. The current medical scanner has a serial reliability configuration, where the critical components fail independent of each other as expected by the system experts (i.e. Philips employees who have thorough understanding of the technical part of the system).

In contrast to a serial system, in a standby configuration either the main component or the backup should function properly for the system to function. As stated before, the cold-standby backup is used as decision variable in this research project.

The cold-standby backup considered by Philips can take over limited functionality of the main component when it has no functionality. An automatic switch triggers the backup when the main component has no functionality. This automatic switch should work properly for the backup to take over the functionality of the main component. After the main component is restored in working condition the system is switched back to the main component. It is preferred to use the main component, since the backups considered in this project can only take over limited functionality. However, when the backup takes over limited functionality of a critical component, there is no downtime. It should be noted that the backup does not have to be identical to the main component. It could be a different component that can perform the limited functionality of the main component, which is enough to prevent the system for downtime.

The failure process of a cold-standby backup configuration with a successful switch is as follows:

1. The main components fails
2. The automatic switch triggers the backup
3. The backup takes over the functionality of the main component
4. The main component is repaired
5. The main component takes over the functionality of the backup

Figure 11a and Figure 11b gives an example of a system with three critical components: 1, 2.1, and 3. Critical component two has a backup component (2.2) installed which can take over limited functionality. In Figure 11a all the components are working which result that the complete system is working. In Figure 11b component 2.1 is broken. However, the switch triggered the backup (2.2) and subsequently the system is still up and running due to the fact that component 2.2 has taken over limited functionality of component 2.1.

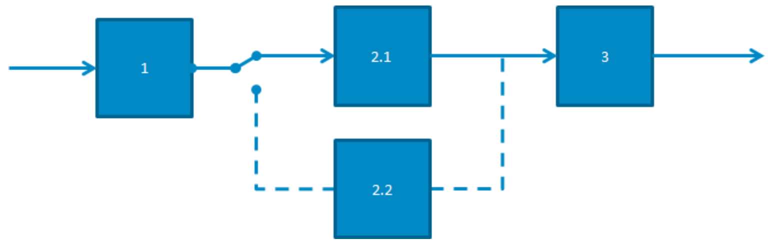

Figure 11a: Cold stand-by system where all components 1, 2.1, and 3 are working

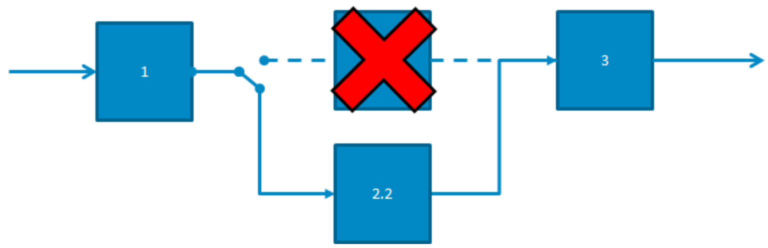

Figure 11b: Cold stand-by system where component 2.1 has no functionality

Preventive maintenance actions

Maintenance policy is a strategy that determines the type of maintenance at which event (e.g. failure, time passing). According to Wang (2002) maintenance policies can be categorized into two major classes: failure based policies and preventive maintenance policies. In a failure based policy maintenance action are applied after a failure. Preventive maintenance occurs when a component is operating to reduce the probability of a failure.

The uptime can be increased by preventive maintenance actions for critical components that are wearing out over time since preventive maintenance actions are excluded from the downtime. The block replacement policy and failure based maintenance policy are considered as two scenarios as shown in Figure 12a and Figure 12b.

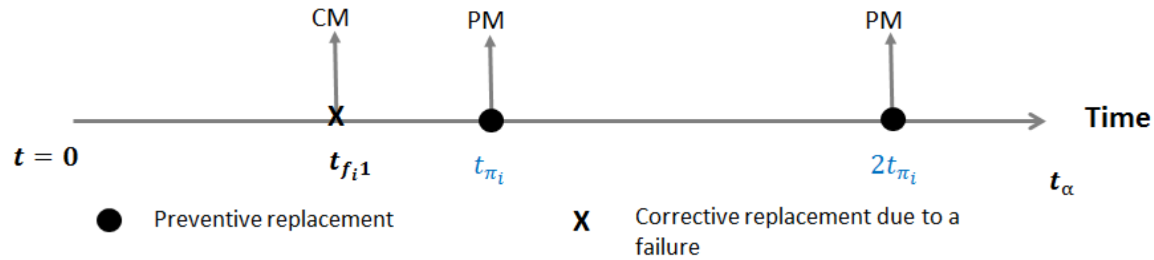

Figure 12a: Example of block replacement policy during period $t = 0$ to t_α, where t_{π_i} is the preventive maintenance interval of component i and $t_{f_i 1}$ denotes the first failure of component i

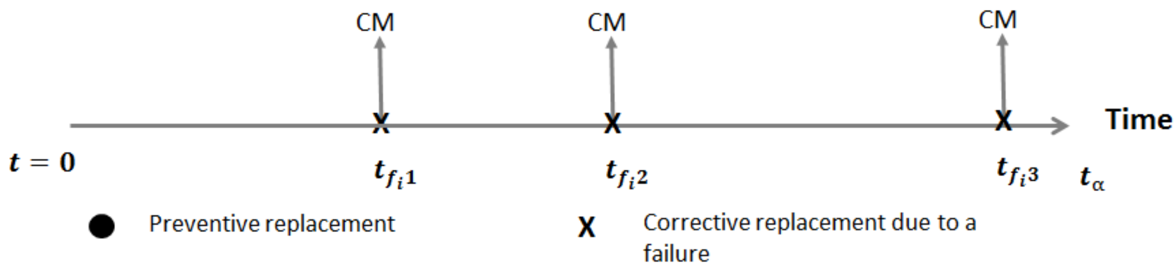

Figure 12b: Example of failure based policy during period $t = 0$ to t_α, where $t_{f_i 1}$ denotes the first failure of component i

During a preventive maintenance action an operating critical component is replaced by an as good as new one. In a block replacement policy, preventive maintenance is performed to an operating component at a fixed time interval and corrective maintenance is performed at a failure. The block replacement interval is used as decision variable in this research project.

Modification and upgrades

The availability of the medical scanner may also be improved by modification/upgrades during the operations phase. Upgrades refer to replacement of critical components in operating systems due to introduction of new technologies, functionality changes, reliability improvements etc. The effect of upgrades on the availability of the system is excluded from this research since it is almost impossible to predict what kind of upgrades will be made for the medical scanners in the future.

It should be noted that Philips has to decide whether or not to extend service contract under which conditions at the end of each year. For this purpose it may be interesting to further investigate the effect of upgrades on the availability and life cycle costs.

Downtime

The time that the system is unable to perform its intended function is defined as downtime. Due to time limitations, the downtime is partly considered as one variable which is estimated based on the current Fault discovery process, Capacity management, Spare part management, Disassembly, Maintenance action efficiency. The specific relation between these five downtime elements and the total downtime is left for further research. These variables are not considered as decision variables in this research.

Fault discovery process

The fault discovery process refers to the action that have to be performed to obtain which critical component causes the systems downtime. In the design phase the system can be designed in such a way that it makes the fault discovery process more efficient which reduces the maintenance delay. For example, sensors for condition monitoring can be included in the design which makes remote diagnostic possible.

Disassembly

The system can be designed in such a way that in case of a failure the system can be disassembled quick and easy. Design decisions made to facilitate the disassemble process can reduce the replacement time and subsequently reduces the downtime.

Capacity management

Capacity management refers to how the Field Service Engineers (FSE) and tools are allocated to maintain the systems in a service contract. When the system is in operation by the customer, the way the capacity is managed affects the maintenance delay. Efficient capacity management ensures that sufficient service engineers are available at the right location, with the right knowledge and tools at the right time to provide customer service and support.

Spare part management

Spare part management consist of the replenishment strategy, location and safety stock of the spare components. When there are not enough spare components available at a failure the maintenance delay may increase significantly. Thus, the spare components should be managed efficient to keep the maintenance delay short. Furthermore, the downtime of a critical component does also depend on the distance between the warehouse and location of the system. Thus, the downtime of the critical component should be estimated for a specific location of the system.

Maintenance action efficiency

Maintenance action efficiency refers to the efficiency of the action that should be taken to replace the critical component. For instance, maintenance training for FSEs and manuals about how to perform maintenance action may reduce the replacement time.

Decision variables:

Based on the availability elements three decision variables in relation with design and maintenance policy have been selected for this research: the selection of (critical) components in the system, reliability configuration, and maintenance policy.

2.4. LCC and Availability

2.4.1. Life cycle Costs that are related to the decision variables

In this section the first level cost elements of the medical scanner are described. The graphical representation of the cost breakdown structure can be found in Appendix A. The relations between the main cost elements and the decision variables of this research are shown in Table 1, where x means that the cost are sensitive to modifying the decision variable.

Table 1: the relation between main cost elements and decision variables

	The selection of (Critical) Components in the system	Reliability configuration	Maintenance Policy
Purchase prices components	x	x	
Assembly costs	x	x	
Shipment and Installation costs	x	x	
Warranty costs	x	x	x
Maintenance service costs	x	x	x
Contract penalty costs	x	x	x

Purchasing price components

Selecting a more reliable component reduces the costs when the system is in operation. However, a more reliable component is, in general, more expansive than a less reliable component. Furthermore the configuration of the critical components influences the reliability. Transforming a serial system into a cold standby configuration by adding a backup to the critical component increases the reliability of the system (Kumar et al., 2000). However, the total purchasing price of the components increases by adding a backup to the design. The purchasing price of the component is determined by decisions on selection of critical components and reliability configuration.

Assembly costs

The cost to assemble (i.e. the process of putting all the individual components together to one complete system) the individual component to a complete system depends on the system design. The complete design determines these costs. For this reason, the assembly costs should be determined per system design.

Shipment and Installation costs

The shipment and installation (i.e. the process of getting the system to the customer and install the system at the customer site) costs are partly determined by the decision variables of this project. The design of the system does play a role at the installation process of the system at side, since the system is prepared for the customer. However, the shipment and installation cost does also depend on the location of the system. Therefore the shipment and installation costs should be determined for each specific system.

Warranty costs and Maintenance Service costs

Preventive maintenance action can be performed to reduce the number of unexpected failures of degrading components (i.e. components that wear out over time). The more preventive actions are performed the less corrective maintenance actions have to be performed. Moreover the more preventive maintenance action are performed the higher the availability will be since the preventive maintenance action are excluded from downtime. However, at some point the preventive maintenance costs may outweigh the cost for corrective maintenance. Furthermore, the design decisions about selection of critical components and the reliability configuration influence the frequency of corrective maintenance and preventive maintenance actions. The corrective maintenance and preventive maintenance costs are determined by the Labour costs, spare component supply costs, i.e. to transport the spare component from the warehouse to the customer location plus the transport cost to transport the damaged component to the repair shop, administration costs, and repair costs that are made for repairing or scrapping the damaged component including labour and material at the repair shop.

Additional to the corrective and preventive maintenance costs the medical scanners suffer coolant loss. Coolant is used to cool the system. During the cooling process of the system coolant is lost, which is called coolant loss. Depending on the subsystems installed in the system design, the system has to be filled with a given amount of coolant each year. During warranty and service, Philips pays for the coolant. These costs are called coolant costs.

Contract penalty costs

The expected downtime cost is a result of the decision about design and maintenance policy. The availability can be increased by selecting more reliable components, more redundant configurations, and to perform more preventive replacements of critical degrading components. If the availability increases the contract penalty costs decreases. Thus, all the decision variables are related to contract penalty costs.

The contract penalty cost is a result of the guaranteed availability, explained in chapter 1. It depends on the achieved availability in given year whether or not Philips has to give a penalty discount to their customer for next year. These costs are called contract penalty costs.

Finally it should be noted that components which are not classified as critical are not related to availability of the system. However, the life cycle costs elements of the critical components apart from the contract penalty costs are also associated with non-critical components. The developed tool can also be used to determine the life cycle costs of the non-critical components.

2.4.2. Life cycle costs that are not related to the decision variables

Besides the cost elements of section 2.4, other life cycle costs, which are not related to the decision variables, occur for a medical scanner. These costs are estimated as constant which means that these costs do not vary when decision are made on the selection of critical components, reliability configuration, and preventive maintenance interval.

As explained in section 1.1.4 the planned maintenance[1] visits are excluded as decision variable in this research. The planned maintenance action are predetermined and for every system the same with the same frequency. Decision about modifying the planned maintenance actions are left for further research. However, the current costs for the planned maintenance are included in the model.

2.5. Assumptions

Several assumptions have been made in the conceptualisation phase (section 2.1-2.4). The assumptions are listed in this section. A few assumptions are described in more detail in appendix B.

1. In case the customer decides to buy a service contract, the service contract will be prolonged for a given number of years denoted as the contracting lifetime. (Section 2.2)
2. It is expected by the medical scanner experts that the critical components fail independently of each other. (section 2.3 and Appendix B)
3. At the beginning of the warranty period all the components are as good as new since only new components are installed in a new system. (section 2.3)
4. At a failure the component is replaced by an as good as new component since the FSEs has the policy to replace damaged components by an as good as new component at a failure. (section 2.3)
5. In order to calculate the expected number of failures, the replacement times are neglected. (Appendix B)
6. There is downtime when the system is not able to perform its intended function during contract hours (i.e. The hours that the medical scanner is required by the customer to perform its intended function) (section 2.3)
7. Operating hours are used as time unit for the failure distribution since the contract hours and scan hours varies per system. (section 2.3)
8. The operating hours per year are constant over time for a customer (Appendix B)
9. Only downtime during contract hours is considered to determine the availability section 2.3
10. The backup component and automatic switch are as good as new after a corrective replacement of the main component. (section 2.3)
11. Preventive maintenance does not lead to system downtime since it is not performed during contract hours. (section 2.3)
12. The failure rate of the components may increase or decrease over time

[1] Planned maintenance is different from the decision variable preventive maintenance in this research. Planned maintenance consists of predetermined actions which are currently performed by the field service engineers of Philips.

3. Mathematical models for availability and life cycle costs

In this chapter the life cycle cost functions (section 2.1), and the mathematical model to determine the expected availability in an interval (section 2.2) are described. The notation of the mathematical model can be found in Appendix C.

3.1. LCC function

The life cycle cost of the medical scanner can be calculated by the first level cost-elements: the sum of purchasing prices of the components, assembly costs, shipment and installation costs, warranty costs, maintenance service costs and contract penalty costs as explained in section 1. A schematic overview of the costs for Philips during the system lifetime is made in Figure 13.

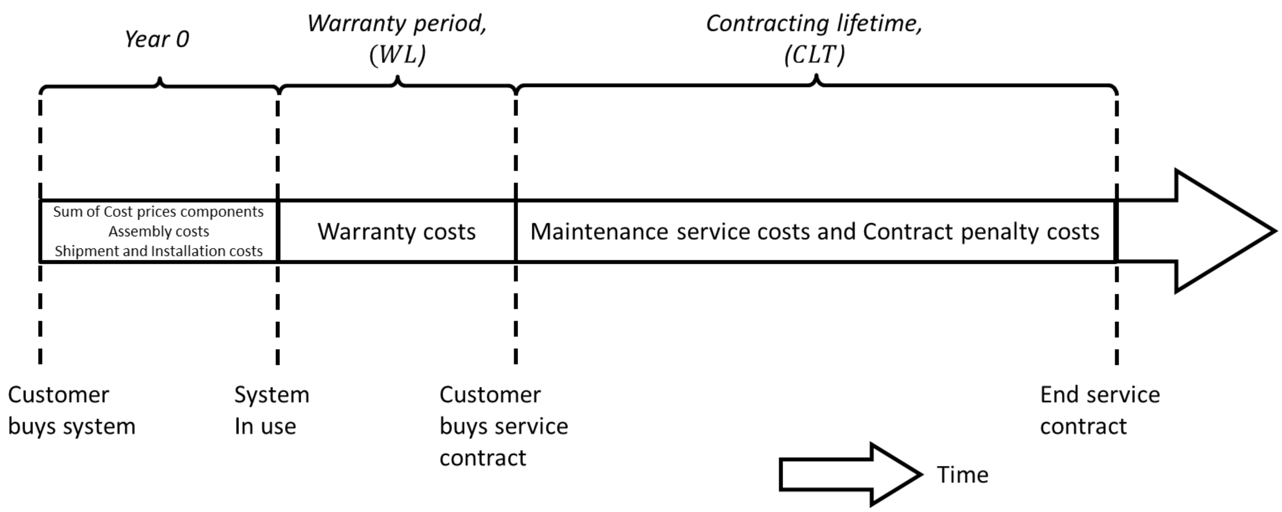

Figure 13: Philips Life Cycle Costs overview

When a customer has decided to buy the new system, the sum of purchasing prices of the components, assembly costs, and shipment and installation costs occur for Philips in year 0. The warranty costs occur after the system is in use by the customer for the length of the warranty period. The maintenance service costs and contract penalty costs occur after the end of the warranty period for the contracting lifetime. In contrast to a service contract, the warranty contract does not contain a downtime restriction.

The total expected LCC for system s from a Philips perspective is calculated via equation (2).

$$ELCC_s = TCP_s + EAC_s + ESIC_s + \sum_{n=1}^{wl_s} EWC_{s,y'_n} + \sum_{l_s=0}^{\infty}\left[P(CLT_s = l_s) * \sum_{n=wl_s+1}^{wl_s+l_s}\left((EMTSC_{s,y'_n} + EPC_{s,y'_n})\right)\right] \quad (2)$$

The first three terms represent respectively the total purchasing price of the components, assembly costs, and shipment and installation costs. The fourth term represents the warranty costs. The last term represents the costs during a service contract.

During the selling process between Philips and the customer the warranty length of the system is determined which is usually one year. After this warranty period the customer decides whether or not to buy a service contract of Philips. The probability that the duration of the service contract is equal to l_S is denoted by $P(CLT_s = l_s)$.

The contract penalty costs, total maintenance service costs, and warranty costs may vary over the years due to decreasing and increasing failure rates of the critical components. The performances of the warranty and service contracts are measured over one calendar year. Furthermore, the warranty and contract duration is a discrete variable in whole years denoted by n. For these reasons, the costs should be calculated per year until the end of either the warranty period or the contracting lifetime.

In the rest of this section the mathematical functions of first level cost elements are given. The first level cost elements can be broken down into costs that are relevant to the design and maintenance decision of critical components and costs which are not influenced by these decisions. The costs that are not related to the decision variables are included in the model since it can help the user to see the effect of design and maintenance decision relative to the total life cycle cost from a Philips perspective.

3.1.1. Purchase price components

The total price of all components together can be calculated by equation (3).

$$TCP_s = \sum_{i=0}^{Q_s} pp_{i,s} \tag{3}$$

The purchasing price of the component i in system s is denoted by $pp_{i,s}$. The sum of all the components results in the total purchasing price of system s, where Q_s denotes all the components that are installed in system s.

3.1.2. Assembly costs

The total assembly costs are determined for each system design. The expected assembly costs for system s are denoted as EAC_s. In this research, these costs are not broken down in more costs elements.

3.1.3. Shipment and installation costs

As explained in section 2.1, the shipment and installation costs are determined by the location and the design of system s. The expected shipment and installation costs of system s are denoted as $ESIC_s$.

3.1.4. Warranty costs

The expected warranty costs is the sum of expected coolant costs (ECC_{s,y'_n}), expected corrective maintenance costs ($ECMC_{s,y'_n}$), expected preventive maintenance costs ($EPMC_{s,y'_n}$), and expected planned maintenance costs (EPM_{s,y'_n}). This is shown in equation (4)

$$EWC_{s,y'_n} = ECC_{s,y'_n} + ECMC_{s,y'_n} + EPMC_{s,y'_n} + EPM_{s,y'_n} \tag{4}$$

In contrast to the corrective maintenance costs, expected preventive maintenance costs and the coolant costs, the planned maintenance costs are not related to the decision variables in this research.

3.1.5. Maintenance service costs

The cost elements of the warranty cost: do also apply for the maintenance service costs. However, the length of the periods may be different. This results in equation (5) for calculating the expected maintenance service costs.

$$EMTSC_{s,y'_n} = ECC_{s,y'_n} + ECMC_{s,y'_n} + EPMC_{s,y'_n} + EPM_{s,y'_n} \quad (5)$$

Corrective maintenance costs

The total corrective maintenance costs, equation (6), can be calculated by multiplying the expected number of failures ($E\left[M_i\left[y_{i,n}\right]\right]$) by the expected cost per corrective maintenance activity($ECMC_{s,i}$).

$$ECMC_{s,y'_n} = \sum_{i=1}^{Q_s} \left[E\left[M_{s,i}\left[y_{i,n}\right]\right] * ECMC_{s,i} \right] \quad (6)$$

$$ECMC_{s,i} = \left(RPT_{s,i} + DT_{s,i} + 2TT_s\right) * h_{FSE} + A_{s,i} + ESCC_{s,i} + ECMRC_{s,i} \quad (7)$$

The expected cost per corrective maintenance consists of labour cost, administration costs, spare component supply costs, and repair costs. The FSE needs time to diagnose the failure ($DT_{s,i}$), travel to the customer (TT_s), and restore the system back in working condition ($RPT_{s,i}$). This determines the labour costs. Furthermore, Administration costs ($A_{s,i}$) are the costs for registering the failure, the good as new component, and damaged component. The transportation costs of both the component that has been replaced and the good as new component determines the spare part supply costs ($ESCC_{s,i}$) . When a critical component fails, the spare component is sent to the customer and the damaged component is sent back to the repair shop. Finally, when the damaged component is repaired (if possible), the repaired component is sent back to the forward stocking location. This sequence is explained in Appendix G.

The repair costs ($ECMRC_{s,i}$) are the costs that are made to restore the used component to an as good as new component at the repair shop.

The expected repair cost for component i can be calculated with equation (8).

$$ECMRC_{s,i} = \sum_{c_i=0}^{pp_i} P(CMR_i = c_i) * c_i + \sum_{rt_i=0}^{\infty} P(RT_i = rt_i) * rt_i * h_{FSE} \quad (8)$$

The expected repair costs is determined by the material costs including the stocking costs (i.e. the cost to stock the spare component) and the labour that is necessary to repair the part. The material costs are between zero and the purchasing price since it is superfluous to repair a component when the material costs are more than the new price. In case that the material costs are more than the new price, the replaced component is scrapped and a new one is ordered. The first term of equation (8) represents the material costs, where $P(CMR_i = c_i)$ denotes the probability that the material costs of component i are equal to c_i. The repair time is equal to the time the field service engineer needs to repair the component or to find out that the component is not repairable. The second term of equation (8) represent the labour costs, where $P(RT_i = rt_i)$ denotes the probability that the repair time is equal to rt_i.

The spare components supply costs can be calculated with equation (9).

$$ESCC_{s,i} = W_i * 2DR_s * TR_{wh} \qquad (9)$$

The cost to transport a component can be calculated by the weight of the component (W_i), distance to travel DR_s, and the cost to transport one kilogram one kilometre (i.e. transportation rate TR_{wh}). Distance and the transportation rate depend on the warehouse area where the system is established. The customer can be established in the area of three different time zone warehouses labelled as Roermond, Louisville, and Singapore.

The route that the component has to travel from the customer to the repair shop via the time zone warehouse is defined as the distance from the customer to the repair shop. This should be multiplied by 2 since the used component has to travel from the customer to the repair shop and the good as new component has to travel in the opposite direction.

Preventive maintenance costs

The cost of one preventive replacement consists of the repair costs, labour costs and the cost to transport the component to the customer. This leads to equation (10).

$$EPMC_{s,y_n'} = \sum_{i=1}^{Q_s} EPR_{i,y_n} * EPMC_{s,i} \qquad (10)$$

$$EPMC_{s,i} = \left[ESCC_{s,i} + EPMRC_{s,i} + \left(RPT_{s,i} + TT_s\right) * h_{FSE}\right] \qquad (11)$$

The preventive maintenance costs per critical component are determined by the number of preventive replacement (EPR_{i,y_n}) during year y_n multiplied by the costs per preventive replacement of component i. The number of preventive replacement during year y_n is calculated via equation (26) which is explained in section 3.2.3.

The repair costs of one preventive maintenance replacement can be calculated with equation (12), where the probability that a component that has been replaced preventively is greater than the probability that a component that has been replaced due to a failure: $P(PMR_i) \geq P(CMR_i)$.

$$EPMRC_{s,i} = \sum_{c_i=0}^{pp_i} P(PMR_i = c_i) * c_i + \sum_{rt_i=0}^{\infty} P(RT_i = rt_i) * rt_i * h_{FSE} \qquad (12)$$

Expected Coolant costs
The coolant costs per year can be determined with equation (13)

$$ECC_{s,y'_n} = cc * \sum_{hb=0}^{\infty} P(CL_s[y'_n] = cl) * cl \tag{13}$$

The first term, cc, represents the coolant costs per litre. In order to obtain the total coolant costs per year, the coolant cost per litre should be multiplied by the expected coolant loss per year of system s. The summation in equation (13) (second term) determines the expected coolant loss per year of system s, where $P(CL_s[y'_n] = cl)$ denotes the probability that the coolant loss of system s is equal to cl.

3.1.6. Contract penalty costs

The expected contact penalty cost in year n is determined by the expected system downtime in year n, the guaranteed availability, and the service contract fee. Three different formulas of the expected downtime are constructed since the customer can choose between three different availability service levels (i.e. 96%,98%, and 99%) with different availability boundaries of the discount percentage.

The expected contract penalty costs in year n can be calculated by the integrals of equation (14). The probability that the availability of the system in year y'_n is equal to a is denoted by $P(A_s[y'_n] = a)$. This probability is multiplied by the product of the contract fee, denoted as F_{sc}, and the discount percentage of the integral. The probability that the availability in year n is equal to a is explained in more detail in section 3.2.

$$\begin{aligned} EPC_{s,y'_n,99} = & \int_0^{0.93} P(A_s[y'_n] = a)\, da * (F_{sc} * 0.15) \\ & + \int_{0.93}^{0.96} P(A_s[y'_n] = a) da * (F_{sc} * 0.1) \\ & + \int_{0.96}^{0.99} P(A_s[y'_n] = a) da * (F_{sc} * 0.05) \end{aligned} \tag{14}$$

$$\begin{aligned} EPC_{s,y'_n,98} = & \int_0^{0.92} P(A_s[y'_n] = a) da * (F_{sc} * 0.15) \\ & + \int_{0.92}^{0.95} P(A_s[y'_n] = a) da * (F_{sc} * 0.1) \\ & + \int_{0.95}^{0.98} P(A_s[y'_n] = a) da * (F_{sc} * 0.05) \end{aligned}$$

$$\begin{aligned} EPC_{s,y'_n,96} = & \int_0^{0.91} P(A_s[y'_n] = a) da * (F_{sc} * 0.1) \\ & + \int_{0.91}^{0.96} P(A_s[y'_n] = a) da * (F_{sc} * 0.05) \end{aligned}$$

3.2. Availability

In this section the mathematical model is derived to calculate the interval availability (i.e. the cumulative uptime fraction over period with a finite time horizon (Mello, Waldman, & Quitério, 2011)).

As explained in chapter 1, Philips is making new designs of medical scanner with respect to critical components where cold standby backup are implemented to improve the availability of the systems. Another goal is to improve the availability of the system by applying the preventive maintenance policy where a critical component with increasing failure rate over time is replaced at a fixed time interval. In order to compare the expected availability of the different design options and maintenance policies the following mathematical models have been developed:

1. Serial configuration with failure-based maintenance policy
2. Cold standby configuration with failure-based maintenance policy
3. Serial and cold standby configuration with block replacement policy

3.2.1. Serial system with failure based maintenance

The availability of the medical scanner depends on the reliability of the critical components. As mentioned before, a component is defined as critical if in case of failure the system may not be able to perform its intended function when required. In other words, all the critical components must function for the system to function. This is called a serial reliability structure (Ebeling, 2010) . The serial relationship is represented by the reliability block diagram of Figure 14, where each block represents a critical component, and where I denotes the total number of critical components of the system. Moreover, critical failures of component i occur at $t_{f_i 1}, t_{f_i 2}, \dots, t_{f_i k}$ and system failures occur at $t_{f_s 1}, t_{f_s 2}, \dots, t_{f_s k}$.

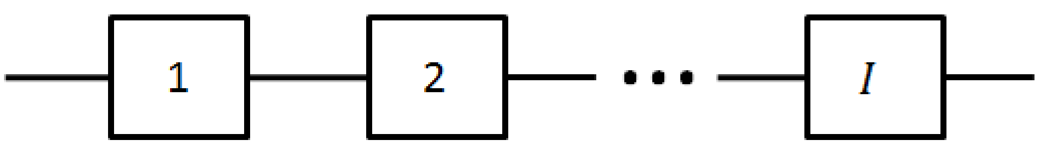

Figure 14: Reliability block diagram for components in series

At the moment of writing this report, Philips applies a failure-based maintenance policy with regular planned maintenance. This policy implies that corrective maintenance activities are performed at a failure to restore an item to the condition as good as new (Kumar et al., 2000). This section concerns the failure based policy, which means that no preventive maintenance actions occur.

According to Mello, Waldman, and Quitério (2011) interval availability should be considered for service level agreement between users and manufacturers with respect to cumulative downtime over a finite window. This is in line with the definition of availability in the service contracts of Philips. In the service contract of Philips, availability is defined as one minus the percentage downtime during contract hours as shown in equation (15).

$$EA_s[\alpha'] = 1 - \left(\frac{ED_s[\alpha']}{CH_s[\alpha']}\right) \tag{15}$$

where the expected uptime ,i.e. $EU_s[\alpha']$, is equal to $CH_s[\alpha'] - ED_s[\alpha']$

Thus, the total expected system downtime can be determined by equation (16).

$$ED_s[\alpha'] = \sum_{i=1}^{I_s} dtcm_{s,i} * E\left[MN_{s,i}[\alpha_i]\right] \tag{16}$$

Where, $dtcm_{s,i} = dtcm'_i * \left(\frac{CH_s[\alpha']}{[\alpha']}\right)$ and $[\alpha_i] = EO_i * [\alpha']$

As stated in chapter 2, the system downtime due to a critical component failure is equal to the number of contract hours that is needed to restore the critical component back in working condition denoted as $dtcm_{s,i}$. This should be multiplied by the total number of no functionality failures in interval $[\alpha']$ of component i (i.e. $E\left[MN_{s,i}[\alpha_i]\right]$). As explained in section 2 a failure of a component could lead to limited functionality or no functionality of the critical component.

When the critical component has limited functionality the operator can still perform scan, which means that the failure does not cause system downtime. The expected number of no functionality failures is probability that k failures occur, i.e. $P(f_i[\alpha_i] = k)$, times the probability that a failure is a no functionality failure, i.e. $P(FM_i = nf)$. This results in equation (17), for determining the expected number of no functionality failure of component i in interval $[\alpha_i]$.

$$E\left[MN_{s,i}[\alpha_i]\right] = \sum_{k=0}^{\infty} P(f_i[\alpha_i] = k) * k * P(FM_i = nf) \tag{17}$$

The derivation of $P(f_i[\alpha_i] = k)$ is explained in Appendix E.

The expected number of no functionality failures can be calculated by equation (18) since both the replacement times are neglected for the expected number of (no functionality) failures calculations, and the fact that the critical components fail mutually independent.

$$E\left[MN_s[\alpha']\right] = \sum_{i}^{I_s} E\left[MN_{s,i}[\alpha_i]\right] \tag{18}$$

where I_s represent the total number of critical components.

Expected number of failures during interval $[\boldsymbol{\alpha_i}]$

The expected number of failures of component i , as used in the corrective maintenance costs equation, is determined via equation (19).

$$E\left[M_{s,i}[\alpha_i]\right] = \sum_{k=0}^{\infty} k * P(f_i[\alpha_i] = k) \tag{19}$$

The expected number of failures of the system s during interval $[\alpha]$ is calculated via equation (20)

$$E\left[M_s[\alpha']\right] = \sum_{i}^{Q_s} E\left[M_{s,i}[\alpha_i]\right] \tag{20}$$

where Q_s denotes the total number of components in system s.

Figure 15 gives a graphical representation of the situation with the assumptions made in this section for a system with two critical components: A and B, where $F_s(t)$denotes the cumulative time to failure distribution function of system s. $F_s(t)$ and other reliability functions are explained in more detail in Appendix D.

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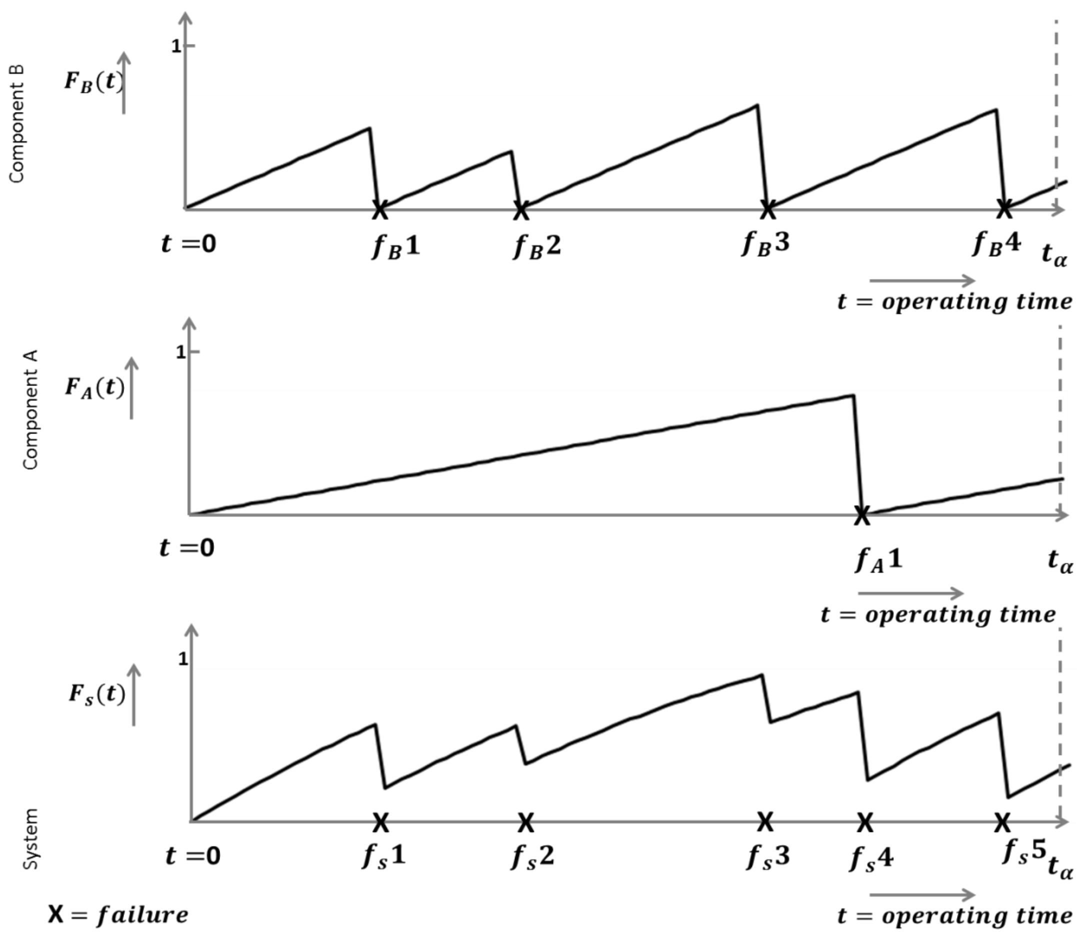

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Figure 15: Serial system with failure based maintenance policy

In the example of Figure 15 it is shown that $F_A(t)$ and $F_B(t)$ drop to zero at a failure of respectively component A and component B. This is the case since a broken component is replaced by an as good as new component. The $F_s(t)$ drops when of one of the critical components fail. However, it does not drop to zero due to the fact that one of the critical components is replaced by a new one instead of the complete system. The relation between the reliability distribution function of the system and the reliability distribution function of the underlying critical components is given by the following:

$$R_s(t) = \prod_{i=1}^{I} R_i(t) \tag{21}$$

where $F_s(t) = 1 - R_s(t)$

It can also be noted that after a failure the $F_s(t)$ rises directly in Figure 15. This occurs due to the assumption that the time between a failure and that the component is replaced by an FSE is neglectable.

The expected number of failures during year n

So far, only the expected number of failures between the beginning of the warranty period and t_{α_i} (interval $[\alpha_i]$is determined as $[0, t_{\alpha_i}]$) is explained. As explained in chapter 1, the availability performance of the medical scanner is penalized over one calendar year. For this reason, Philips is interested in the availability and expected number of failures in year n. From now on year n is defined as interval $\left[y_{i,n}\right]$, which is equal to $\left[t_{i,y_{n-1}}, t_{i,y_n}\right]$

The expected number of failures and expected number of no functionality failures in interval $\left[y_{i,n}\right]$ are calculated via respectively equation (22) and equation (23).

$$E\left[M_{s,i}\left[y_{i,n}\right]\right] = E\left[M_{s,i}\left[0, t_{i,y_n}\right]\right] - E\left[M_{s,i}\left[0, t_{i,y_{n-1}}\right]\right] \tag{22}$$

$$E\left[MN_{s,i}\left[y_{i,n}\right]\right] = E\left[MN_{s,i}\left[0, t_{i,y_n}\right]\right] - E\left[MN_{s,i}\left[0, t_{i,y_{n-1}}\right]\right] \tag{23}$$

Where $t_{i,y_n} = t'_{\ i,y_n} * EO_i$

The percentage operating hours, denoted by EO_i, depends on the operating category of component i as explained in section 2.3. Component that are operating the entire year are classified in Category (A). Category (B) consists of components that are operating during contract hours. The components that are operating when system s is scanning are classified in category (C).

The percentage operating hours with respect to number of calendar hours in year n $(H_{s,i}[y'_n])$ is determined by equation (24)

$$EO_{s,i} = \begin{Bmatrix} (A), & 1 \\ (B), & \frac{CH_{s,i}[y'_n]}{H_{s,i}[y'_n]} \\ (C), & \frac{SH_{s,i}[y'_n]}{H_{s,i}[y'_n]} \end{Bmatrix} \quad (24)$$

Figure 16 gives an example of a component installed in system s. The warranty length, denoted by wl, is equal to one calendar year and the contracting lifetime, denoted by clt, is equal to three calendar years. The first interval $[y_{i,1}]$ is the time between t_{i,y_0} and t_{i,y_1}, and the last interval $[y_{i,4}]$is the time between t_{i,y_3} and t_{i,y_4} . At t_{i,y_1}, the component is one calendar year in use by the customer and at t_{f_i1} the component has failed for the first time.

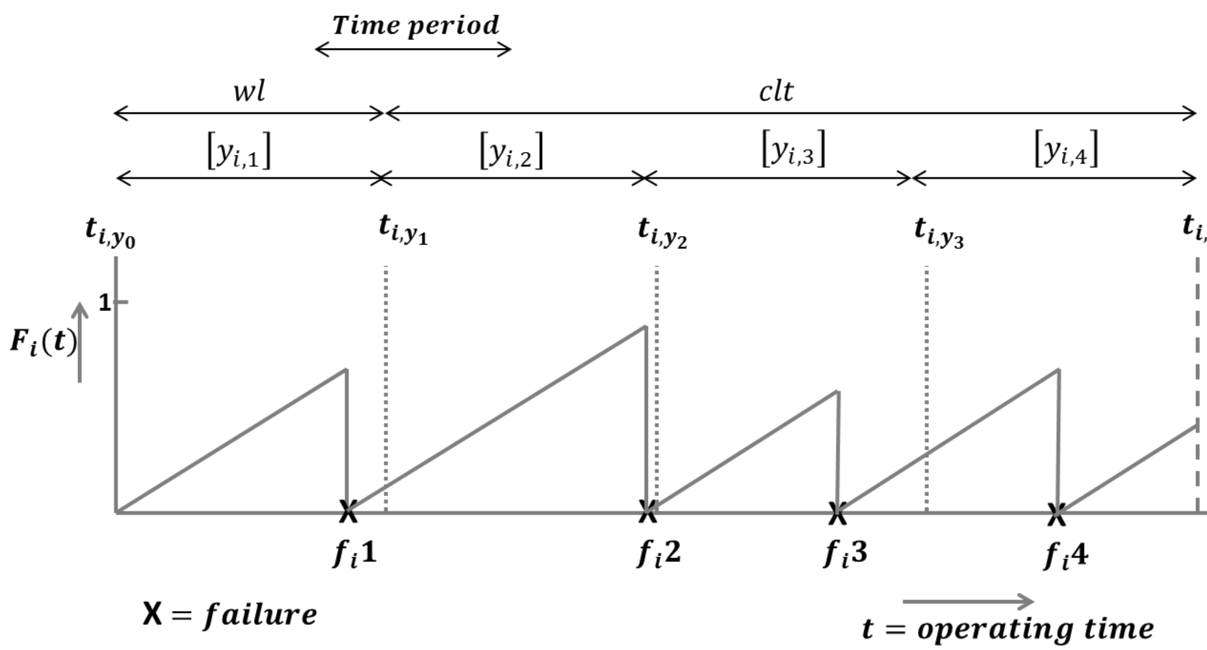


Figure 16: Example of a system with a warranty length of 1 year and contracting lifetime of 3 year

3.2.2. Stand-by system with failure based maintenance

In this section the model of section 3.2.1 is applied to a cold stand-by system with a failure base maintenance.

<u>*Cold Stand-by situation*</u>

In the previous section a serial system was considered. The serial system considered has only one critical component to perform one critical function. In case that a critical component does not function the system is unable to perform its intended function which means that the system is down. In this section a cold stand-by system with one critical component and one backup component per function with an automatic switch is considered.

As explained in section 2.3, the downtime regarding a critical component failure can be avoided by a cold standby backup, which can take over limited functionality of the critical component. However, when the automatic switch does not work the system with automatic switch is still down. Thus, a no functionality failure only occurs when the automatic switch does not trigger the backup at a no functionality failure. The probability that the automatic switch fails at a no functionality failure of component i is denoted by $P(AS_i = sf)$.

Due to the fact that $P(FM_i = nf)$ and $P(AS_i = sf)$ are assumed to be mutually independent, the expected number of no functionality failures in a cold standby configuration is calculated via equation (25)

$$E\left[MN_{s,i}[\alpha_i]\right] = \sum_{k=0}^{\infty} P(f_i[\alpha_i] = k) * k * P(FM_i = nf) * P(AS_i = sf) \qquad (25)$$

When the critical component does not have a backup component then it does not have an automatic switch and $P(AS_i = sf) = 1$, which means that equation (25) is equal to equation (17).

3.2.3. Serial/ cold standby system with block replacement policy

In this scenario, a preventive block replacement policy is applied instead of a failure based policy. The preventive maintenance interval is determined per individual component. Preventive maintenance replacement takes place after t_{π_i} operating hours at $1t_{\pi_i}, 2\,t_{\pi_i}, 3\,t_{\pi_i} \dots, pt_{\pi_i}$. The time it takes to perform preventive maintenance actions are excluded from the contract hours as defined in the service contracts of Philips.

The number of preventive replacements of component i during year n can be determined by

$$E\left[PR_{s,i}[y_n]\right] = \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor \qquad (26)$$

where $\lfloor \quad \rfloor$ means round down to nearest integer.

When Philips decides to perform preventive replacement, equation (22) and (23) are not valid anymore. The schematic representation of Figure 16 is adapted to this scenario and shown in Figure 17.

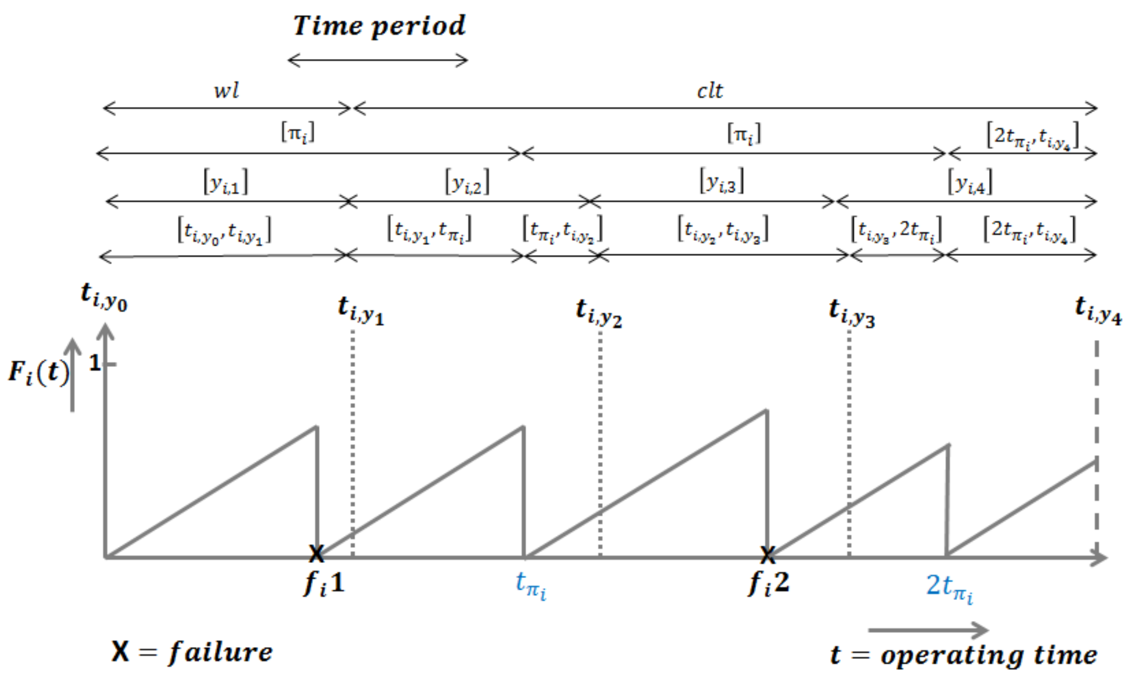


Figure 17: Serial system with block replacement policy with a warranty length of one year and a contracting lifetime of 4 years

After t_{π_i} operating hours, component i is replaced by an as good as new component i. Thus, at $t_{\pi_i}, 2t_{\pi_i}, 3t_{\pi_i} \ldots, pt_{\pi_i}$, the cumulative failure distribution function $F_i(t)$ drops to 0. This means that the expected number failures and the expected number of no functionality failures between two preventive replacements can be calculated with equation (19) and (25), where $[\alpha]$ is equal to $[\pi_i] = [0, t_{\pi_i}]$.

$$E[M_i[\pi_i]] = \sum_{k=0}^{\infty} kP(f_i[\pi_i] = k) \tag{19}$$

$$E[MN_i[\pi_i]] = \sum_{k=0}^{\infty} P(f_i[\pi_i] = k) * k * P(FM_i = nf) * P(AS_i = sf) \tag{25}$$

However, (22) and (23) cannot be used to obtain the expected number of failures in interval $[y_i]$ when preventive replacements are performed.

Based on the two intervals $[\pi_i]$and $[y_i]$ three scenarios have to be distinguished:

1. $[y_{i,n}] = N_i * [\pi_i],$ $\quad N_i \in \{1,2, \ldots\},$
2. $[y_{i,n}] = N_i * [\pi_i] + \varepsilon_i,$ $\quad 0 < \varepsilon_i < [\pi_i],$ $\quad N_i \in \{1,2, \ldots\}$
3. $[y_{i,n}] < [\pi_i]$

Based on equation (19), and (25) the equations on the next pages are derived which determine the excepted number of failures and the excepted number of no functionality failures in year n. The total derivation can be found in Appendix F.

Scenario 1

$$E\left[M_{s,i}\left[y_{i,n}\right]\right] = N_i * E\left[M_{s,i}[\pi_i]\right]$$

$$E\left[MN_{s,i}\left[y_{i,n}\right]\right] = N_i * E\left[MN_{s,i}[\pi_i]\right]$$

Scenario 2

$$E\left[M_{s,i}\left[y_{i,n}\right]\right] = \begin{cases} \left(NR_{i,y_n}\right) * E\left[M_{s,i}[\pi_i]\right] + E\left[M_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & if\ \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor = \frac{t_{i,y_{n-1}}}{t_{\pi_i}}, \\ \left(NR_{i,y_n} + 1\right) * E\left[M_{s,i}[\pi_i]\right] - E\left[M_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] + E\left[M_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & otherwise \end{cases}$$

$$E\left[MN_{s,i}\left[y_{i,n}\right]\right] = \begin{cases} \left(NR_{i,y_n}\right) * E\left[MN_{s,i}[\pi_i]\right] + E\left[MN_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & if\ \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor = \frac{t_{i,y_{n-1}}}{t_{\pi_i}}, \\ \left(NR_{i,y_n} + 1\right) * E\left[MN_{s,i}[\pi_i]\right] - E\left[MN_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] + E\left[MN_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & otherwise \end{cases}$$

Scenario 3

$$E\left[M_{s,i}\left[y_{i,n}\right]\right] = \begin{cases} E\left[M_i\left(t_{i,y_n} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right)\right] - E\left[M_i\left(t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right)\right] & if\ E\left[PR_{s,i}\left[y_n\right]\right] = 0 \\ E[M_i(\pi_i)] - E\left[M_i\left(t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right)\right] + E\left[M_i\left(t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right)\right] & otherwise \end{cases}$$

$$E\left[MN_{s,i}\left[y_{i,n}\right]\right] = \begin{cases} E\left[MN_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] - E\left[MN_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & if\ E\left[PR_{s,i}\left[y_n\right]\right] = 0 \\ E\left[MN_{s,i}[\pi_i]\right] - E\left[MN_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] + E\left[MN_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & otherwise \end{cases}$$

3.3. Optimal preventive maintenance interval

In this section the optimal preventive maintenance interval with respect to preventive maintenance cost and corrective maintenance costs is determined.

The objective is to find t_{π_i}, which give the optimal maintenance costs per time unit G_i^*. The maintenance cost per time unit is equal to :

$$G_i = \frac{EPMC_{s,i} + E\big[M_i[\pi_i]\big] * ECMC_{s,i}}{t_{\pi_i}}$$

Where $EPMC_{s,i}$ represents the cost for one preventive maintenance action and $ECMC_{s,i}$ represents the cost for one corrective maintenance action. In the case of the medical scanner,$ECMC_{s,i}$ and $EPMC_{s,i}$ are equal to:

$$ECMC_{s,i} = \Big(\big(RPT_{s,i} + DT_{s,i} + TT_s\big) * h_{FSE} + A_{s,i} + ESCC_{s,i} + ECMRC_{s,i}\Big)$$

$$EPMC_{s,i} = \big[ESCC_{s,i} + EPMRC_{s,i} + \big(RPT_{s,i} + TT_s\big) * h_{FSE}\big]$$

It has been decided to perform an enumeration with a given step within a given range to determine the optimal $t_{\pi_i}^*$ which gives the optimal G_i. For instance if a range of 0 up to 100 days has been chosen with a step of 10 days, G_i is calculated for $t_{\pi_i} = \{0,10,20,\dots,100\}$. The lower the step, the more precise the solution will be. The drawback is that decreasing the step increases the computational time.

In the enumeration, all the possible preventive maintenance intervals are calculated over the simulated period. The one with the lowest maintenance cost per time unit is the optimal solution for the preventive maintenance interval within given range and step. More information of determining the optimal preventive maintenance interval is given in chapter 4 and Appendix K.

The optimal solution of the block replacement policy can be compared with the maintenance costs per time unit of the failure based policy. The policy with the lowest costs gives the optimal maintenance policy of component i. It should be noted that when the preventive maintenance interval goes to infinity, the block replacement policy is equal to the failure based policy.

4. Decision support Tool

In order to use the mathematical model to compare different scenarios without a lot of manual computation time, it has been decided to implement the mathematical model in a tool. In order to calculate the contract penalty costs and sequentially the LCC, the system availability distribution should be known. Due to the fact that it is hard to obtain the system availability distribution analytically, it has been decided to perform a Monte Carlo simulation (Banks et al., 2005) (Zio, 2013).

A Monte Carlo simulation is a discrete event simulation which generates random events based on distributions. The logic of a Monte Carlo simulation is explained by a graphical example shown in Figure 18

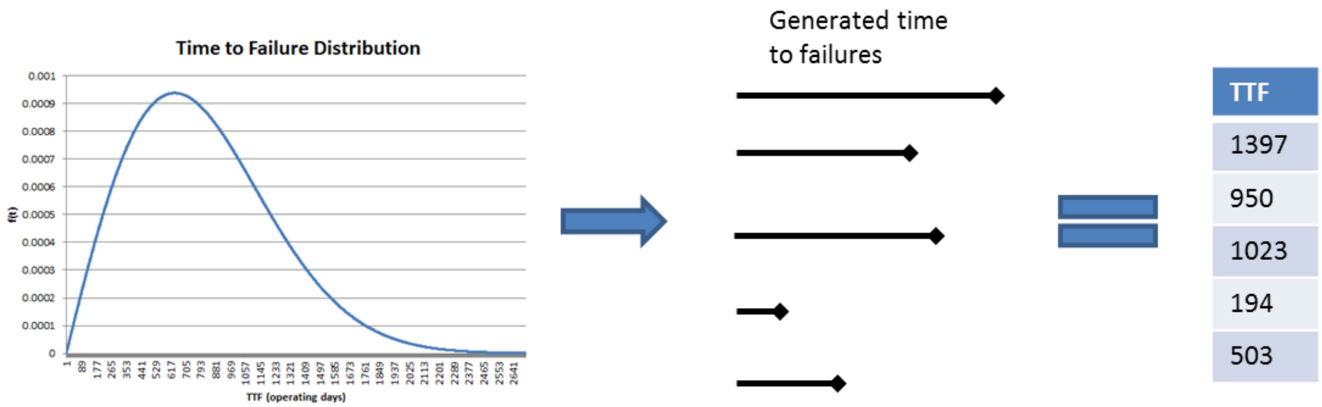


Figure 18: Graphical representation of a Monte Carlo simulation

The left graph of Figure 18 shows the time to failure distribution that is used by the Monte Carlo simulation. Based on this distribution, the Monte Carlo simulation generates random time to failures as shown in the middle. Finally, the time to failures are tabulated as shown on the right of Figure 18. The events that are generated randomly by the Monte Carlo simulations are described in Appendix H.

When enough runs are performed the expected number of failures and availability distribution in year n can be determined. This can be used to obtain the contract penalty costs. In addition to the contract penalty costs, the Monte Carlo simulation is also used to determine the corrective maintenance and preventive maintenance costs. Finally, the prices of the installed components, assembly costs, and shipment & installation costs can be added to these costs, which give the life cycle costs from a Philips perspective. Another advantage of a simulation is that it is easy to implement in an organisation as decision support tool. After the managers understand the underlying logic they can use the tool to make decisions about the design and maintenance policy of a system for a specific customer.

It has been decided to perform the Monte Carlo simulation in R, which is a free object oriented programming language for statistical purpose. In order to make it user friendly, a user interface has been built in Microsoft Excel. The interface contains input and output screen. After the user has defined the input, the Monte Carlo simulation can be launched by pressing a button. The screenshots of the tool can be found in the user manual as shown in Appendix K. The tool requires the input of the three decision variables and the customer input data.

4.1. Output

The output of the simulation can be divided into availability related output and LCC related output. Each run gives the number of failures, downtime and availability of all the components, which are used in the simulation, together over one year period. The LCC related output consists of corrective maintenance, preventive maintenance, and contract penalty costs. This is also calculated for each run. If the user would like to get the output for one individual component, the user should simulate the component individually. This is explained in Appendix K.

Finally the average number of failures, downtime, availability, corrective maintenance costs, preventive maintenance costs and contract penalty costs are given and exported to Microsoft Excel. The distribution of the availability and the LCC, which include all the costs described in section 2.2, are also given. Screenshots of the output are shown in Appendix K.

It should be noted, that the simulation tool does only provide the output for one scenario, where a scenario is one design with one maintenance policy for a specific customer. In order to get the optimal design and maintenance policy for a specific customer with respect to availability and life cycle costs, different scenarios should be simulations and compared.

4.2. Decision variables

In order to run the Monte Carlo simulation the values of the decision variables should be filled in in the input board. Decisions should be made on:

- The (critical) components in the system
- Reliability configuration
- Maintenance policy

The (critical) components in the system

First it should be determined which (critical) components are installed in the (sub) system design. Both the critical and non-critical components can be included in the tool. The availability is calculated based on the critical components. The non-critical component and the critical components together are used to determine the life cycle costs of the (sub) system. For each component included in the design the following input should be given:

- The time to failure distribution and its parameters values
- The downtime time distribution and its parameters values
- Probability that it is a “no functionality failure”
- The operating time category
- Purchasing price
- The expected cost per corrective maintenance action

All above mentioned input apart from the downtime time distribution does not depend on the customer parameters. The downtime time distribution may vary along different customers since the location of some customers is closer to the forward stocking location than others, which influence the downtime time distribution. The estimation methods of the input parameters are described in chapter 5.

Reliability configuration

After the (critical) components are identified, it should be decided whether a backup component is installed for the critical components. For each critical component it should be filled in whether the critical component has a backup. When a backup component for a critical component is included in the design, the following information should be given in addition to the above mentioned input:

- The purchasing price of the cold-standby backup component with automatic switch
- The probability that the automatic switch does not switch when it should switch
- The downtime distribution and the value of the parameters when the backup takes over the functionality

Maintenance policy

In the tool it can be decided to perform a failure based policy or preventive block replacement policy. For each component it should be decided which policy is applied. In case preventive block replacement policy is applied, the preventive maintenance interval should be given. In order to help the user, the tool consists of a feature that determines the optimal preventive maintenance interval with respect to corrective maintenance and preventive maintenance costs. This leads to the following input with respect to the decision variable maintenance policy:

- Whether to apply a preventive block replacement policy or failure based policy
- The preventive maintenance interval
- The expected cost for a preventive replacement

4.3. Customer input data

In addition to the decision variables the tool requires customer related input data. As explained in chapter 1, the quality of the medical institute cooling and the mains power are related to the availability of the system. For the medical institute cooling and the mains power, the time to failure and downtime distributions with the values of tis parameters should be obtained. Furthermore the following customer related input parameters should be given:

- Guaranteed availability
- Contract Fee
- Warranty length
- Expected contracting lifetime
- Contract hours per year
- Scan hours per year
- Hour wage of a FSE

4.4. Simulation steps

A schematic overview of the simulation steps that are performed by R for one scenario is given in Figure 19.

First of all, the input given by the user is read by the R software. One of the inputs is the component input lists, which contains the components installed in the design with its parameter values. A screenshot of the component input list can be found in Appendix K. Based on this list the software generates failures and downtimes of component i, which is represented by the orange box in Figure 19. The number of the component is represented by i, where $i = 1$ is the first component in the list. The simulation always starts with i is equal to 1. The flowchart of generating downtime process is given in Appendix I.

After the failures and downtimes are generated for component i, the costs regarding this component are determined, which is represented by the green box in Figure 19. The detailed flowchart for this process is also given in Appendix I. When the costs are calculated, the software checks whether component i is the last component to simulate. This is done by comparing the total number of components (I) in the component input list and the value of i. If i is smaller than the total number of components, which means that component i is not the last component, the software picks the next component (component $i + 1$). Thereby, the failure and downtime generating process starts again. This loop ends when i is equal to the total number of components in the component input list, which means that all the failures, downtime, and costs of each individual component are simulated. After this loop is finished the availability (per year) and corresponding contract penalty costs (per year) of the scenario are calculated based on the downtime of the individual components and the contract hours of the system. Based on the calculated downtime it is checked whether or not enough simulation runs are performed.

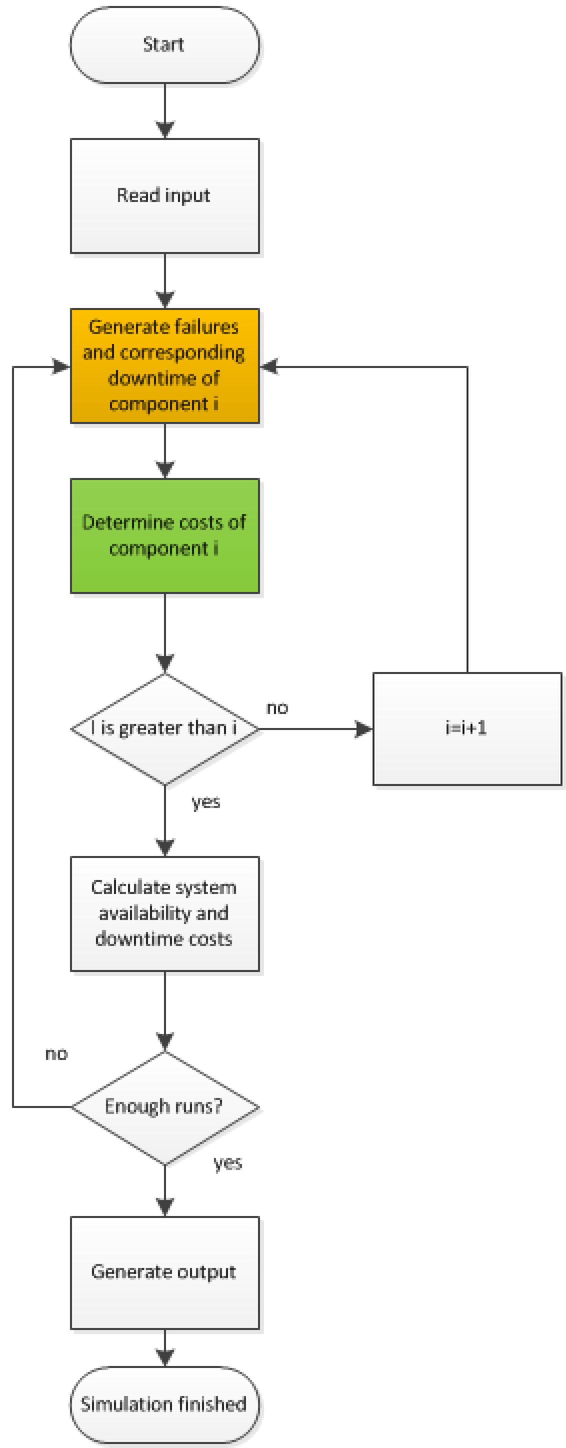


Figure 19: Simulation Flowchart

In case that not enough runs are performed the simulation starts again with generation more runs. The process of determining the number of runs is explained in section 4.5. The final step that is performed after enough simulation runs have been performed is generating the output as explained in section 4.1.

4.5. Number of simulation runs

As stated before the Monte Carlo simulation generates one set of random numbers for each random variable at each run. In order to make sure that desired precision of the simulation (i.e. the relative error with respect to mean that is tolerated by the user (Law & Kelton, 2000)) is obtained, an appropriate number of runs should be simulated. If too many runs are performed then computational time is wasted: if too less runs are performed the results does not have the desired precision.

The question is to determine the number of simulation runs to get the desired precision in a confidence interval. In this project, the distribution of the downtime and corresponding availability is the desired outcome of the simulation. In case that the precision is considerably low, which means that the error with respect to the mean is considerably low, the distribution is estimated well.

Together with Philips the desired precision and confidence interval have been set on respectively 0.1% and 95%. According to the central limited theory it is known that when the number of simulation runs n is large enough (>30) the precision is equal to

$$d_n = \frac{\left(100 * t_{n-1,\frac{\alpha}{2}}\left(\frac{s_n}{\sqrt{n}}\right)\right)}{\overline{X_n}} \tag{27}$$

Where

$$d_n = desired\ precision$$

$$t_{n-1,\frac{\alpha}{2}} = student\ t\ distribution$$

$$s_n = estimated\ standard\ deviaton\ when\ n\ runs\ are\ performed$$

$$n = number\ of\ performed\ runs$$

$$\overline{X_n} = estimated\ mean\ when\ n\ runs\ are\ performend$$

Banks et al (2005) describes a method to determine the number runs based on the desired precision and confidence interval. The number of simulation runs is predicted from an initial set of runs. The initial set of runs is performed to estimate the variance and the mean of the output. The sample variance S_n is estimated by:

$$S_n = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \overline{X_n})$$

Where X_i is the output of run i and $\overline{X_n}$ is the estimated sample mean which can be calculated with:

$$\overline{X_n} = \frac{1}{n}\sum_{i=1}^{n} X_i$$

Based on the estimated variance, estimated mean, and the desired precision the required number simulation runs is calculated. The S_n and $\overline{X_n}$ estimated by the initial simulation runs can be used in equation (28) to determine the required number of runs.

$$n = \left[\frac{S_n * t_{n-1,\frac{\alpha}{2}}}{\overline{X_n} * d_n}\right]^2 \tag{28}$$

4.6. Computational time

As mentioned in chapter 1, the computational time of the decision support is restricted since the user should be able to quickly calculate and compare different scenarios. The computational time of the scenario analyses in chapter 6 varies from 1 minute up to 12 minutes. The variation of the computational can be explained by the fact that the computational time increases when the number of components increases or/and the simulation period increases. The simulation period depends on the number of scans, the contract hours per year, and the warranty length plus contracting lifetime. Different number of components and different lengths of simulation period have been used in the scenario analyses. In one scenario, the decision support tool has been used to calculate the availability of one complete system design with a simulation period which is considerable long for the majority of the systems. Due to the fact that the computational time of this simulation was less than 15 minutes, it can be concluded that the decision support tool satisfy the computational restriction.

4.7. Verification of the simulation tool

The verification of the Monte Carlo simulation determines whether the mathematical model has been implemented correctly in the simulation model. This verification is done by comparing simulation results with analytically obtained results. In order to obtain analytical results simple input parameters are used.

Due to the fact that it is hard to obtain the availability distribution, it has been decided to verify the Monte Carlo simulation based on the results of expected downtime and its variation. These two parameters are important indicators of the downtime distribution[2]. In Appendix J, the analytical obtained results are described and the simulation results are given.

The simulation error of the expected downtime and its variation during a ten year interval are respectively 0.02% and 0.39%. Together with Philips, it has been decided that this error is tolerated.

4.8. Validation of the simulation tool

Validation is the process of determining whether the simulation model is able to generate results that correspond with the real world (Law & Kelton, 2000). When an existing system is modelled by the simulation model, the output of the simulation model can be compared to those from the existing system. If the two tests of data compare “closely” then the simulation model of existing system is considered as valid (Law & Kelton, 2000).

[2] The availability distribution is derived from the downtime distribution

In chapter 6, System Design 1, which is currently used in the field, is modelled by the simulation tool. Unfortunately, no accurate data regarding the availability of the medical scanners are available in the organisation. However, the results of this case study are compared with the expectation in the organisation. This is called *face validity.* The output of the System Design 1 has been discussed during several meetings with customer service employees, and field service employees. Based on these discussions it can be concluded that the output of the model is in line with the expectation of the expert.

Moreover, different designs of subsystem A have been compared in the case study as described in chapter 6. The effect of adding a backup to a certain configuration has been modeled. The simulation results correspond to the expectation of the development department of Philips.

Based on the case study of different designs of subsystem A and the simulation results of the availability of System Design 1, the simulation model is considered as valid.

5. Parameter Estimation

The values of the input parameters described in section 4.2 should be estimated to run the simulation. In this section the estimation procedure of the time to failure and downtime time distribution, the probability of no functionality failure, probability of automatic switch failure, and the cost parameters are described.

5.1. Time to Failure and downtime distribution

In this section the procedure to fit time to failure data or downtime time data to a theoretical distribution is explained.

In general, two types of reliability distribution exist: empirical distributions and theoretical distributions. Empirical distributions are directly derived from the data by non-parametric methods or distribution free methods. Theoretical distributions are distributions that are already exist which can be fitted to sample data. Fit is defined as a statistical test in order to accept or reject the hypothesis that the observed times come from a specific distribution. For several reasons, a theoretical distribution is preferred over empirical developed distribution. First, empirical models do not provide information beyond the range of the sample. Second, small sample size give little information concerning the failure or corrective maintenance process. Third, theoretical distributions can be easily used in complex statistical analyses which are applied by software. Based on these reasons, it has been decided to fit the sample failure and downtime data to a theoretical distribution (Ebeling, 2010) .

According to Ebeling (2010), fitting data to a theoretical distribution consists of three steps: 1) identifying candidate distributions, 2) estimating parameter values, and 3) performing a goodness of fit test.

Identifying the distribution candidates (1) should be based on understanding the underlying process of the data. Based on discussion with reliability experts it has been decided to select the three well known distributions, Weibull, Exponential, and Normal, as candidates for the time to failure distribution. In addition to the three well known distributions, the uniform distribution is added as distribution candidate for the repair distribution. It should be noted that the Normal distribution can result in negative values. However, the normal distribution is truncated in the simulation to correct for the negative values (Geweke, 1991). In this truncated normal distribution no negative values can be generated.

In order to test how well the candidates fit to the data and to **estimate the values of the parameters (2)** the least square fitting technique is used. The least square fitting technique estimate the coefficient of variation R^2 (i.e. index of fit) based on a linear regression of the form $y = a + bx$ to a set of transformed data depending on theoretical distribution. In the regression the values for a and b are estimated that gives the highest R^2. The time to failures and the downtimes should be ordered in $t_1, t_2, \dots, t_k$ where $t_k \leq t_{k+1}$. According to the least square technique, the values for a and b can be calculated with the equations shown in Table 2. Furthermore, the R^2 is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{k}(y_i - a - bx_i)^2}{\sum_i^n(y_i - \bar{y})}$$

Distribution	Cumulative function	x_i	y_i	Parameter a	Parameter b
Exponential	$F(t) = 1 - e^{-\lambda t}$	t_i	$\ln\left(\frac{1}{1-\hat{F}(t_i)}\right)$	$a = 0$	$b = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2} = \hat{\boldsymbol{\lambda}}$
Weibull	$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^\beta}$	$\ln(t_i)$	$\ln\ln\left(\frac{1}{1-\hat{F}(t_i)}\right)$	$a = \bar{y} - \bar{b}x = -\hat{\boldsymbol{\beta}}\ln(\hat{\boldsymbol{\alpha}})$	$b = \frac{\sum_{i=1}^n(x_i-\bar{x})(y_i-\bar{y})}{\sum_{i=1}^n(x_i-\bar{x})} = \hat{\boldsymbol{\beta}}$
Normal	$F(t) = \phi(z) = \phi\left(\frac{t-\mu}{\sigma}\right) = \int_{-\infty}^{z}\frac{1}{2\sqrt{\pi}}e^{-\frac{y^2}{2}dy}$	t_i	$z_i = \phi^{-1}\hat{F}(t_i)$	$a = \bar{y} - \bar{b}x = -\hat{\boldsymbol{\mu}}b$	$b = \frac{\sum_{i=1}^n(x_i-\bar{x})(y_i-\bar{y})}{\sum_{i=1}^n(x_i-\bar{x})} = \hat{\boldsymbol{\sigma}}$

Table 2: Least square curve fitting method (Manzini & Pham, 2010)

The estimate of the cumulative distribution, $\hat{F}(t_i)$, is used in the calculation of a and b. Due to the fact that the data of Philips consists of multiple censored data (i.e. data that consist of different failure and censored data), the rank adjustment method along with the approximated median rank method is used to determine $\hat{F}(t_i)$ (Ebeling, 2010). Based on the approximated median rank method the cumulative distribution estimate is equal to:

$$\hat{F}(t_i) = \frac{i_{t_i} - 0.3}{n + 0.4}$$

where n is total number of units at risk and $i_{t_i}$is the adjusted rank order of failure time t_i,which is obtained by the rank adjustment method.

$$i_{t_i} = i_{t_{i-1}} + RI$$

The Rank Increment RI is determined by:

$$RI = \frac{\left((n+1) - i_{t_{i-1}}\right)}{1 + n^{**}}$$

Where n^{**} is the number of units beyond present censored unit (i.e. $n - i$). In section 5 of the user manual (Appendix K), an example of the least square estimation technique with the rank increment and approximated median rank method is given.

$\hat{F}(t_i)$ can be used in the equations of Table 2 to determine the values of the distribution parameters and the fit index (R^2).

The final step (3) in the selection of the theoretical distribution is to test whether the data are distributed according to the fitted distribution. This can be done by a goodness of fit tests. For the exponential and Weibull distribution respectively the Barletts test and Mann's test can be performed.

More information about these tests can be found in Ebeling (2010) chapter 16. In case the data does not consist of multiple censored data points, the uniform, and normal distribution can be tested by the Chi Square test. Otherwise, the Hollander & Proschan test can be used. This is a goodness of fit test for multiple censored data. It should be noted that the power of this goodness of fit test decreases when the percentage of censored data increases (Kostagiolas & Bohoris, 2010). More information about this goodness of fit test can be found in the article of Kostagiolas and Bohoris.

When all these steps are performed the distribution that passed the goodness of fit test with the highest R^2 should be used in the simulation tool. An Excel file has been developed to simply perform all the above tests. The Excel file does also propose the best distribution. In case that none of the distributions pass the goodness of fit test, the data is considered as invalid since it is expected that failure distribution should fit one of these distribution. If this occurs the data should be checked on outliers and validity. When the data has lack of validity, the data does not represent the correct time to failures of a given component or downtimes due to a component failure. For example, it could be that a component has been upgraded in the past which improved the reliability of that component. This means that the component has two time to failure distributions: one before the upgrade, one after the upgrade. In this case, the data should be split into time to failures before the upgrade and after the upgrade, before the distribution is fitted.

When either no data is available or the data is considered as invalid after it has been checked on outliers and validity, the $\hat{F}(t_i)$ can be estimated by experts. These estimations can be used in the above described fitting procedure, which give at least an indication of the time to failure or downtime distribution. Appendix O describes the steps that have been performed during the case study, chapter 6, to check for validity and outliers of the data. Section 5 of Appendix K describes how the time to failure distribution and the values of its parameters can be estimated by the Excel templates.

5.2. Probability of no functionality failure

At each failure it is determined whether it is a limited functionality failure or no functionality failure. This probability is estimated based on failure classification data and a sample study about the misinterpretation/bias of the failure classification. More information about this estimation process can be found in Appendix O.

5.3. Probability of switch failure

As explained in section 2, the automatic switch installed at a backup component can fail when it should switch from the main component to the backup component. This success or failure event occurs at each failure of a component with installed backup. The probability that the automatic switch fails can be estimated based on the percentage of time a model of the switch has been failed with respect to the total number of switches. In case such information is not available the probability of switch failure can be estimated by experts.

5.4. Cost Parameters

In this section, it is described which aggregated cost elements can be estimated based on the current data of Philips. More information about the estimation process can be found In Appendix O. In this appendix it is explained how the aggregated cost elements, described in this section, are estimated for the case study (chapter 6).

Unfortunately, not all the lower level cost elements of the life cycle costs function are stored in the databases of Philips individually. Some costs elements are aggregated to one cost elements including lower level cost elements. Data are available for following aggregated cost elements 1) purchasing price, 2) Repair cost for one corrective maintenance action, 3) FSE labour for one corrective maintenance action, 4) Repair cost for one preventive maintenance action, 5) FSE labour costs for one preventive maintenance action.

The repair costs and the FSE labour costs for one corrective maintenance action together determines the expected cost per corrective maintenance action ($ECMC_{s,i}$). The repair costs and FSE labour costs for one preventive maintenance costs together determines the expected cost per preventive maintenance action ($EPMC_{s,i}$). The purchasing price, expected costs per corrective maintenance action, and expected costs per preventive maintenance action are used as input parameter of the tool.

6. Case study: System Design 1

In this section, the decision support tool is applied to an existing project within Philips to obtain insight with respect to the decision variables which can be evaluated by using the tool. The project concerns (new) designs of subsystem A, which may be used in System Design 1. The reasons behind the selection of this project are: 1) In this project a decision should be made whether or not to install a backup component, 2) In case sub system A is not working the medical scanner is down, which means that subsystem A is a critical subsystem, 3) Philips logged sufficient data of the System Design 1.

Subsystem A is an assembly of critical components that makes sure that System Design 1 is able to make scans. Moreover, subsystem A requires a well-functioning mains power and cooling of the customer's location (e.g. hospital). More information about the reliability configuration of subsystem A can be found in Appendix M.

A new design of subsystem A contains a standby configuration and different (critical) components. The current and new designs are applied to different scenarios to make their effect on the lifecycle costs and the availability visible. The results of the scenario are given in section 6.2.

As explained before, several input parameters are customer specific. For this reason, different customer specifications are used in the scenarios. The estimation of the customer specific parameters for one individual customer requires a reasonable amount of effort since not all the data required for the input parameters is available for one individual customer. This means that depending on the customer some customer specific input parameters should be estimated together with experts. Due to time limitation it has been chosen to select two different areas instead (Area A and Area B) of two customers, for this scenario analyses. The data of all the customers in these areas are aggregated to estimate the customer specific input parameters. More information about the data preparation steps can be found in Appendix O. This means that the results should be interpreted as average results for customers in Area A, and average results of customers in Area B. More information about the selection of these areas can be found in section 6.1.2.

This chapter is structured as follows: section 6.1 gives the input of the customers and the different designs, and in paragraph 6.2 the results of the different scenarios are given

6.1. Input parameters

In this section the different designs and customers are described together with its estimated distributions and the value of the parameters.

6.1.1. Component related parameters

The following different subsystem A designs are used in the scenario analyses: subsystem A1, Subsystem A2, and subsystem A2 with backup. Subsystem A1 is currently used in System Design 1. Subsystem A2 and A2 with backup are new designs of subsystem A1. In the current design of subsystem A1, component A1 is installed, where subsystem A2 has component A2 in its design instead of component A1. Component A1 and component A2 have the same functionality, nevertheless the design is different.

In the rest of this section components and subsystems with the same functionality are denoted with the same letter.

Due to the fact that component A2 is installed in subsystem A2 and subsystem A2 with backup, subsystem A2 and subsystem A2 with backup require less coolant to cool the system than subsystem A1. Moreover, subsystem A2 and subsystem A2 with backup do not lose coolant when the system is used.

In addition, no coolant is lost at failure of component A2 in contrast to component A1. However, component A2 is more sensitive to cooling problems than component A1, which may cause more downtime. Component A1 can survive without cooling for about 2 weeks due the large amount of coolant in subsystem A1. Component A2 can survive much less than 2 weeks without cooling. Each hour that the cooling of subsystem A2 and subsystem A2 with backup are down for more than the time the system can survive without cooling, the system is down for 2 hours. It is assumed, based on the expectation of the service experts, that the probability that a cooling related component is down for more than 2 weeks is negligible.

This results that the medical institute cooling, component C1 and component B1 are not critical in subsystem A1. In contrast, the medical institute cooling component C2 and component B2 are critical in subsystem A2 and subsystem A2 with backup. The new subsystem A2 with backup has an extra component in its design: Component D. This backup can prevent subsystem A2 for cooling problems by taking over the functionality of both the medical institute cooling and component C2 when one of these components fails. The reliability configuration of the different subsystem A designs are shown in Appendix M.

Thus, subsystem A2 and subsystem A2 with backup consist of more critical components than subsystem A1. Conversely, the downtime due to a failure of component A2 is only 2.5 days where the system has on average 4 days downtime at a failure of component A1.

All the critical components apart from the backup in the design of subsystems A1, A2, and A2 with backup are operating “24/7”, which means that these components can be classified in the operating hours category A. The results of the time to failure distribution estimation approach as explained in section 5.1, are shown in Table 3. More information about the data preparation of the time to failures can be found in Appendix O. It should be noted that the time to failure distribution of the medical institute cooling is not shown in this table due to the fact that this distribution is customer specific.

Table 3: Time to failure distribution results of the least square fitting method

Component	Distribution and values of the parameters (days)	R^2	Goodness of fit test	Selected distribution
Component B1	Exponential λ = 0.00016 Weibull: β = 1.254, η= 4311 Normal: μ = 1746, σ = 756	0.949 0.986 0.914	Rejected Accepted Rejected	Weibull: β = 1.254, η= 4311
Component B2	Exponential λ =0.000072 Weibull: β = 0.973 , η= 17285 Normal: μ = 2329, σ =909	0.937 0.963 0.920	Accepted Accepted Rejected	Weibull: β = 0.973 , η= 17285
Component C1	Exponential λ = 0.00009 Weibull: β = 0.821, η= 18910 Normal: μ = 2009, σ = 856	0.915 0.985 0.722	Accepted Accepted Rejected	Weibull: β = 0.821, η= 18910.362
Component C2	Exponential λ = 0.00017 Weibull: β = 0.888, η= 8356 Normal: μ = 1715, σ = 766	0.954 0.986 0.866	Accepted Accepted Rejected	Weibull: β = 0.888, η= 8356.115
Component A1	Exponential λ = 0.000137	N.A.	N.A.	Exponential λ = 0.000137
Component A2	Exponential λ = 0.000137	N.A.	N.A.	Exponential λ = 0.000137

The time to failure distribution of component A1,A2,B1,B2 are based on failure data as explained in Appendix O. The data consist of failure data and several censored data points. The number of data points is between 700-1200 points, which are different per critical component. For component A1 and A2 only failure rates (i.e. number of failures per year) are available. It is expected by the product experts that the subsystem A failures are exponential distributed. Due to time limitation, this expectation is adopted. The time to failure distribution estimation approach of section 5.1 can be used for further research on the failure behaviour of component A1 and A2.

The purchasing prices of the components, corrective maintenance repair costs, corrective maintenance FSE labour hours, preventive maintenance repair costs, and preventive maintenance FSE labour hours are shown in Table 4. More information about the estimation of these costs can be found in Appendix O.

Table 4: Purchasing price components subsystem A1 and A2

Component	Purchasing Price pp_i	Corrective maintenance Repair costs per failure $ECMRC_{s,i}$	Corrective maintenance FSE Labour hours Per failure $RPT_{s,i} + DT_i$	Preventive maintenance repair costs Per replacement $EPMRC_{s,i}$	Preventive maintenance FSE Labour hours Per replacement $RPT_{s,i}$	Coolant cost per year $EHC_{y'_n}$
Component B1	€ 10,000	€ 1,505	8.2	€ 452	1.64	
Component B2	€ 10,000	€ 1,469	15.0	€ 441	3	
Component C1	€ 5,147	€ 4,368	6.9	€ 1,310	1.38	
Component C2	€ 5,147	€ 4,368	9.8	€ 1,310	1.96	
Component A1	€ 129,956	€ 20,800	0	DNA	DNA	€ 4,555
Component A2	€ 96,156	€ 0	0	DNA	DNA	€ 0
Component D	€ 3,676	DNA	DNA	DNA	DNA	

The relative high corrective maintenance repair costs of component A1 are due to the coolant loss at a failure. Unfortunately, there is no data available of the repair and labour cost for a preventive maintenance action. In order to take preventive maintenance in consideration, the preventive maintenance repair costs and labour costs are estimated by product experts. The preventive maintenance labour hours and repair costs are respectively estimated on 20% of the corrective maintenance labour hours and 30% of the corrective maintenance repair costs. Furthermore, it is expected by the development department that in 99% of the cases the automatic switch incorporated in component D will work.

The results of the no functionality failure probability estimations are shown in Table 5. It should be noted that the no functionality failure probability of the medical institute cooling in component A2 designs is based on the expectation of component A2 developers since component A2 is not released yet.

Table 5: The no functionality failure probabilities of the subsystem A components

	Component	$P(FM_i = nf)$
Sub System A2	**Component B2**	0.69
	Component C2	0.70
	Component A2	1.00
	Medical institute cooling	1.00
Sub System A1	**Component B1**	0.68
	Component C1	0.00
	Component A1	1.00
	Medical institute cooling	0.00
Sub System A2 with backup	**Component B2**	0.69
	Component C2	0.70
	Component A2	1.00
	Medical institute cooling	1.00
	Component D	0.00

6.1.2. Customers related input data

Two areas have been selected for the scenario analyses: Area A and Area B. The selection is based on the number of cooling failures of the customers. In Area B the medical institute cooing fails on average 0.98 per year, which is relative low, and in Area A: 7.02 per year, which is relatively high. It should be noted that these numbers represents cooling failures where the cooling outages was more than the time that subsystem A2 can survive without cooling. Unfortunately, no time to failure data can be generated from the data available. It is expected by the service engineers that these time to failures are exponentially distributed. For this scenario analysis, the assumption has been adopted.

In contrast to the time to failure data, the downtime data of the medical institute is logged in MMU files of the component C1 and C2. Due to the fact the system downtime only occurs after a given time of medical institute cooling downtime, the medical institute cooling downtime has been adjusted to system downtime. More information about this adjustment can be found in Appendix O. After this modification, the downtime distributions are estimated by following the least square method. The results are shown in Table 6.

Table 6: Downtime distributions of both the medical institute cooling in Area B and the medical institute cooling in Area A

Component	Distribution and values of the parameters (Calendar hours)	R^2	Goodness of fit test	Selected distribution
System downtime due to medical institute cooling failures in Area B	Exponential λ = 0.05419 Weibull: β = 0.8767, η= 15.85 Normal: μ = 7.235023, σ = 30.363	0.9879 0.9935 0.9495	Accepted Accepted Accepted	Weibull: β = 0.8767, η= 15.85
System downtime due to medical institute cooling failures in Area A	Exponential λ =0.07719 Weibull: β = 0.9283, η= 12.43 Normal: μ = 18.883, σ = 6.960	0.9312 0.9672 0.9653	Accepted Accepted Accepted	Weibull: β = 0.9283, η= 12.43

The Weibull distribution fits the best for both downtime distributions. The expected system downtime due to a medical institute cooling failure in Area B is bit longer than in Area A.

The average travel time and replenishment lead-time of the components to the customers in Area B and Area A are shown in Table 7. Other customer specific input parameters are also shown in this table.

Table 7: The average values of the Input parameters of customers in Area B and customers in Area A

Parameter	Area B	Area A
Travel time one way (Calendar hours) TT_i	1.37	0.74
Replenishment Lead-time (Calendar hours)	14.2	34.7
Contract hours per year $CH[y']$	2500	2500
Scan hours per year ($SH[y']$)	1600	1600
Warranty length (years) wl_s	1	1
Contracting lifetime (years) $ECLT_s$	9	9
Wage of field service engineer hour f_{FSE}	€100,-	€100,-
Medical institute cooling failure rate per year	0.98	7.02
Power Failure rate per year	12	4
Mean Power Downtime (hours)	1	2.6
Contract Fee	€100,000.-	€100,000.-

The travel time and replenishment time are averages in these countries, which are obtained by respectively the data of Field Data View (FDV) and SAP MM01. The other input parameters have been selected after discussions with service innovation employees.

6.2. Scenario simulation results

In this section several scenarios have been made. First in section 6.2.1, the availability and life cycle costs of the subsystem A1, A2, and A2 with backup are calculated for customers in Area B and Area A. These scenarios show the effect of decision on selection of components and reliability configuration on the availability and life cycle cost for different customer parameters.

Design	Area A	Area B
Subsystem A1	Scenario 1	Scenario 4
Subsystem A2	Scenario 2	Scenario 5
Subsystem A2 with backup	Scenario 3	Scenario 6

In order to make to obtain the penalty costs for different service contract types, scenarios 1 to 6 are applied to the complete system of System Design 1. This results in scenario 7 to 12.

Design	Area A	Area B
System design 1 with Subsystem A1	Scenario 7	Scenario 10
System design 1 with Subsystem A2	Scenario 8	Scenario 11
System design 1 with Subsystem A2 with backup	Scenario 9	Scenario 12

In scenario 1 to 12, the number of scan hours and contract hours are the same. In order to show the effect of scan hours and contract hours on the availability and contract penalty costs, the number of scan hours and contract hours of scenario 7 and 10 have been increased in scenario 13 and 14.

Design	Area A	Area B
System design 1 with Subsystem A1	Scenario 13	Scenario 14

It should be noted that the contract penalty costs, the assembly, shipment and installation, and planned maintenance are excluded of the life cycle costs in this case study since it is expected that these costs are almost the same for the different scenarios.

6.2.1. Scenario 1-6

In this section the final input parameter and the results of scenario 1-6 are given.

The purchasing prices of the components can be found in Table 4. The failure distributions and the no functionality failure probabilities can be found in respectively Table 3 and Table 5.

For each scenario the costs for one corrective maintenance action and the cost for one preventive maintenance action have been determined per component as explained in Appendix O. Moreover, the total expected system downtime time per critical component has been determined for each scenario.

At the moment of writing this, it is unknown how the downtime is distributed. Due to time limitation, for this scenario analyses the assumption has been made that the downtime is constant. In order to see the effect of the downtime variation on the availability and life cycle cost, further research should be done to downtime and its distribution.

The costs for one corrective maintenance action, the cost for one preventive maintenance action, and the mean downtime due to a critical component failure are determined based on the input parameters of section 6.1.1. The results of these parameters are shown in Table 8. The downtime distribution of the medical institute cooling of customers in Area B and customers Area A can be found in Table 6

Table 8: Corrective maintenance costs, Preventive maintenance costs, and mean downtime at a failure of component i for customers in Area B and customer in Area A

	Component i	*Corrective Maintenance costs in Area B at a failure* $ECMC_{i,s}$	*Preventive Maintenance costs in Area B at a failure* $EPMC_{i,s}$	*Mean system downtime at a failure of component i in Area B(Calendar hours)* $dtcm'_i$	*Corrective Maintenance costs in Area A at a failure* $ECMC_{i,s}$	*Preventive Maintenance costs in Area A costs at a replacement* $EPMC_{i,s}$	*Mean system downtime at a failure of component i in Area A(Calendar hours)* $dtcm'_i$
Subsystem A2	**Component B2**	€ 3,243	€ 1,015	57.14	€ 3,117	€ 889	96.88
	Component C2	€ 5,622	€ 1,780	42.74	€ 5,496	€ 1,654	82.48
	Component A2	€ 0	DNA	60	€ 0	DNA	60
	Medical institute cooling	€ 0	DNA	16.9	€ 0	DNA	12.9
Subsystem A1	**Component B1**	€ 2,599	€ 890	0	€ 2,473	€ 764	0
	Component C1	€ 5,332	€ 1,722	0	€ 5,206	€ 1,596	0
	Component A1	€ 20,800	DNA	96	€ 20,800	DNA	96
	Medical institute cooling	€ 0	DNA	0	€ 0	DNA	0
Subsystem A2 with backup	**Component B2**	€ 3,243	€ 1,015	57.14	€ 3,117	€ 889	96.88
	Component C2	€ 5,622	€ 1,780	0	€ 5,496	€ 1,654	0
	Component A2	€ 0	DNA	60	€ 0	DNA	60
	Medical institute cooling	€ 0	DNA	0	€ 0	DNA	0
	Component D	€ 3,676	DNA	DNA	DNA	DNA	DNA

Furthermore, the probability that the automatic switch fails is equal to 99% as explained in section 6.1.1. The other customer related input parameters can be found in Table 7.

In the results, the contract penalty costs are excluded due to the fact that only a part of the systems' critical components are simulated. The contract penalty costs can only be determined by the availability of the entire system which is done in section 6.2.2.

Life cycle costs

The three designs of subsystem A have been used in the simulation model for customers in Area A and customers in Area B. The results of the life cycle costs over 10 years of customers in the Area A are given in Table 9. The life cycle costs over 10 years of customers in Area B are shown in Table 10

Table 9: Simulation result of the life cycle costs of each system design for customers in Area A

Cost Elements	Subsystem A1	Subsystem A2	Subsystem A2 with backup
Purchasing Price	€ 145,103	€ 111,303	€ 114,979
Coolant Costs	€ 45,550	€ 0	€ 0
Warranty costs	€ 1,372	€ 420	€ 421
CM Service costs	€ 12,294	€ 2,985	€ 2,954
Life cycle costs	€ 204,319	€ 114,707	€ 118,354

Table 10: Simulation result of the life cycle costs of each system design in Area B

Cost Elements	Subsystem A1	Subsystem A2	Subsystem A2 with backup
Purchasing Price	€ 145,103	€ 111,303	€ 114,979
Coolant Costs	€ 45,550	€ 0	€ 0
Warranty costs	€ 1,380	€ 423	€ 434
CM Service costs	€ 12,406	€ 3,059	€ 3,107
Life cycle costs	€ 204,395	€ 114,785	€ 118,520

In both tables it is shown that the life cycle costs of subsystem A2 and A2 with backup are less than the life cycle costs of the subsystem A1. This difference is mostly due to the coolant costs. The coolant increases the purchasing price of the subsystem A1 significantly. In addition, subsystem A2 and A2 with backup do not suffer coolant loss, which is a cost saving of €45,550.- over 10 years. Moreover, subsystem A1 loses coolant at a failure of component A1 which leads to higher corrective maintenance costs compared to subsystem A2 and A2 with backup. The simulation results also show that the purchasing price of subsystem A2 with backup is slightly higher than subsystem A2. The difference in purchasing price between these designs is due to the price of the backup (component D) and its switch.

The expected warranty cost and corrective maintenance service costs for customers in Area A are, on average, less than for customers in Area B. The reason behind this is that the average travel time needed by the FSE Area B (1.37 hours) is longer than in Area A (0.74 hours). Furthermore, the Purchasing price and the coolant cost are the same, as expected, for customers in both countries.

Corrective maintenance per year

In order to get more insight in the corrective maintenance cost, the costs are shown per year in Table 11 and Table 12, where Table 11 represent scenario 1-3, and Table 12 represent scenario 4-6.

Table 11: Results of the average corrective maintenance costs in year n of Subsystem A1 and A2 in Area A

Year n	Subsystem A1	Subsystem A2	Subsystem A2 with backup
1	€ 1,371.83	€ 419.62	€ 420.91
2	€ 1,309.55	€ 358.29	€ 354.49
3	€ 1,364.41	€ 336.73	€ 340.87
4	€ 1,356.35	€ 341.82	€ 319.79
5	€ 1,393.81	€ 332.79	€ 337.12
6	€ 1,363.77	€ 330.56	€ 327.86
7	€ 1,374.70	€ 319.41	€ 328.45
8	€ 1,414.39	€ 321.99	€ 322.37
9	€ 1,353.65	€ 324.53	€ 305.25
10	€ 1,363.26	€ 318.41	€ 318.08

Table 12: Results of the average corrective maintenance costs in year n of Subsystem A1 and A2 in Area B

Year n	Subsystem A1	Subsystem A2	Subsystem A2 with backup
1	€ 1,379.50	€ 423.13	€ 434.02
2	€ 1,357.43	€ 368.30	€ 405.16
3	€ 1,382.41	€ 353.74	€ 343.94
4	€ 1,352.45	€ 354.73	€ 328.52
5	€ 1,365.72	€ 332.27	€ 333.19
6	€ 1,388.09	€ 334.36	€ 351.24
7	€ 1,386.49	€ 346.36	€ 340.92
8	€ 1,392.40	€ 335.02	€ 333.66
9	€ 1,400.33	€ 329.07	€ 343.98
10	€ 1,380.22	€ 305.26	€ 326.79

As shown in both tables, the average corrective maintenance cost of subsystem A1 has some variation over the years. However, there is not an increasing or decreasing trend of the corrective maintenance costs over the years. In contrast to subsystem A1, the corrective maintenance costs of subsystem A2 and A2 with backup decreases over the years. This means that the corrective maintenance costs during warranty period are higher than the corrective maintenance costs during service period. Based on Table 11 and Table 12 it can be concluded that from a cost point of view it is not beneficial to replace one of the subsystem preventively.

More insight in the corrective maintenance distribution can be found in Appendix Q.

Availability

In addition to the costs, the availability of the different designs for customers in Area B and Area A are simulated as well. The results of the expected availability in year n of the different subsystem A designs are given for both customers in the Area A, Table 13, and customers in Area B, Table 14.

Table 13: Expected availability in year n of Subsystem A1 and A2 for customers in Area A

Year	Subsystem A1	Subsystem A2	Subsystem A2
1	99.81%	98.74%	99.80%
2	99.81%	98.74%	99.80%
3	99.81%	98.75%	99.80%
4	99.81%	98.75%	99.80%
5	99.81%	98.75%	99.80%
6	99.81%	98.75%	99.80%
7	99.81%	98.75%	99.80%
8	99.81%	98.76%	99.80%
9	99.81%	98.75%	99.80%
10	99.81%	98.75%	99.80%

Table 14: Expected availability in year n of Subsystem A1 and A2 for customers in Area B

Year	Subsystem A1	Subsystem A2	Subsystem A2 with backup
1	99.83%	99.62%	99.83%
2	99.83%	99.63%	99.83%
3	99.83%	99.63%	99.84%
4	99.83%	99.63%	99.83%
5	99.83%	99.63%	99.84%
6	99.83%	99.63%	99.83%
7	99.83%	99.63%	99.84%
8	99.83%	99.63%	99.84%
9	99.83%	99.63%	99.84%
10	99.83%	99.63%	99.84%

It is shown in both tables that the expected availability of the different designs of subsystem A is constant over time. Moreover, subsystem A2 has a lower availability over the years than subsystem A1. The reason for the lower availability is that subsystem A2 has more components that are critical than subsystem A1. However, the availability over the years of subsystem A2 with backup is better than the availability of subsystem A2 without backup. This is in line with the expectation since component D of subsystem A2 with backup can take over the functionality of the medical institute cooling and component C2, which are both critical. Moreover, the availability of subsystem A2 with backup is more or less the same as the availability of subsystem A1. Thus, by adding component D to the design of subsystem A2 more or less the same availability can be reached as subsystem A1 for less life cycle costs.

It is also shown in Table 13 and Table 14 that the availability of subsystem A1 and subsystem A2 with backup for customers in Area B are slightly higher than the availability of the subsystems A1 and subsystem A2 with backup for customers in Area A. This is caused by both that the replenishment time in Area B is less than in Area A and that the expected power outages per year at customers in Area B is less than in Area A. Moreover the availability of subsystem A2 for customers in Area B is considerable higher than subsystem A2 in Area A. This difference is due to the fact that less medical institute cooling failures occur at customers in Area B than at customers in Area A. This means that the backup of

Subsystem A2 with backup increases the availability of customers in Area B with ±0.11%, which is considerably less than for customers in Area A, where the availability of subsystem A2 can be increased with±1.05% by adding the backup to its design. Based on this, it can be concluded that it depends on the customer what the availability improvement of the backup in subsystem A2 will be.

More insight about how the availability of scenario 1-6 is distributed over 10 year time period can be found in Appendix R.

6.2.2. Scenario 7-12

In order to obtain the system availability and corresponding contract penalty costs, the three designs of subsystem A are applied to the System Design 1 for customers in Area B and Area A. The contract penalty costs have been determined for 96%,98%, and 99% service contract. Due to time limitation it was not possible to determine the other costs elements of all the System Design 1 components. In order to determine the system availability, the other critical subsystems with their critical components in System Design 1 have been determined in cooperation with the system expert. These critical subsystems with their critical components can be found in Appendix N. The time to failure distribution, expected downtime at a failure, and the probability of no functionality failure is estimated for each critical component by following the procedure of chapter 5. These input parameters can be found in Appendix P. The customer input data of Table 7 have been used in the simulation model to obtain the availability. Furthermore, the expected service contract fee of the 96%,98%, and 99% service contract are chosen to be constant[3].

The average availability in year n of System Design 1 with different subsystems A for customers in Area A can be found in Table 15. The average availability in year n of System Design 1 with different subsystems A for customers in Area B can be found in Table 16.

Table 15 Average availability in year n of System Design 1 of different subsystem A designs for customers in Area A

Year n	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	99.52%	98.45%	99.51%
2	99.57%	98.50%	99.56%
3	99.58%	98.52%	99.57%
4	99.58%	98.52%	99.57%
5	99.58%	98.53%	99.58%
6	99.58%	98.53%	99.58%
7	99.59%	98.53%	99.58%
8	99.58%	98.53%	99.58%
9	99.58%	98.53%	99.58%
10	99.58%	98.53%	99.58%

[3] Although, in reality, the service contract fee increases when the guaranteed availability of the service contract increases, the contract fee for the three service contracts with different guaranteed service level are chosen to be equal in this scenario analyses. The reason beyond this is to exclude the effect of varying service contract fee on the penalty cost in comparing the different scenarios.

Table 16 Average availability in year n of System Design 1 of different subsystem A designs for customers in Area B

Year	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	99.68%	99.47%	99.68%
2	99.70%	99.50%	99.71%
3	99.70%	99.51%	99.71%
4	99.71%	99.52%	99.72%
5	99.71%	99.51%	99.72%
6	99.71%	99.51%	99.72%
7	99.71%	99.51%	99.72%
8	99.71%	99.52%	99.72%
9	99.71%	99.52%	99.72%
10	99.71%	99.52%	99.72%

In both tables it is shown that the availability the subsystem A designs increases over time. This means that the availability during warranty period is less than during the service period. This is in line with the expectations since the β of the Weibull time to failure distribution for the majority of the critical subsystems is below 1 as shown in Appendix P. Furthermore, the availability of System Design 1 with subsystem A2 installed is lower than the availability of System Design 1 with either subsystem A1 or subsystem A2 with backup installed. Moreover, the availability of System Design 1 in Area B is higher than the system availability in Area A due to the shorter replenishment time of the critical components. It is also shown that on average the availability of System Design 1 with subsystem A2 for customers in Area A does not satisfy the service level of the 99% service contract.

The contract penalty costs of the different service contracts are determined based on the availability distribution of the System Design 1. Based on the simulation results histograms of the availability of year 1 have been made for scenario 7-12. These histograms can be found in Appendix S. The penalty cost for the 96%, 98%, and 99% service contract for scenario 7-12 are given in Table 17 -22.

Scenario 7-9

Table 17: Yearly expected contract penalty cost of 96% service contract of System Design 1 with different subsystem A designs for customers in Area A

Year n	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	€ 0	€ 0	€ 0
2	€ 0	€ 17	€ 0
3	€ 0	€ 18	€ 0
4	€ 0	€ 16	€ 0
5	€ 0	€ 13	€ 0
6	€ 0	€ 17	€ 0
7	€ 0	€ 18	€ 0
8	€ 0	€ 15	€ 0
9	€ 0	€ 17	€ 0
10	€ 0	€ 16	€ 0

Table 18: Yearly expected contract penalty cost of 98% service contract of System Design 1 with different subsystem A designs for customers in Area A

Year n	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	€ 0	€ 0	€ 0
2	€ 43	€ 1,081	€ 24
3	€ 33	€ 1,096	€ 17
4	€ 31	€ 1,073	€ 20
5	€ 32	€ 1,057	€ 22
6	€ 32	€ 1,057	€ 17
7	€ 31	€ 1,053	€ 19
8	€ 32	€ 1,057	€ 20
9	€ 27	€ 1,064	€ 19
10	€ 33	€ 1,065	€ 17

Table 19 Yearly expected contract penalty cost of 99% service contract of System Design 1 with different subsystem A designs for customers in Area A

Year n	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	€ 0	€ 0	€ 0
2	€ 692	€ 3,673	€ 622
3	€ 648	€ 3,634	€ 593
4	€ 648	€ 3,641	€ 581
5	€ 627	€ 3,635	€ 583
6	€ 649	€ 3,633	€ 575
7	€ 626	€ 3,616	€ 562
8	€ 635	€ 3,591	€ 551
9	€ 633	€ 3,638	€ 563
10	€ 630	€ 3,618	€ 563

Scenario 10-12

Table 20 Yearly expected contract penalty cost of 96% service contract of System Design 1 with different subsystem A designs for customers in Area B

Year n	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	€ 0	€ 0	€ 0
2	€ 0	€ 0	€ 0
3	€ 0	€ 0	€ 0
4	€ 0	€ 0	€ 0
5	€ 0	€ 0	€ 0
6	€ 0	€ 0	€ 0
7	€ 0	€ 0	€ 0
8	€ 0	€ 0	€ 0
9	€ 0	€ 0	€ 0
10	€ 0	€ 0	€ 0

Table 21: Yearly expected contract penalty cost of 98% service contract of System Design 1 with different subsystem A designs for customers in Area B

Year n	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	€ 0	€ 0	€ 0
2	€ 9	€ 28	€ 1
3	€ 7	€ 27	€ 0
4	€ 11	€ 27	€ 0
5	€ 7	€ 27	€ 1
6	€ 6	€ 25	€ 0
7	€ 7	€ 24	€ 1
8	€ 7	€ 24	€ 0
9	€ 7	€ 24	€ 1
10	€ 6	€ 26	€ 1

Table 22 Yearly expected contract penalty cost of 99% service contract of System Design 1 with different subsystem A designs for customers in Area B

Year n	System design 1 with Subsystem A1	System design 1 with Subsystem A2	System design 1 with Subsystem A2 with backup
1	€ 0	€ 0	€ 0
2	€ 249	€ 548	€ 126
3	€ 270	€ 536	€ 115
4	€ 261	€ 508	€ 116
5	€ 255	€ 525	€ 108
6	€ 255	€ 525	€ 113
7	€ 262	€ 533	€ 118
8	€ 259	€ 525	€ 118
9	€ 247	€ 526	€ 111
10	€ 259	€ 519	€ 111

For all the scenarios it is shown that the penalty costs per year increases when the guaranteed availability of the service contract increases. It is also shown that the penalty costs of the different designs of 96% service contract are almost equal to 0. This means that the penalty costs does not influence the life cycle cost, which implies that from a life cycle costs point of view scenario 9 and 12 are optimal among considered scenarios for a 96% service contract.

The penalty costs of 98% service contract for customer in Area A with System Design 1 and subsystem A2 is more than €1,000 per year. In contrast, the penalty costs of 98% service contract for customer in Area A with System Design 1 and subsystem A1 or A2 with backup is less than €50 per year. This implies that from a life cycle cost point of view that the System Design 1 with Subsystem A2 with backup is optimal among the considered scenarios. However, the penalty costs of 98% service contract for customer in Area B with System Design 1 and subsystem A1, A2, and A2 with backup are less than €30. In contrast for customers in Area B, the scenarios 9 and 12 are optimal with respect to the life cycle costs for the 98% service contract for customers in Area A. In case a 99% service contract is used scenarios 9 and 12 are optimal from a life cycle cost point of view compared to the other scenarios considered in this section.

Furthermore it should be noted that the penalty costs of System Design 1 with subsystem A1 are higher than the penalty costs of System Design 1 with subsystem A2 with backup, where the average availability is more or less the same as shown in Table 15 and Table 16. The reason behind this is that The availability distribution of System Design 1 with subsystem A1 is a slightly more left tailed than the availability distribution of System Design 1 with Subsystem A2 with backup. This can be seen in Appendix S.This implies that the probability that penalty costs occur is higher for System Design 1 with subsystem A1 than for System Design 1 with Subsystem A2 with backup.

6.2.3. Scenario 13 and 14

In scenario 1-12 the contract hours and scan hours are the same. In order to make the effect of increasing contract and scan hours on the availability visible, scenario 13 and 14 have been created. Apart from the contract hours and scan hours, scenario 13 and 14 are respectively the same as scenario 7 and 10. The contract hours have been increased from 2500 to 6000 hours per year. The scan hours have been increased from 1600 to 5250 hours per year.

The availability results of System Design 1 with subsystem A1 for customers in Area A (scenario 13) and customers in Area B (Scenario 14) can be found in Table 23.

Table 23: Average availability in year n of scenario 13 and 14

Year	**Scenario 13**	*Scenario 7*	**Scenario 14**	*Scenario 10*
1	99.06%	*99.52%*	99.44%	*99.68%*
2	99.13%	*99.57%*	99.48%	*99.70%*
3	99.14%	*99.58%*	99.48%	*99.70%*
4	99.14%	*99.58%*	99.48%	*99.71%*
5	99.16%	*99.58%*	99.49%	*99.71%*
6	99.16%	*99.58%*	99.49%	*99.71%*
7	99.16%	*99.59%*	99.50%	*99.71%*
8	99.17%	*99.58%*	99.50%	*99.71%*
9	99.17%	*99.58%*	99.50%	*99.71%*
10	99.17%	*99.58%*	99.50%	*99.71%*

As expected, the expected availability decreases both for scenario 13 compared to scenario 7 between 0.41% and 0.46% per year and for scenario 14 compared to scenario 10 between 0.21 % and 0.24%. From this it can be concluded that the effect of contract hours and scan hours on availability for customers in Area B is less than for customers in Area A. This is in line with the expectations, since the mean downtime at a failure in Area B is less than in Area A.

The penalty costs of the 96%,98%, and 99% service contracts of scenario 13 and 14 compared to scenario 7 and scenario 10 can be found in respectively Table 24, Table 25, and Table 26.

Table 24: Penalty costs of 96% contract in year n of scenario 13 and 14

Year	Scenario 13	*Scenario 7*	Scenario 14	*Scenario 10*
1	€ 0	*€ 0*	€ 0	*€ 0*
2	€ 2	*€ 0*	€ 0	*€ 0*
3	€ 1	*€ 0*	€ 0	*€ 0*
4	€ 1	*€ 0*	€ 0	*€ 0*
5	€ 1	*€ 0*	€ 0	*€ 0*
6	€ 1	*€ 0*	€ 0	*€ 0*
7	€ 1	*€ 0*	€ 0	*€ 0*
8	€ 1	*€ 0*	€ 0	*€ 0*
9	€ 1	*€ 0*	€ 0	*€ 0*
10	€ 1	*€ 0*	€ 0	*€ 0*

Table 25 Penalty costs of 98% contract in year n of scenario 13 and 14

Year	Scenario 13	*Scenario 7*	Scenario 14	*Scenario 10*
1	€ 0	*€ 0*	€ 0	*€ 0*
2	€ 307	*€ 43*	€ 26	*€ 9*
3	€ 293	*€ 33*	€ 27	*€ 7*
4	€ 286	*€ 31*	€ 26	*€ 11*
5	€ 279	*€ 32*	€ 25	*€ 7*
6	€ 266	*€ 32*	€ 24	*€ 6*
7	€ 261	*€ 31*	€ 24	*€ 7*
8	€ 265	*€ 32*	€ 23	*€ 7*
9	€ 264	*€ 27*	€ 23	*€ 7*
10	€ 258	*€ 33*	€ 24	*€ 6*

Table 26 Penalty costs of 99% contract in year n of scenario 13 and 14

Year	Scenario 13	*Scenario 7*	Scenario 14	*Scenario 10*
1	€ 0	*€ 0*	€ 0	*€ 0*
2	€ 2,200	*€ 692*	€ 520	*€ 249*
3	€ 2,177	*€ 648*	€ 516	*€ 270*
4	€ 2,164	*€ 648*	€ 504	*€ 261*
5	€ 2,149	*€ 627*	€ 504	*€ 255*
6	€ 2,097	*€ 649*	€ 487	*€ 255*
7	€ 2,087	*€ 626*	€ 480	*€ 262*
8	€ 2,075	*€ 635*	€ 480	*€ 259*
9	€ 2,069	*€ 633*	€ 474	*€ 247*
10	€ 2,073	*€ 630*	€ 481	*€ 259*

Again, the contract penalty costs of these scenarios are determined based on the availability distribution in year n. The graph of the availability distribution in year 1 is shown in appendix T. In these tables it can be seen that the contract penalty costs of both scenario 13 and 14 increases compared to scenario 7 and

10. Moreover, the tables show that the penalty costs for customers in Area A increases more with respect to contract and scan hours than the penalty costs for customer in Area B. This indicates that is important to know both what the amount scan hours and contract hours are when a service contract is sold.

7. Implementation

In this chapter it is described what has been done to make sure that the decision support tool can be applied by Philips. The process of determining the life cycle costs and the availability by using the decision support tool consist of three steps:

1. Collect the input data
2. Estimate the input parameters
3. Apply the decision support tool

7.1. Collect the input data

After a (sub) system design and a customer is selected to determine the life cycle costs, the input data should be collected to estimate the values of the input parameters in the tool. The data of the input parameters are distributed over four databases, FDV, GDWH, iCube, and SAP. In order to make clear where the data of the input parameter can be found, the name of the database has been addressed for each input parameter in chapter 5 and Appendix O. Moreover, to get operating time to failure data a couple of data transforming steps are required. The steps that have been performed to get operating time to failure data for the case study in chapter 6 are explained in Appendix O.

7.2. Estimate the input parameters

The approach that should be taken to estimate the parameters is explained in chapter 5. Moreover, in Appendix O, it is explained how the parameters have been estimated for the case study in chapter 6. Furthermore, an Excel file has been made that can be used to estimate the time to failure or downtime distribution and the values of its parameters. More explanation and screenshots can be found in section 5 of Appendix K.

7.3. Apply the decision support tool

When the distributions and the values of the input parameters are estimated, the tool can be used to calculate the availability and life cycle costs for different scenarios. A manual has been made that explains how the tool should be used. This manual can be found in Appendix K. Furthermore, it has been described how the tool should be installed. The manual and the installation instructions have been discussed in several meetings with three users of the decision support tool. During these meetings the users were able to install the tool and to run the simulations based on the installation manual and user manual.

Moreover, workshops have been given to a service specialist and a reliability engineer about the R script which consist the code of the simulation. Although the tool is able to cope with small changes in the conceptual model of the medical scanner, it might be that in the future the R script should be adjusted. Both the service specialist and reliability engineer understand the R script and should be able to make changes to the script if necessary.

8. Conclusion and Recommendations

This chapter gives the conclusion of the research project by answering the research questions as described in chapter 1. In addition to the conclusion, recommendations are given to Philips. Finally, further research possibilities are given and the academic relevance is described.

8.1. Conclusion

In this project, a mathematical model and a decision support tool have been developed. The first model is a mathematical model that determines the availability and life cycle costs for one specific customer based on the design and the maintenance policy. This model has been implemented in a decision support tool, which makes use of a Monte Carlo simulation.

First, the life cycle cost elements have been determined and broken down level by level. These life cycle costs contain all the costs that occur for Philips from the moment that the system is produced until the system is out of service by Philips. The six main cost elements of the medical scanners' life cycle costs consist of purchasing price of all the components, assembly costs of the system, shipment and installation costs, warranty costs, maintenance service costs, and contract penalty costs. Secondly the availability elements have been determined. Based on these availability elements the decision variable design has been broken down into selection of components and reliability configuration of the system, where can be decided to install a cold standby backup component. Two maintenance policies have been taken into account in the models: the failure based policy and the preventive block replacement policy. In order to determine the calculation model the conceptual relations between the individual life cycle costs elements and decision variables, design and maintenance policy, have been addressed. This answers the first research question:

What are the life cycle cost elements for a medical scanner and how are they related to system availability and the decision variables?

From the conceptual model, assumptions had to be made to make a calculation model which can calculate the system availability and its life cycle costs by modifying decision variables. However, the assumptions listed in section 2.5 seem to be reasonable for the medical scanner. In order to determine the expected number of failure during a one year time interval the operating time to failure has been selected for the mathematical model. This as it has been found that operating days would be a more appropriate measurement of the time to failure instead of calendar days, which is currently used in reliability studies by Philips. The causal relations between the decision variables and the availability and life cycle costs have been translated into mathematical terms, which make it possible to implement the relations into a computer model.

In order to satisfy the computational time restriction of determining the availability and life cycle costs for one customer, the mathematical model has been implemented to a decision support. Due to the fact that it was not possible to determine the contract penalty costs for the medical scanner situation analytically, the mathematical model has been modelled by a Monte Carlo simulation. The number of failures per year, downtime per year, availability per year, and the values of the life cycle costs elements are given by the decision support tool, based on the decision variables and other customer related input data. In addition to the availability and life cycle costs, the optimal preventive maintenance block interval with respect to corrective maintenance and preventive maintenance costs can be determined by the decision support tool. The testing results of the decision support tool has shown that the computational time of the decision support tool is between 1 and 12 minutes, which is below the restriction of 15 minutes. This answers the second research question:

How can the availability and life cycle costs of a system be determined for one customer within restricted computational time based on the system design and maintenance policy?

Before the decision support tool has been applied to different scenarios, the estimation approaches of the values of the input parameters have been described. Analyses of the available data have shown that the databases consist of considerable missing and incorrect data. In order estimate the values of the input parameters as accurate as possible, the data available has been described and the outliers have been removed for the case study. The steps that have been taken to estimate the values of the input parameters have been described in the estimation approaches described in chapter 5. This answers the third research question:

How can the values of the input parameters be estimated based on the data available by Philips?

As described, the decision support tool has been applied to different designs of the subsystem A used in System Design 1 for customers in Area A and Area B. The different designs of subsystem A consist of the current subsystem design A1 and the new subsystem design A2. The new design can be produced with or without a cold standby backup. The simulations of the different scenarios have shown that the life cycle costs of the subsystem A2 are considerable lower than the life cycle costs of subsystem A1. The biggest savings is due to the lower coolant costs. The drawback of the subsystem A2 is that the availability is lower compared to subsystem A1. However, by adding the backup to subsystem A2 the availability increases to more or less the same level as the availability of subsystem A1. The scenario results show that it depends on the customer data whether it is optimal to install the backup for the subsystem A2 with respect to the life cycle costs. In the case study, it is shown that the availability decreases and life cycle costs increases when the contract hours increases, scan hours increases, customers' cooling get worse, or customers' mains power get worse. Note that the described designs are based on fiction data, but it clearly shows that the effect of design decisions on availability can be calculated successfully with the decision support tool

Thus, it can be concluded that the life cycle costs and availability of one system depend on its utilization and the values of the input parameters of the customers.

Overall, it can be concluded that the decision support tool enables the user to take decisions about design and maintenance policy based on availability and life cycle costs for specific customers. This answers the main research question

What are the availability and life cycle costs of different system designs and maintenance policies for one specific customer?

8.2. Recommendations to the organisation

The scenario analyses have shown that both the design of the medical scanner and the customer input data, influences the availability and the life cycle costs of the system. For this reason, it is recommended to the Philips organisation to use the developed tool during the selling process of a new system to a specific customer. The tool supports the account manager to determine the optimal design for a specific customer. In addition to the optimal design, the tool can be used to determine the price of the service contract, since the expected costs for Philips during the service period are given.

To implement the tool in the process of developing new system designs are also recommended, since the tool can support development engineers to compare the expected availability and life cycle costs of different (sub) system designs. Furthermore, the developed model can be easily adapted to model the total expected profit for a complete new system design by adding the design costs and sales distribution of the system and service contracts. This can support the management of Philips in making strategic decision about new system design. For this reason, it is recommended to further investigate this possibility.

Accurate data is important for the decision support tool to provide the user accurate results. It is recommended to the organisation to record more data about the downtime of the systems due to component failures. Downtime data makes it possible to estimate the downtime distribution and use downtime distributions instead of deterministic downtimes in the availability and life cycle costs analyses. This increases the accuracy of the results

The critical components have been classified into operating time categories in order to transform the time to failures measured in calendar hours into operating time to failures. This made it possible to take into account the average utilization of the medical scanner users. Further research on the effect of utilization might lead to more accurate failure prediction and better result with respect to availability and life cycle costs.

8.3. Academic Relevance and Further Research

The literature consists of many models about determining the optimal maintenance policy or design with respect to the lowest costs. In the last decade, the number of companies that provide maintenance service contracts for capital goods with availability service levels has been increased. This has led to more availability models in the literature. However, most of the availability models consist of the relation between either availability and maintenance policy, or availability and spare component levels. A couple of years ago a new research topic, “Design for Availability”, had been introduced. Within this research, it is tried to indicate the relation between the design of a capital good and the availability or downtime. At the moment, limited articles are available about this topic. This mathematical model contributes to this new research topic, since the relation between availability and both the reliability configuration of the medical scanner design and the selection of the critical components is analysed. Moreover, the developed model contains the relations between different maintenance policies and designs, and the availability and life cycle costs. This combination is rare in the literature. Furthermore, the model is applied to a practical case, where it is in most literature unclear how the model should be applied into practice. The model is not only useful for the medical scanner: it can also be applied to other capital goods.

The model has been implemented in a Monte Carlo simulation and is applied to different subsystems and one system design. It is recommended to apply this tool to different systems to make the validity of the decision support tool stronger.

In this project, only an optimisation function of the preventive block replacement interval is given. An optimization function for a system with different backup possibilities and different maintenance possibilities has not been investigated in this research. Further research on this function is recommended. Furthermore, assumptions have been made regarding the medical scanner. In case that the replacement times at failure are not neglected, the model can be applied to more capital goods. For this reason it is recommended to further investigate the effect of relaxing this assumption.

9. Bibliography

Akkermans, H., van Oppen, W., & Voss, C. (2012). Incentive Issues in Outsourced Maintenance Supply Networks: A Delphi study in the Process Industry. *Euro Maintenance*, (pp. 1-14).

Banks, J., Carson, J., Nelson, B., & Nicol DM. (2005). *Discrete-Event System Simulation.* Prentic Hall: Upper Saddle River.

Bertrand, J. W., & Fransoo, J. C. (2002). Modelling and simulation: Operations management research methodologie using quantitative modeling. *Interantional journal of operations & production management*, 241-264.

Brezavscek, A. (2013). A simple discrete approximation for the Renewal Function. *Business System Research*, 65-75.

Cohen, M. A., Agrawal, N., & Agrawal, V. (2006). Winning in the aftermarket. *Harvard Business Review*, 129-138.

Dersin, P., Péronne, A., & Arroum, C. (2008). Selecting test and maintenane strategies to achieve availability target with lowest life cycle cost. *Annual Reliability and Maintainability Symposium*, (pp. 301-306). Las Vegas.

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

Echeverría, P., & López-Vallejo, M. (2013). High Performance FPGA-oriented Mersenne Twister Uniform Random Number Generator. *J Sign Process Syst*, 105–109.

Geweke, J. (1991). Efficient Simulation from the Multivariate Normal and Student-t Distributions Subject to Linear Constraints and the Evaluation of Constraint Probabilities. *Computing Science and Statistics: Proceedings of the 23-rd Symposium on the Interface* (pp. 571-578). Seattle: Interface Foundation of North America.

Hatch, M. L., & Badinelli, R. D. (1999). Concurrent optimization in designing for logistic support. *European Journal of Operations Research*, 77-97.

Hoad, K., Robinson, S., & Davies, R. (2010). Automated selection of the number of replications for a discrete-event simulation. *The Journal of the Operational Research Society*, 1632-1644.

Kostagiolas, P. A., & Bohoris, G. A. (2010). Finite sample behaviour of the Hollander-Proschan goodness of fit with reliability and maintenance data. *Engineering Asset Lifecycle Management*, 831-840.

Kumar, U Dinesh: Crocker, John: Knezevic, J: El-Haram, M. (2000). *Reliability, Maintenance and Logistic Support - A Life Cycle Approach.* Boston/Dordrecht/London: Kluwer Academic Publisher.

Law, A. M., & Kelton, D. W. (2000). *Simulation modelin and Analysis.* New York: The McGraw-Hill.

Manzini, R., & Pham, H. (2010). *Maintenance for Industrial Systems.* London: Springer.

Matsumoto, M., & Nishimura, T. (1998). Mersenne twister: a 623-dimensionally equidistributed uniform pseudo-random number generator. *ACM Transactions on Modeling and Computer Simulation*, 3-30.

Mattheij, P. J. (2013). *An Analysis of the Warranty and Service Costs of MRI Scanners at Philips Healthcare.* Eindhoven: TU/e.

Mello, D. A., Waldman, H., & Quitério, G. S. (2011). Interval availability estimation for protected connection in optical network. *Computer Networks*, 193-204.

Mitroff,, I. I., Betz, F., Pondy, L. R., & Sagasti, F. (1974). On managing science in the system age: two schemas for the study of science as a whole system phenomenon. *Interfaces*, 46-58.

Oliva, R., & Kallenberg, R. (2003). Managing the transition from products to services. *International Journal of Services Industry Management*, 160-172.

Öner, K. B., Alan, S. W., & van Houtum, G. J. (2013). Redundancy Optimization for Critical Components in High Availability Technical Systems. *Operations Research*, 244-264.

Öner, K. B., Franssen, R., Kiesmüller, G. P., & Van Houtum, G. J. (2007). Life cycle costs measurement of complex systems manufactured by an engineer-to-order company. *International conference on flexible automation and intelligent manufacturing*, 569-589.

Öner, K. B., Kiesmüller, G. P., & van Houtum, G. J. (2010). Optimization of components reliability in the design phase of capital goods. *European Journal of Operational Research*, 615-625.

Philips Medical Systems. (1990). *Basic Principle of MR imaging.* Eindhoven: Philips NV.

Philips NV. (2012). *Finanicial Report 2012.* Philips NV.

Smets, P. M., van Houtum, G. J., & Langerak, F. (2012). Design for availability: A holistic approach to create value for manufacturers and customers of capital goods. *Journal of Sytems Science and Sytems Engineering*, 403-421.

van Houtum, G. J. (2010). *Maintenance of capital goods.* Eindhoven: Eindhoven University of Technology.

Woodward, D. G. (1997). Life cycle costing - theory, information acquisition and application. *International journal of project management, 15*(6), 335-344.

Zephat, A. (2009). *Life cycle costs model and determination of failure rate targets.* Best: Philips NV.

Zio, E. (2013). *The Monte Carlo Simulation Method for System Reliability and Risk Analysis.* London: Springer.

Appendix A: Life cycle costs Breakdown of the medical scanner

In cooperation with the customer service team of Philips, the life cycle costs breakdown have been developed based on both the first level cost breakdown structure of capital goods developed by Öner et al. (2007), and the life cycle cost model for a medical scanner component developed by Zephat (2009).

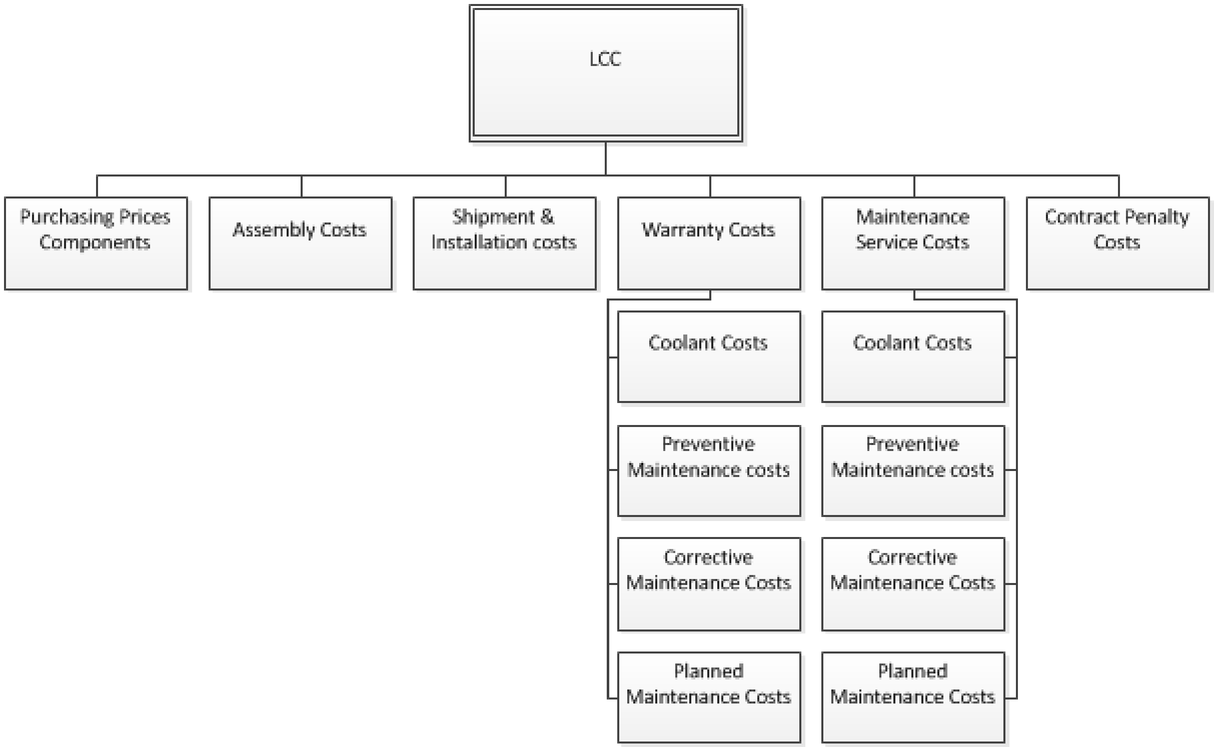


Figure 20: Life cycle cost breakdown for a medical scanner

Appendix B Assumption Justification

In this section the assumption made in section 2 are justified for the medical scanners situation

1. *Critical components fail independently of each other*

The product experts of Philips expect that no relation exists between the failures of different critical components. The expectation of these engineers is based on the fact that the critical components operate independent of each other. In order to test the independency of failure events of two critical components more failure data is needed. To be more precise, the current database does not contain more than three failure events per individual critical component of one medical scanner. However the expectation of the product experts seems to be reasonable. Therefore, the expectation is adopted.

2. *Operating hours per year are constant over time for one specific customers*

The time to failures in the data base of Philips is logged in calendar days. In order to determine the time to failure in operating days the utilization of the system should be known since the utilization per system differ significantly. Philips has a database consisting of the scan hours per day per system. However, the database has a considerable amount of missing values due to missing log files. For this reason, the average operating hours per day in a given year are obtained: the total number of logged operating hours in given year divided by the number of log files in given year, where one log file represents one day of information.

The service innovation department expect both that the utilization of the medical scanner by a customer is constant over the years and the variation of the utilization per day is very low . The latter one cannot be tested due to the missing data. Nevertheless, this expectation is assumed to be valid. Based on the first assumption, it is expected that the average operating hours per day over the years does not vary a lot. In order to test this assumption the coefficient of variation (COV) of the utilization per year is calculated for investigated medical scanners in the field. The coefficient of variation is used since the mean utilization per system differs significantly. The COV can be calculated with:

$$COV = \frac{Standard\ deviation}{Mean}$$

The utilization over year 2011 up to April 2014 of 1391medical scanners in the field has been examined. The scatter plot of the coefficient of variation of the average operating hours per day over the years is shown in Figure 21.

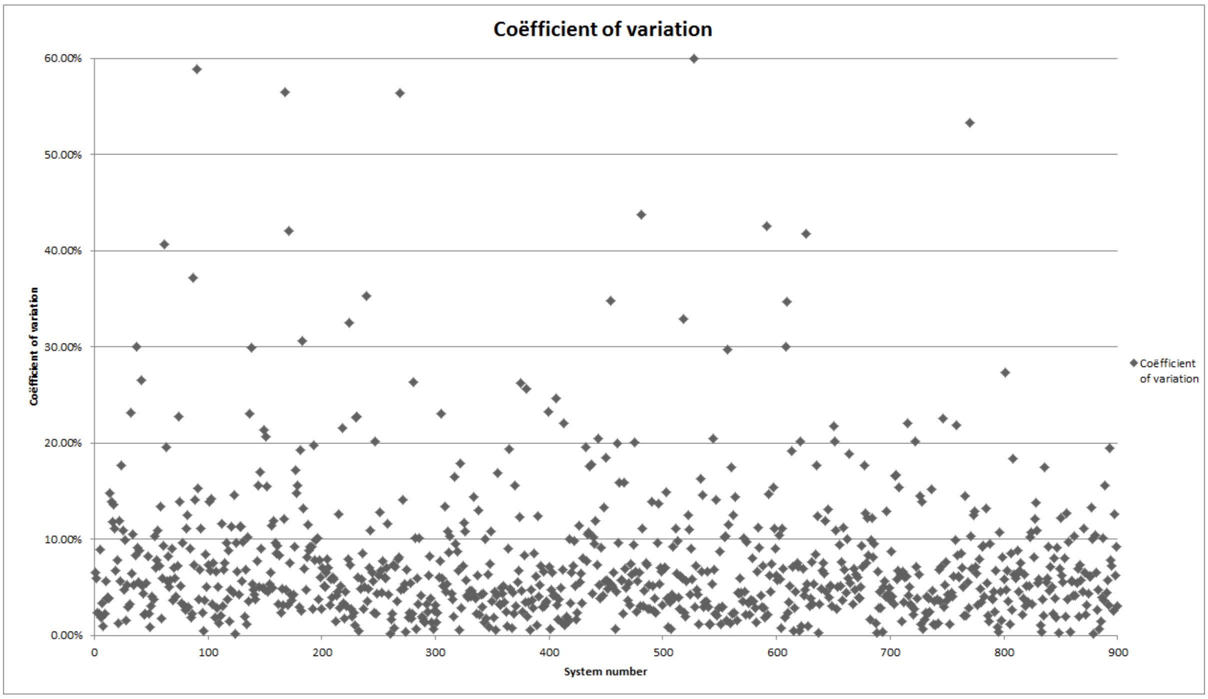


Figure 21: scatter plot of the systems' coefficient of variation of the average operating hours per day over the years

This scatterplot shows that 1062 of 1391 investigated medical scanners have a COV of less than 10%. The COV of 241 medical scanners is between 10% and 20%, and only 88 medical scanners have COV of more than 20%. From these results, it can be concluded that the number of operating hours per year is constant over time.

3. *<u>The replacement times can be neglected for the calculation of the expected number of failures.</u>*

From the failure data available at Philips it can be derived that the components of the medical scanner do not fail very often. The mean time to failure of a component is usually a couple of years. In contrast, the time of the corrective maintenance action to get the system up and running again usually takes a day which is negligible compared to the mean time to failure. The data also shows that the probability that a component fails during a corrective maintenance action is very low. Due to facts that the replacement time is relatively short and the probability that a component fails during a corrective maintenance action is negligible, the replacement times can be neglected for the calculation of the expected number of failures

Appendix C: Notation Mathematical Model

Table 27 gives an overview of the mathematical notation used in this section

Table 27: Overview of mathematical notation Model Assumptions

Notation	Explanation
a	$availability$
$A_{s,i}$	$Administration\ cost\ per\ replacement\ of\ componet\ i\ in\ system\ s$
c_i	$Repair\ costs\ for\ component\ i$
cc	$coolant\ cost\ per\ liter$
cl	$coolant\ loss$
clt	$contracting\ lifetime$
$CH_{s,i}[.]$	$Total\ number\ of\ contract\ hours\ of\ system\ s\ in\ a\ interval$
DR_s	$Distance\ from\ the\ customer\ to\ the\ nearest\ repairshop$
$DT_{s,i}$	$Mean\ diagnostic\ time\ of\ comopnent\ i\ in\ system\ s$ $(i.e. the\ time\ that\ last\ to\ indentify\ the\ cause\ of\ a\ failure\ )$
$dtcm'_{s,i}$	$Downtime\ of\ sytem\ s\ due\ to\ a\ corrective\ maintenance\ action\ of\ component\ i$ $(calender\ hours)$
$dtcm_{s,i}$	$Downtime\ of\ sytem\ s\ due\ to\ a\ corrective\ maintenance\ action\ of\ component\ i$ $(contract\ hours)$
$EA_s[.]$	$Expected\ availability\ of\ system\ s\ during\ an\ interval$
EAC_s	$Expected\ assembly\ cost\ of\ system\ s$
ECC_{s,y'_n}	$Expected\ coolant\ costs\ of\ system\ s\ in\ year\ n$
$ECMC_{s,i}$	$Expected\ costs\ at\ a\ corrective\ maintenance\ action\ of\ component\ i\ in\ sytem\ s$
$ECMC_{s,y'_n}$	$The\ total\ expected\ corrective\ maintenance\ cost\ of\ system\ s\ in\ year\ n$
$ECMRC_{s,i}$	$Expected\ repair\ costs\ \ of\ component\ i\ \ in\ system\ s\ for\ a\ corrective$ $maintenance\ action$
ECO_{s,y'_n}	$Expected\ capacity\ overhead\ cost\ per\ year\ of\ system\ s$
$ED_s[.]$	$Expected\ downtime\ during\ contract\ hours\ in\ an\ interval\ of\ system\ s$
$ELCC_s$	$Expected\ Life\ cycle\ cost\ of\ system\ s$
$E\left[M_{s,i}[.]\right]$	$Expected\ number\ of\ failures\ of\ component\ i\ in\ system\ s\ during\ an\ interval$

$E\left[M_s[.]\right]$	Expected number of failures of system s during an interval
$E\left[MN_{s,i}[.]\right]$	Expected number of no functionality failures of component i in system s during an interval
$E\left[MN_s[.]\right]$	Expected number of no functionality failures of system s in an interval
$EMTSC_{s,y'_n}$	Expected maintenance service cost of system s in year n
$EO_{s,i}$	Expected perecentage operating hours with respect to calaendar hours of compont i
EPC_{s,y'_n}	Expected contract penalty costs of system s in year n
EPM_{s,y'_n}	Expected planned maintenance costs per year of system s
$EPMC_{s,y'_n}$	Expected preventive maintenance costs of system s in year n
$EPMC_{s,i}$	Expected costs at preventive replacement of component i in system s
$EPMRC_{s,i}$	Expected repair costs of component i in system s at a preventive maintenance
$E\left[PR_{s,i}[.]\right]$	Expected number of preventive replacements of component i in system s during an interval
$ESCC_{s,i}$	Expected Spare component supply cost of component i in system s per failure
$ESIC_s$	Expected Shipment and Installation costs of system s
$EU_s[.]$	Expected uptime of sytem s during an interval
EWC_{s,y'_n}	Expected warranty cost of system s in year n
f_ik	failure number k of critical component i
$f_i(t)$	Probability density function of the time to failure which is the probability that component i fails at time t
$f_s(t)$	Probability density function of the time to failure which is the probability that system s fails at time t
$F_i(t)$	Cumulative distribution function of the time to failure, which is the probability that componet i fails before t in interval $[0, t]$
$F_s(t)$	Cumulative distribution function of the time to failure, which is the probability that system s fails before t in interval $[0, t]$
f_sk	failure number k of system s

F_{sc}	$Service\ contract\ Fee\ of\ contract\ type\ sc$
G_i	$The\ maintenance\ cost\ per\ time\ unit\ of\ compoent\ i$
G_i^*	$The\ optimal\ maintenance\ cost\ per\ time\ unit\ of\ compoent\ i$
h_{FSE}	$hour\ wage\ of\ Field\ Service\ Engineer\ in\ euros$
$H_{s,i}[.]$	$Number\ of\ calendar\ hours\ in\ a\ interval$
i	$(Critical)\ component$
I_s	$Total\ number\ of\ ciritcal\ components\ installed\ in\ sytem\ s$
l_S	$constracting\ length\ \ of\ system\ s\ in\ years$
k	$Number\ of\ corrective\ replacement$
MD_i	$mean\ maintenance\ delay\ of\ critical\ component\ i$
nf	$no\ fuctionality\ failure$
n	$Number\ of\ calendar\ years$
NR_{i,y_n}	$Number\ of\ regular\ preventive\ mainteance\ \ cycles\ of\ \ component\ i\ in\ year\ n$
p	$number\ of\ preventive\ replacements$
$P(A_s[.] = a)$	$Probality\ that\ the\ avaialbity\ during\ an\ interval\ is\ equal\ to\ a$
$P(AS_i = sf)$	$The\ probability\ that\ the\ automatic\ switch\ of\ component\ i\ is\ equal\ to\ sf$
$P(CL_s[.] = cl)$	$Probability\ that\ the\ coolant\ loss\ of\ system\ s\ is\ equal\ to\ cl\ during\ an\ interval$
$P(CLT_s = l_s)$	$Probability\ that\ the\ contractring\ lifetime\ is\ equal\ to\ l_S$
$P(CMR_i = c_i)$	$Probability\ that\ the\ corrective\ maintenace\ repair\ costs\ of\ component\ i\ are\ equal\ to\ c_i$
$P(FM_i = nf)$	$Probaility\ that\ the\ failure\ is\ a\ no\ functionality\ failure$
$P(PMR_i = c_i)$	$Probability\ that\ the\ preventive\ maintenace\ repair\ costs\ of\ component\ i\ are\ equal\ to\ c_i$
$P(RT_i = rt_i)$	$Probability\ that\ the\ repair\ time\ of\ component\ i\ in\ the\ repair\ shop\ is\ equal\ to\ rt_i$
$P(f_i[.] = k)$	$Probability\ of\ k\ failures\ in\ a\ interval$
pp_i	$Purchasing\ price\ of\ component\ i$
Q_s	$Total\ number\ of\ components\ installed\ in\ system\ s$

$R_i(t)$	$Reliablity\ funciton\ , which\ is\ the\ probability\ that\ component\ i\ does\ not\ fail\ before\ t\ in\ interval\ [0, t]$
$R_s(t)$	$Reliablity\ funciton\ , which\ is\ the\ probability\ that\ system\ s\ does\ not\ fail\ before\ t\ in\ interval\ [0, t]$
$RPT_{s,i}$	$Mean\ replacement\ time\ (i.e. the\ time\ that\ last\ to\ replace\ critical\ component\ i)\ of\ component\ i\ in\ system\ s\ per\ failure$
rt_i	$Time\ that\ is\ needed\ to\ repair\ component\ i\ in\ hours$
s	$One\ MRI\ system$
sc	$\{96,98,99\}$
SC	$Set\ of\ percentage\ service\ contract\ sc$
sf	$swicht\ fails$
$SH_s[.]$	$Number\ of\ scan\ hours\ of\ sysem\ s\ in\ a\ interval$
TCP_s	$Sum\ the\ purchasing\ prices\ of\ the\ componets\ installed\ in\ sytem\ s$
t_{π_i}	$Preventive\ maintenance\ interval\ of\ componet\ i$
t_i	$Time\ unit\ in\ operating\ hours\ of\ component\ i$
t'	$Time\ unit\ in\ calender\ hours$
t_{i,y_n}	$Number\ of\ operating\ hours\ of\ component\ i\ at\ the\ endcalender\ year\ n$
t'_{y_n}	$Number\ of\ calender\ hours\ at\ the\ endcalender\ year\ n$
TR_{wh}	$Transportion\ rate\ to\ transport\ one\ kilograms\ one\ kilometre\ in\ area\ c$
TT_s	$Mean\ travel\ time\ to\ system\ s\ for\ the\ FSE\ per\ replacement$
wh	$Timezone\ warehouses\{Roermond, Louisville, Singapore\}$
wl_s	$Warranty\ length\ of\ system\ s$
W_i	$Weight\ of\ component\ i$
$[y_{i,n}]$	$interval\ [t_{i,y_n}, t_{i,y_{n-1}}]\ (operating\ hours)$
$[y'_n]$	$interval\ [t'_{y_n}, t'_{y_{n-1}}]\ (calander\ hours)$
$[\alpha]$	$Interval\ [t_{i,0}, t_{i,\alpha}]\ (operating\ hours)$
$[\alpha']$	$Interval\ [t'_0, t'_\alpha]\ (calander\ hours)$

$[\pi_i]$	$interval\ \left[0, t_{\pi_i}\right](operating\ hours)$
$\lceil\ \ \rceil$	$Round\ up\ to\ neares\ integer. For\ example$: $\lceil 1.1 \rceil = 2$
$\lfloor\ \ \rfloor$	$Round\ down\ to\ nearest\ integer. For\ example$: $\lfloor 1.9 \rfloor = 1$

Appendix D: Time to failure distribution

The expected number of failures in an interval depends on the time to failure distribution. In this section the distribution related to the time to failure is explained in more detail. Time to failure is defined as the time between the moment that a new component has been installed and the time that the component fails. This time is not deterministic: it is a random variable which follows a probability distribution. The time to failure can be modeled by a probability density function (p.d.f.), denoted as $f(t)$, and cumulative distribution function (c.d.f.), denoted as $F(T)$. The probability densisty function gives the probability that a component fails at a certain point in time. The probability that a component fails at or before a certain point in time is given by the cumulative distribution function. The mathematical relation between c.d.f. and p.d.f. for a new component are shown in equation(29)

$$F(T) = P(component\ fails\ at\ or\ before\ T) = P(TTF \leq T) = \int_0^T f(t)dt \tag{29}$$

The reliability function gives the probability that a component does not fail before a certain point in time, which is denoted by $R(T)$. The relation between $F(T)$ and $R(T)$, and $f(t)$and $R(T)$ are respectively given by equation (30) and (31)

$$R(T) = 1 - F(T) \tag{30}$$

$$f(t) = -\frac{dR(T)}{dt} \tag{31}$$

Examples of the probability denisty function, cumulative distribution function, and the reliablity funcation are shown in figure Figure 22

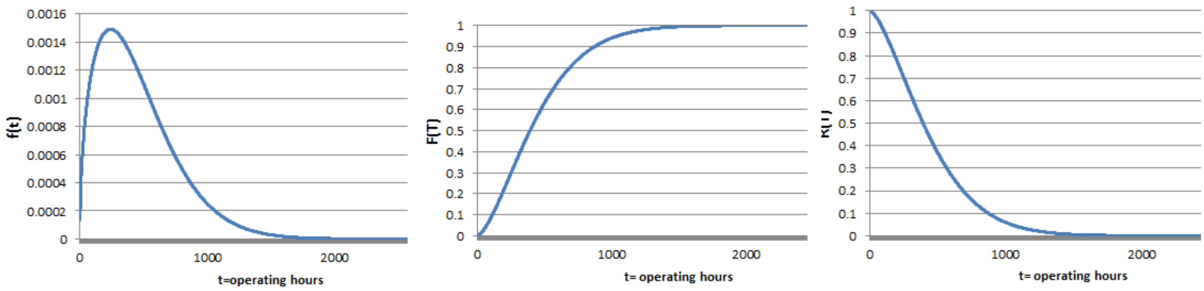


Figure 22: Examples of probability denisty function, cumulative distribution function, and the reliablity funcation

Many distributions can be used to model the time to failures. The exponential, Weibull and normal distribution are widely used in reliability researches. The Weibull distribution is the most flexible distribution since it has a shape (B) and a scale (θ) parameter. Examples of these probability density function and cumulative distribution functions are given in Figure 23

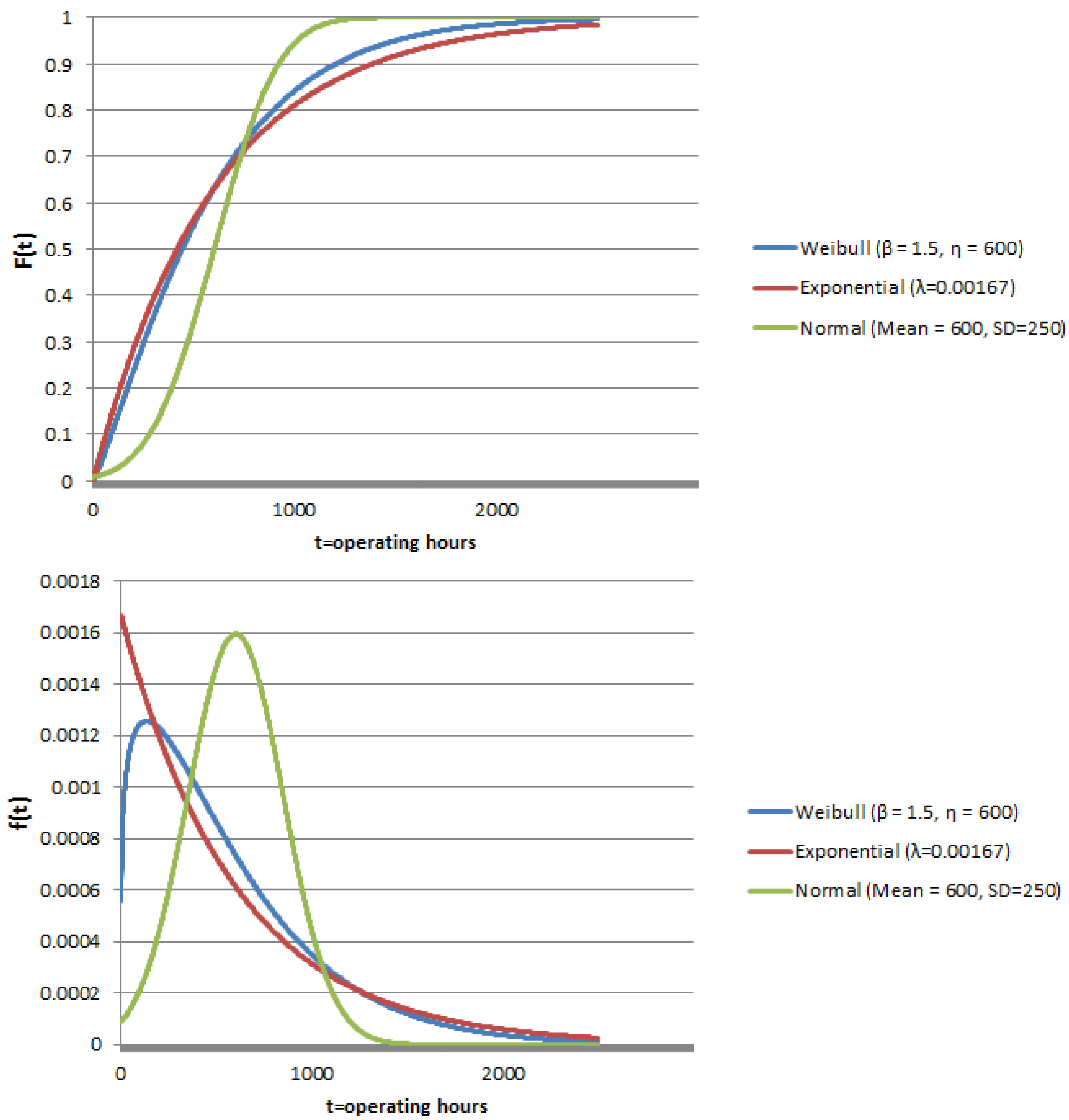


Figure 23: Examples of probability density functions and cumulative distribution functions

Appendix E Determination of $P(f_i[\alpha_i] = k)$

Where $P(f_i[\alpha_i] = k)$ denotes the probability that k failures occur in interval $[\alpha_i]$. The sum of all probabilities on k failures in interval $[\alpha_i]$ must be 1, as shown in equation (32)

$$\sum_{k=0}^{\infty} P(f_i[\alpha_i] = k) = 1 \tag{32}$$

The probability that component i does not fail in interval $[\alpha_i]$ can be obtained by the reliability function denoted as $R_i(T)$. For more information about the reliability function see Appendix D. Thus, $P(f_i[\alpha_i] = 0)$ is determined by equation(33)

$$P(f_i[\alpha_i] = 0) = R_i(t_{\alpha_i}) \tag{33}$$

The probability that the number of failures during interval $[\alpha_i]$ is equal to 1 is determined by the probability that the component fails at time $t_{f_i 1}$ in interval $[\alpha_i]$ multiplied by the probability that component survives the remaining time of the interval which is equal to $(t_{\alpha_i} - t_{f_i 1})$. This is a continuous process since the component can fail at any time. Thus,$P(f_i[\alpha_i] = 1)$ can be determined by equation (34)

$$P(f_i[\alpha_i] = 1) = \int_{t_{f_i 1}=0}^{t_\alpha} f(t_{f_i 1}) * R_i(t_{\alpha_i} - t_{f_i 1}) dt_{f_i 1} \tag{34}$$

The probability of exactly two failures in interval $[\alpha_i]$ is determined by the probability that the system fails at time $t_{f_i 1}$in interval $[\alpha_i]$ multiplied by the probability that component fails before the end of the interval once more, which is equal to the period with length $(t_{\alpha_i} - t_{f_i 1})$, at time $t_{f_i 2}$, multiplied by the probability that the component survives the remaining time which is equal to $(t_{\alpha_i} - t_{f_i 1} - t_{f_i 2})$. Thus, the probability of exactly two failures in interval $[\alpha_i]$ is equal to equation (35)

$$P(f_i[\alpha_i] = 2) = \int_{t_{f_i 1}=0}^{t_\alpha} f(t_{f_i 1}) \left(\int_{t_{f_i 2}=0}^{t_\alpha - t_{f_i 1}} f(t_{f_i 2}) * R_i\left(t_{\alpha_i} - \left(t_{f_i 1} + t_{f_i 2}\right)\right) dt_{f_i 2} \right) dt_{f_i 1} \tag{35}$$

The probability of 3 failures in interval $[0, t_{\alpha_i}]$ can be obtained by equation (36)

$$P(f_i[\alpha_i] = 3) = \int_{t_{f_i 1}=0}^{t_\alpha} f(t_{f_i 1}) \left(\int_{t_{f_i 2}=0}^{t_\alpha - t_{f_i 1}} f(t_{f_i 2}) \left(\int_{t_3=0}^{t_\alpha - (t_{f_i 1} + t_{f_i 2})} f(t_{f_i 3}) \right.\right.$$
$$\left.\left. * R_i\left(t_{\alpha_i} - \left(t_{f_i 1} + t_{f_i 2} + t_{f_i 3}\right)\right) dt_{f_i 3} \right) dt_{f_i 2} \right) dt_{f_i 1} \tag{36}$$

The same approach can be taken to obtain the equation for the probability of 4, 5…., k failures. The number of integrals is equal to the number of failures.

Appendix F: Derivation of $E\left[M_{s,i}\left[y_{i,n}\right]\right]$ and $E\left[MN_{s,i}\left[y_{i,n}\right]\right]$ for a preventive block replacement model

In this section, the derivation of the expected number of failures during interval $\left[y_{i,n}\right]$ with a block replacement policy is given.

Based on the two intervals $[\pi_i]$and $\left[y_{i,n}\right]$ three scenarios have to be distinguished:

4. $\left[y_{i,n}\right] = N_i * [\pi_i]$, $\quad N_i \in \{1,2,\dots\}$,
5. $\left[y_{i,n}\right] = N_i * [\pi_i] + \varepsilon_i$, $\quad 0 < \varepsilon_i < [\pi_i]$, $\quad N_i \in \{1,2,\dots\}$
6. $\left[y_{i,n}\right] < [\pi_i]$

In **scenario (1)** the expected number of failures in an arbitrary year is equal to $N_i * E\left[M_i[\pi_i]\right]$.

In case of **scenario (2),** the time interval of one year can be divided into three cycles regarding the preventive maintenance interval: the first cycle, one or more regular cycles, and the last cycle. The first cycle is the time between $t_{i,y_{n-1}}$ and the first preventive maintenance in interval $\left[y_{i,n}\right]$. The regular cycles indicate the period of time between two consecutive preventive maintenance replacements. The time between the last preventive replacements and t_{i,y_n} in interval $\left[y_{i,n}\right]$ is defined as the last cycle. The lengths of the last and the first cycle are shorter than the length of the regular cycle. It should be noted, that the first cycle with the length of a regular cycle (a regular cycle which start at $t_{i,y_{n-1}}$), is defined as a first cycle instead of a regular cycle. Examples of this scenario are shown in Figure 24a and Figure 24b.

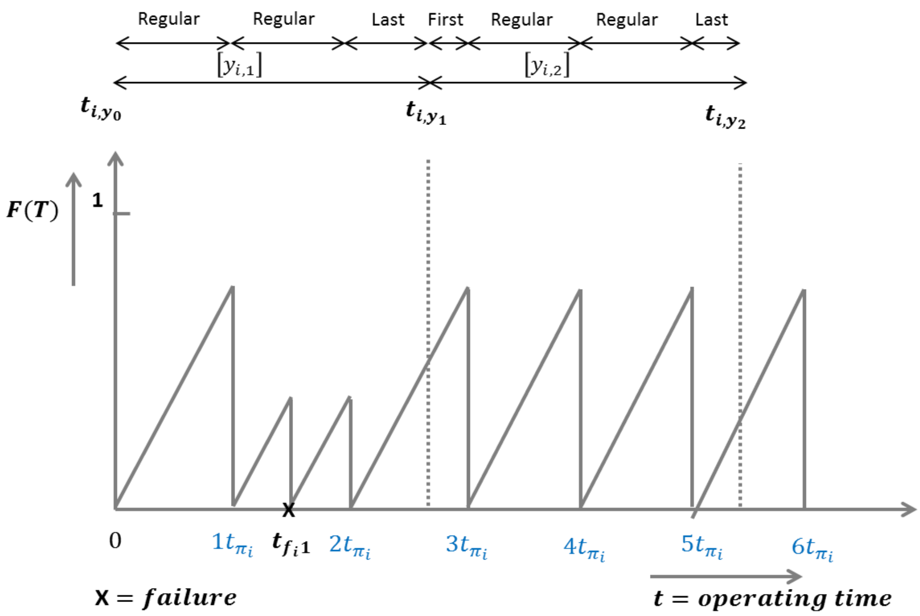


Figure 24a: Example of Scenario 2 of the preventive block replacements

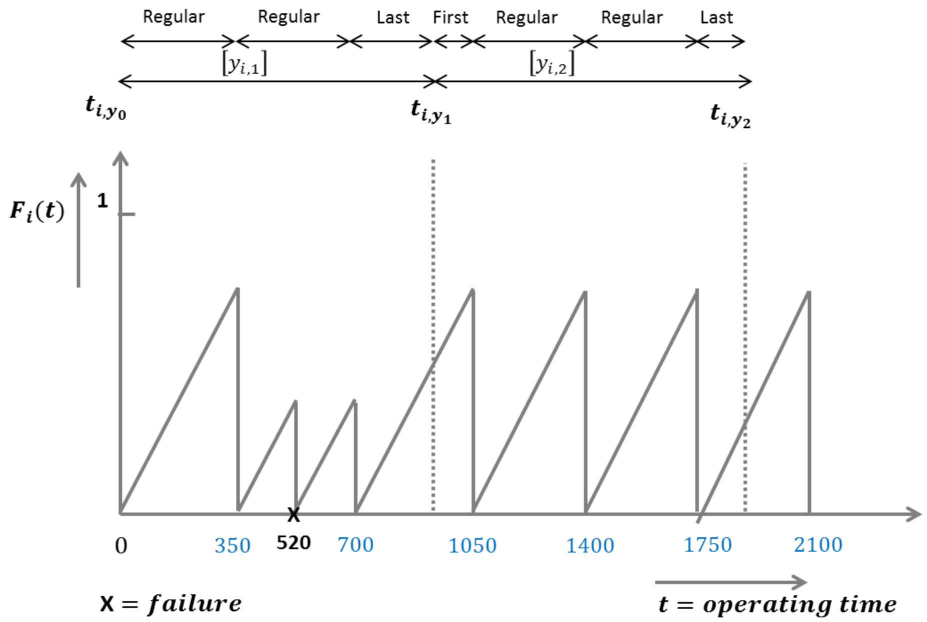


Figure 24b: Numerical example of Scenario 2 preventive block replacements as shown in Figure 24, where one year interval equal to 1000 operating hours and t_{π_i} is equal to 350 operating hours.

In the numerical example of Figure 24b, $[y_{i,2}] = [t_{i,y_1}, t_{i,y_2}])$ contains two regular cycles. The first cycle starts at $t_{i,y_1} = 1000$ and ends at $3 * t_{\pi_i} = 1050$, and the last cycle starts at $5 * t_{\pi_i} = 1750$ and ends at $t_{i,y_2} = 2000$

The length of a first cycle is determined by $t_{\pi_i} * \left\lceil \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rceil - t_{i,y_{n-1}}$, where $\lceil\ \ \rceil$ means round up to nearest integer and $\lfloor\ \ \rfloor$ means round down to nearest integer. If $\left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor = \frac{t_{i,y_{n-1}}}{t_{\pi_i}}$, component i is replaced preventively at $t_{i,y_{n-1}}$, which means that the first cycle is equal to a regular cycle. It should be noted that $t_{\pi_i} * \left\lceil \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rceil - t_{i,y_{n-1}}$ is equal to zero when the period start with a regular cycle.

The expected number of failures during the first cycle is equal to the expected number of failures during the regular cycle minus the expected number of failures of the part of the regular cycle that has passed before the beginning of the year(t_{i,y_1}). In the example of Figure 24b, the expected number of failures in the first cycle, $[1000,1050]$, is equal to $E[M_i(350)] - E[M_i(300)]$. The part of the regular cycle that has passed before the beginning of the year is obtained by $t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}$. Furthermore, in case $\left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor = \frac{t_{i,y_{n-1}}}{t_{\pi_i}}$ the first cycle does not exist. Thus, the expected number of failures in the first cycle is equal to:

$$\begin{Bmatrix} 0 & if \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor = \frac{t_{i,y_{n-1}}}{t_{\pi_i}}, \\ E\left[M_{s,i}[\pi_i]\right] - E\left[M_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & otherwise \end{Bmatrix}$$

The last cycle is equal to the expected number of failures in the period that starts at the last preventive replacement in the interval and ends at the end of the year, which is called the length of the last cycle. In this example, the expected number of failures in the last cycle, $[1750,2000]$, is equal to $E[M_i(250)]$. The length of the last cycle is obtained by $t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}$. In case that $\left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor = \frac{t_{i,y_n}}{t_{\pi_i}}$, the last cycle is equal to a regular cycle. The expected number of failures in the last cycle is determined by:

$$E\left[M_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right]$$

The number of regular cycles depends on the length of the first and last cycle. When the length of the first and cycle together is shorter than $[\pi_i]$, the number of regular cycles, denoted by NR_{i,y_n} ,is equal to N_i. However, it may occur that the length of the first and last cycle is longer than $[\pi_i]$. If this occurs the number of regular cycles is equal to $N_i - 1$.

The length of the first and last cycle together is equal to:

$$t_{\pi_i} * \left\lceil \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rceil - t_{i,y_{n-1}} + t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}$$

Thus NR_{i,y_n} is equal to:

$$\begin{Bmatrix} N_i & if\ \ [\pi_i] < t_{\pi_i} * \left\lceil \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rceil - t_{i,y_{n-1}} + t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i} \\ N_i - 1 & if\ [\pi_i] > t_{\pi_i} * \left\lceil \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rceil - t_{i,y_{n-1}} + t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i} \end{Bmatrix}$$

The expected number of failures in a regular cycle is equal to $E\left[M_{s,i}[\pi_i]\right]$, Thus, the expected number of failures in the all regular cycles together is equal to:

$$NR_{i,y_n} * E\left[M_{s,i}[\pi_i]\right]$$

Scenario (3), where $[\pi_i] > \left[y_{i,n}\right]$.

Figure 25a and Figure 25b show the examples of scenario 3.

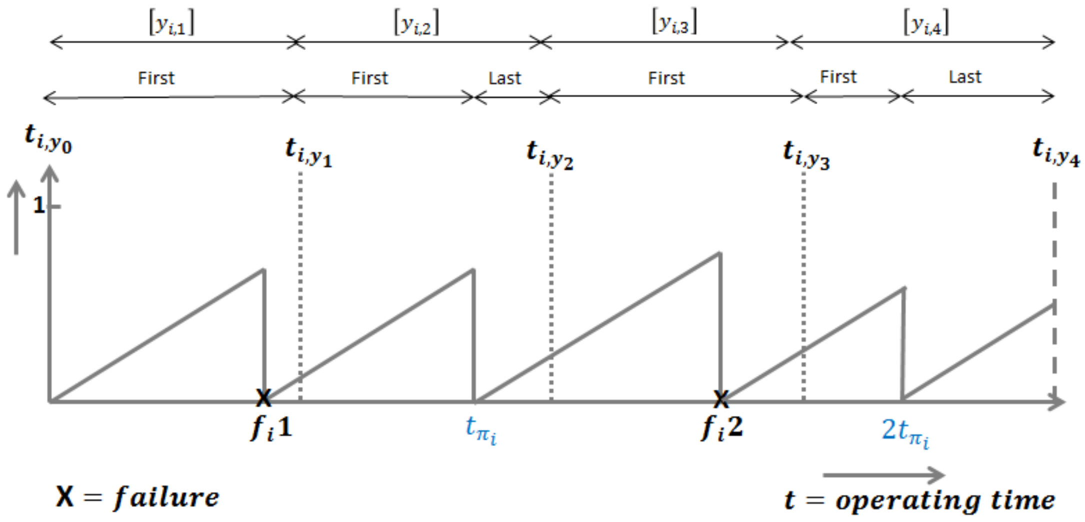


Figure 25a Example of scenario 3 preventive block replacement policy.

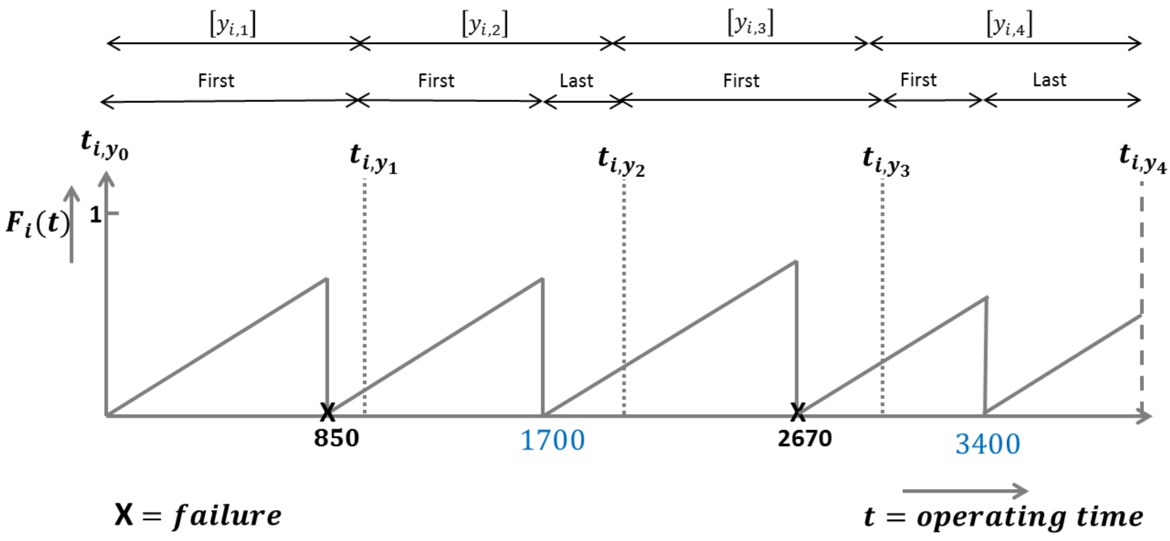


Figure 25b: Numerical example of Figure 17, where one year interval is equal to 1000 operating hours and t_{π_i} is equal to 1700 operating hours

In this scenario, interval $[y_i]$ can consist of a first and a last cycles since the preventive replacement interval is larger than the number of operating hours in one year. This means that $\left\lfloor \frac{t_{i,y_n} - t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor$ is equal to 0. In case that no preventive maintenance is performed in year n, the year only consists of the first cycle.

Now, the expected number of failures in the first cycle is determined by:

$$\begin{Bmatrix} E\left[M_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] - E\left[M_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & if\ E\left[PR_{s,i}[y_n]\right] = 0 \\ E\left[M_{s,i}[\pi_i]\right] - E\left[M_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & otherwise \end{Bmatrix}$$

The expected number of failures in the last cycle can be determined by:

$$\begin{Bmatrix} 0 & if\ E\left[PR_{s,i}[y_n]\right] = 0 \\ E\left[M_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right] & otherwise \end{Bmatrix}$$

These functions are explained via the example of Figure 25. In Figure 25 it is shown that there is no preventive maintenance action in year 3. The expected number of failures in this year ,$[2000,3000]$, is equal to $E[M_i(1300)] - E[M_i(300)]$ since the component is replaced by a new one at operating hour 1700. In this numerical example, $E[M_i(300)]$ is determined by $E\left[M_{s,i}\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right]$ and $E[M_i(1300)]$ is equal to $E\left[M_{s,i}\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right]$.

In case that $E\left[PR_{s,i}[y_n]\right] = \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor = 0$, year n only consists of a first cycle. Otherwise, year n consists of both a first and a last cycle. In the example of Figure 25 there will be a preventive maintenance action in year 2 at 1700 operating hours. The expected number of failures in the first cycle is equal to $E[M_i(1700)] - E[M_i(1000)]$, where $E[M_i(1700)]$ is equal to $E[M_i(\pi_i)]$ and $E[M_i(1000)]$ is determined by $E\left[M_i\left[t_{i,y_{n-1}} - \left\lfloor \frac{t_{i,y_{n-1}}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right]$. The last cycle in this example is equal to $E[M_i(300)]$, which can be determined by $E\left[M_i\left[t_{i,y_n} - \left\lfloor \frac{t_{i,y_n}}{t_{\pi_i}} \right\rfloor * t_{\pi_i}\right]\right]$.

Finally, the first, regular, and last cycle formulas are combined to determine the $E\left[M_i[y_{i,n}]\right]$ and $E\left[MN_i[y_{i,n}]\right]$ of the three scenarios. These functions are shown in section 3.2.3.

Appendix G: Transportation flow of components

In this section the transportation flow of the components at a failure is explained in more detail. At a failure, a good as new component is transported to the customer. After the good as new component is installed, the component that has been replaced is sent to the repair facility. Finally, when the damaged component is repaired, which means that the component is as good as new, it is transported back to the stocking location. This transportation process is explained in more detail in Table 28.

Table 28: Transportation flow critical component at a failure

Sequence	Transport from	To	Component
1.	Forward stocking location	Medical institute	Good as new component
2.	Medical institute	Forward stocking location (for example Japan)	Damaged component
3.	Forward stocking location	Bad stock of the nearest time zone warehouse (Louisville, Roermond or Singapore)	Damaged component
4. (optional)	Time zone warehouse	time zone warehouse near the repair facility	Damaged component
5.	time zone warehouse	repair facility	Damaged component
6.	Repair facility for a repairable and supplier for a consumable.	nearest time zone warehouse	Good as new component
7.	Time zone warehouse	time zone warehouse near the forward stocking location	Good as new component
8.	Time zone warehouse	forward stocking location	Good as new component

Philips has two repair facilities in the world, Best and Copley. The forward stocking locations of Philips are replenished by three time zone warehouses established in Singapore, Louisville and Roermond. The defective components from Roermond are repaired in Best, and the defective components from Louisville are repaired in Copley.

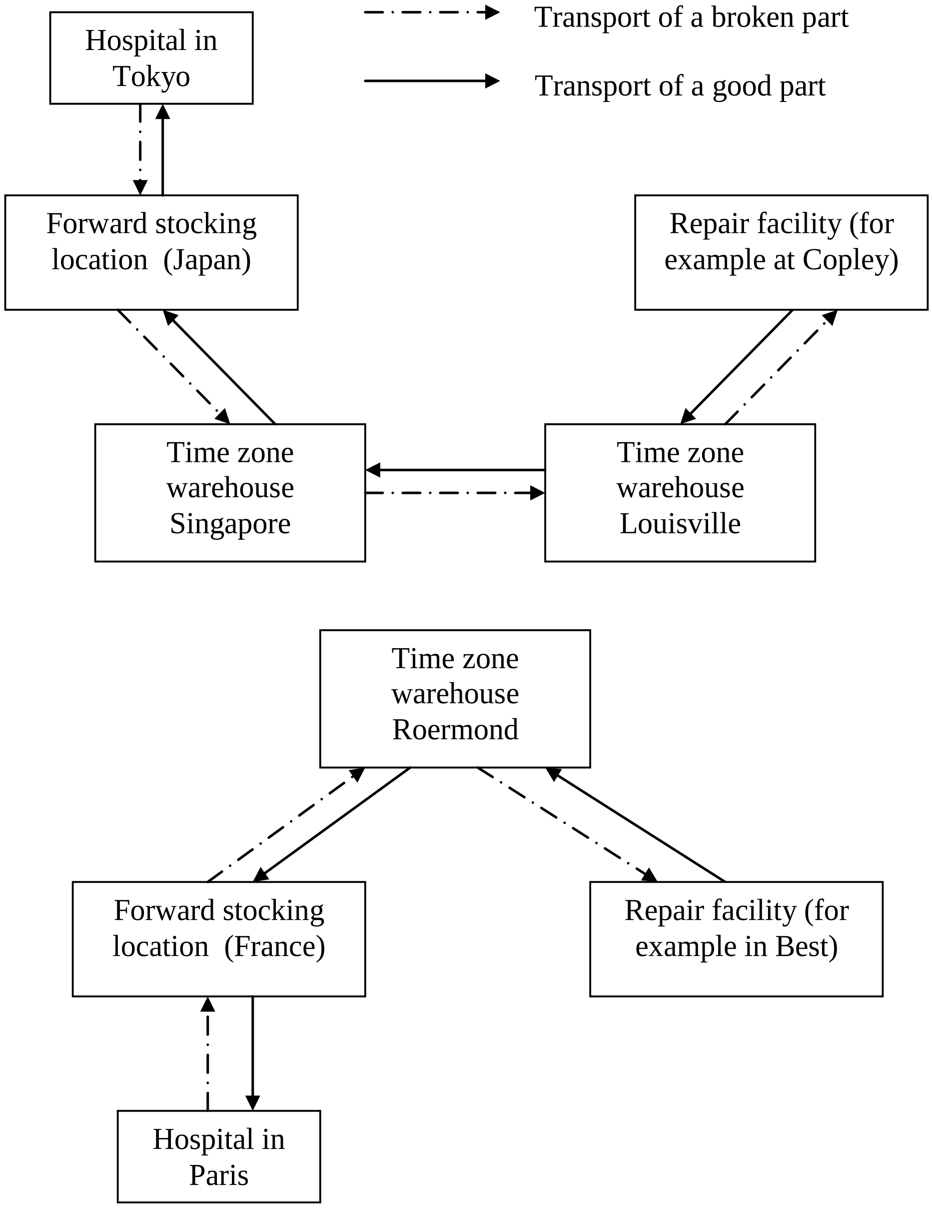


Figure 26: Transport flow component of Medical scanner

Appendix H: Monte Carlo random number generator

As mentioned before the Monte Carlo simulation is a discrete event simulation. It generates the following events randomly:

- Failure

Based on the time to failure distribution the simulation generates time to failures, which are used to determine the time of the failures. For instance, the first time to failure plus the second time to failure gives the failure time of second failure.

- Failure type

As mentioned before a failure of a critical component could be either a system down (i.e. no functionality) failure or a limited functionality failure. Based on the Bernoulli distribution, i.e. discrete distribution with two possible outcomes: success or fail), it is determined whether the generated failure is a no functionality failure or limited functionality failure. The success probability is equal to the probability that the failure is a no functionality failure

- Switch failure

In case the critical component has a backup installed, an automatic switch should trigger the backup when the failure is a system down failure. The random number generator determines whether the switch is successful or unsuccessful based on the Bernoulli distribution, where the success probability is the probability that the switch fails.

- Downtime

In case that both a failure is a no functionality failure and the switch has been failed, a random downtime is generated according to specified downtime distribution.

The random number generator that is used to generate the above mentioned events is called *Mersenne Twister*. The Mersenne Twister is widely used in Monte Carlo simulation due to its high quality and high performance (Echeverría & López-Vallejo, 2013). This random number generator is developed in 1998 by Matsumoto and Nishimura. More information about his random number generator can be found in their article (Matsumoto & Nishimura, 1998).

Appendix I: Simulation flowcharts

In this appendix the failure and downtime generating steps, which represent the orange box in Figure 19 of section 4.4, and the determination of the costs per individual component, which represent the green box in Figure 19 of section 4.4, are explained.

The flowchart of the generating failures is shown in Figure 27.

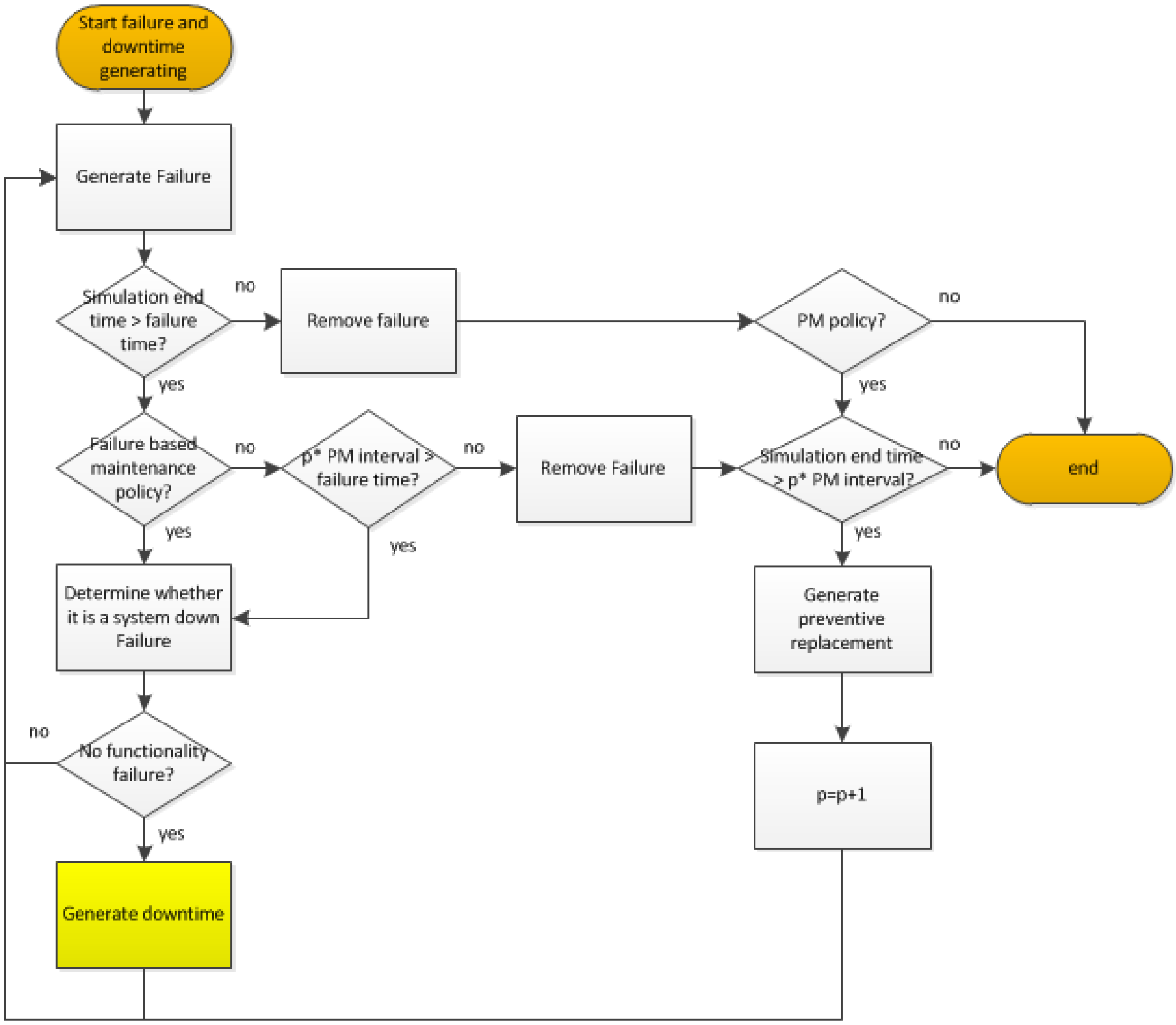


Figure 27 Flowchart of generating failures, where PM means preventive maintenance, and p is equal to 1 at the beginning of this process.

First, the time of the first failure is generated by the Monte Carlo simulation. In case the time of the failure is after the end of the simulation period, the failure is removed. When it is a failure based maintenance policy the process ends. However, it may be that in case of a preventive maintenance policy, the preventive replacement is before the end of the simulation. Therefore, it is checked whether the simulation end time is greater than p times the preventive maintenance interval, in case of the preventive maintenance block policy.

If the simulation end time is after the failure time, it is checked which maintenance policy is applied for component i, since it depends on the maintenance policy what the rest of the process will be.

The next step for the failure based policy is to determine whether it is a system down failure. This is the failure type event, which is generated by the simulation model. When it is a no functionality failure, downtime is generated. No downtime is generated for limited functionality failures. After this, the process starts again with generating the next failure.

The next step for the preventive maintenance policy is to determine whether p times the preventive maintenance interval is greater than the time of the failure. In case the failure time is smaller than p times the preventive maintenance interval, the same steps as for the failure based policy are followed. Otherwise, the failure is removed, since the preventive replacement is earlier than the failure. When the p times the preventive maintenance interval is greater than the end of the simulation, the process stops. Otherwise, a preventive replacement is generated and $p = p + 1$. After this the process starts again with generating the next failure.

The first step in the simulation process of generating downtime is to check whether a backup is installed for component i. In case that there is a backup installed, a switch event is generated which can be successful or not. Both in case that no backup is available and the switch has failed, downtime is generated by the Monte Carlo Simulation. If the switch does not fail, no downtime is generated.

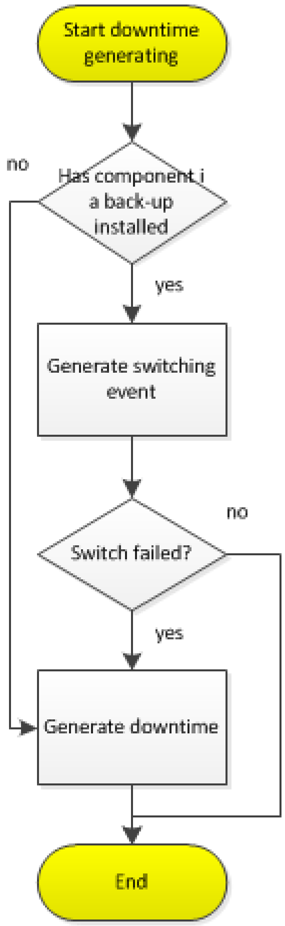


Figure 28: Flowchart of generating system downtime

The flowchart of the costs determination simulation process is given in Figure 29. First, the expected corrective maintenance cost per failure is assigned to each failure time. Next, the preventive maintenance cost is assigned to each preventive replacement time of component i.

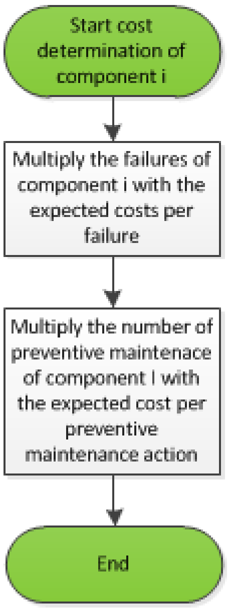


Figure 29: Flowchart of generating the corrective maintenance costs and preventive maintenance costs

Appendix J Verification and Validation of Simulation Tool

The expected number of failures in a given period for a component following an exponential time to failure distribution is easy to calculate manually since a closed form of the renewal function can be determined. Therefore it has been decided to work out the expected downtime and its variation for system with component(s) following a(n) exponential time to failure distribution. Furthermore it has been decided to take deterministic downtime for system s at each failure of component i.

Exponential distribution

The probability density function $f_i(t)$ of the exponential distribution is equal to the following

$$f_i(t) = \lambda_i e^{-\lambda_i t}$$

Where the failure rate in arbitrary period is denoted as λ. Using the Laplace transformation the expected number of failures in interval $[y_{i,n}]$ is equal to equation (37)

$$E\left[MN_i[y_{i,n}]\right] = \lambda_\mathrm{i}\left(t_{i,y_n} - t_{i,y_{n-1}}\right) * P(FM_i = nf) \tag{37}$$

The exponential distribution has lack of memory. This means that the expected numbers of failures are constant over the years of a component following an exponential time to failure distribution. In case that both the contract hours per year are equal over the contracting lifetime and the component is following an exponential time to failure distribution, the expected availability and subsequently the expected contract penalty costs are constant over time.

$$EA_s\,[y'_n] = EA_s\,[y'_1]$$

Furthermore, the lack of memory property does also imply that preventive replacements are superfluous since it do not have any effect on the expected number of failures. When no preventive replacement are performed and the time to failures distribution of the critical components are exponentially distributed the expected maintenance warranty costs and expected maintenance service costs are constant over time.

For this verification a serial system with two critical components is considered. Both critical components are following an exponential time to failure distribution and are operating when the system is scanning. Furthermore, the contract hours are constant over the years, and no preventive replacements are performed. The warranty length is equal to 1 year and the contracting lifetime is expected to last 9 years.

Serial system with two critical components: A and B

Input parameters

$$SH_s[y'_n] = 2400\ hours$$

$$CH_s[y'_n] = 2500\ hours$$

$$dtcm_A = 20\ hours$$

$$dtcm_B = 30\ hours$$

$$wl_s = 1\ year$$

$$ECLT_S = 9\ years$$

$$\lambda_A = \frac{1}{1800}\ hours$$

$$\lambda_B = \frac{1}{2400}\ hours$$

$$P(FM_A = nf) = 1$$

$$P(FM_B = nf) = 1$$

The expected downtime and expected availability is determined by:

$$EO_A = EO_B = \frac{2400}{8760} = 27.4\%$$

$$t_{A,y_{10}} = t_{B,y_{10}} = 0$$

$$t_{A,y_{10}} = t_{B,y_{10}} = 0.274 * (10 * 24 * 365) = 24000\ hours$$

$$E\left[MN_A\left[0, t_{A,y_{10}}\right]\right] = \frac{1}{1800}(24000 - 0) = 13.33$$

$$E\left[MN_B\left[0, t_{B,y_{10}}\right]\right] = \frac{1}{2400}(24000 - 0) = 10$$

$$ED_s\left[0, t'_{s,y_{10}}\right] = 13.33 * 20 + 10 * 30 = 566.67\ hours$$

$$EA_s\left[0, t'_{s,y_{10}}\right] = 1 - \frac{566.67}{25000} = 97.64\%$$

The statistical rule of the variation with respect to the multiplication of a random variable by a constant number, i.e. a, is:

$$V(aX) = a^2 V(X)$$

where $V(X)$ is the variation of random variable X

If random variable X and random variable Y are independent, the variation of the sum of random variable X and Y is equal to :

$$V(X+Y) = V(X) + V(Y)$$

The variation of the downtime of the system is the sum of the downtime variation of component A and component B. The variation of the downtime of component A and B is equal to the variation of the number of failures times the deterministic downtime of the component. For the exponential distribution the variation of the number of failures is equal to the expected number of failures. Therefore the variation of the downtime of the system is determined by:

$$V\left(M_A\left[0, t_{A,y_{10}}\right]\right) = E\left[M_A\left[0, t_{A,y_{10}}\right]\right] = 13.33$$

$$V\left(M_B\left[0, t_{B,y_{10}}\right]\right) = E\left[M_B\left[0, t_{B,y_{10}}\right]\right] = 10$$

$$V\left(D_A\left[0, t_{A,y_{10}}\right]\right) = dtcm_A^2 * V\left(M_A\left[0, t_{A,y_{10}}\right]\right) = 20^2 * 13.33 = 5333.33$$

$$V\left(D_B\left[t_{B,y_{10}}\right]\right) = dtcm_B^2 * V\left(M_B\left[0, t_{B,y_{10}}\right]\right) = 30^2 * 30 = 9000$$

$$V\left(D_s\left[0, t'_{s,y_{10}}\right]\right) = 5333.33 + 9000 = 14333.33$$

The estimated downtime and variation during the first 10 years of simulation of 103684 runs are equal to:

$$ED_s\widehat{\left[0, t'_{s,y_{10}}\right]} = 566.80$$

$$V\left(D_s\widehat{\left[0, t'_{s,y_{10}}\right]}\right) = 14278$$

The simulation error of the expected downtime and its variation are equal to:

$$simulation\ error\ mean = \frac{|566.67 - 566.80|}{566.67} = 0.000235$$

$$simulation\ error\ variation = \frac{|14333.33 - 14278|}{14333.33} = 0.00386$$

The small simulation error of the two values of the downtime distribution parameters imply that the downtime distribution of the simulation correspond to the exact downtime distribution. Based on this the tool is verified.

Appendix K User Manual of the decision support tool

By opening the Excel User interface the input dashboard as shown in Figure 30 pops up. The colored buttons give commands to Excel to perform a specific action, for instance to run the simulation. These individual command buttons are explained in section 2-4 of this appendix. The grey part of the sheet represents the input fields for the components to simulate. Each line represents one component, where the white colered columns give information about the input that is required. More information about the input of the components is explained in section 1 of this appendix

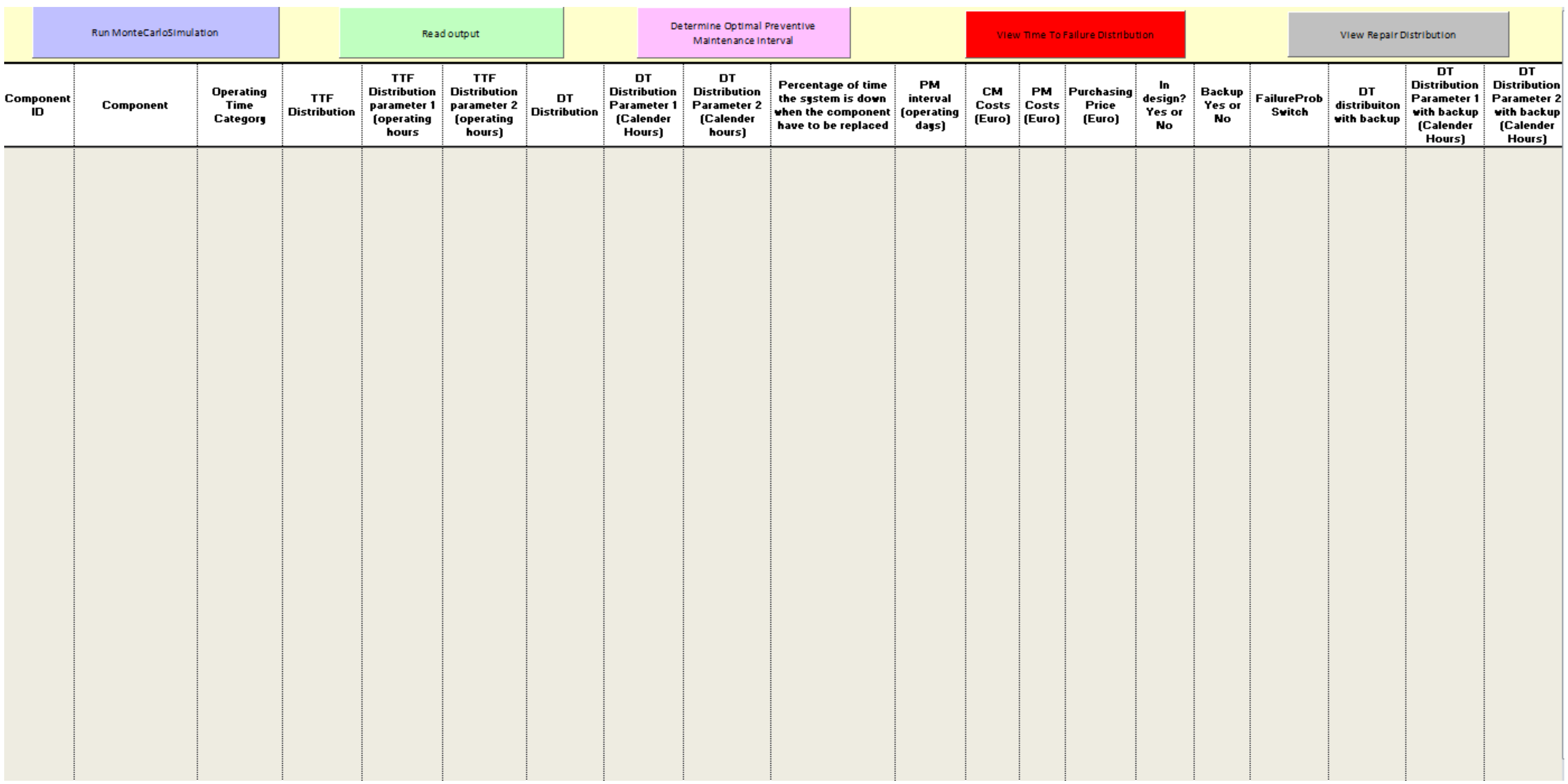


Figure 30: Input Dashboard

1. *Input components*

A component can be added to the input list by putting its name in the column "Component". For instance in Figure 31, "Component A" is added to the input list. When a component is added to the input list, a unique ID is automatically assigned to the component in column "ComponentID".

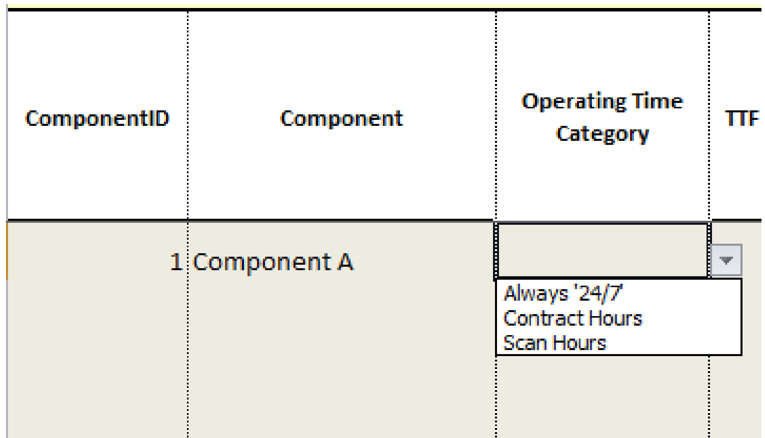


Figure 31: How to add a component to the input list

Note: Please do not leave empty rows between components!

After a component is added to the lists, the operating time category in column "Operating Time Category" should be filled in. By clicking on the fold down arrow three categories appears: "Always 24/7", "Contract Hours", and "Scan Hours". The right category should be chosen for the component. For instance, the scanning components operate only during "Scan Hours", the computer of the scanner is working during "Contract hours", and component B is operating "always 24/7".

In the column "In design? Yes or No", it can be decided whether or not to simulate the component. When "No" is selected, the component is not incorporated in the simulation. Figure 32 shows the fold down arrow where the decision can be made to use the component in the simulation or not.

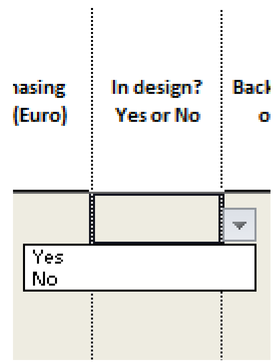


Figure 32: Use the component in the simulation?

Note: By saving the Excel File, the input of the components is saved.

1.1. *Time to Failure distribution*

The next input category is the time to failure distribution of the component.

Note: For this analysis the operating time to failure distribution is used instead of calendar time to failure data.

Note: The units of the parameters are operating <u>DAYS</u>, 1 operating hour is equal to 1/24 operating day!

By clicking on the fold down arrow of the column "TTF Distribution", two time to failure distributions can be chosen: the Weibull and the Normal distribution. It should be noted that the exponential distribution can be modelled by the Weibull Distribution

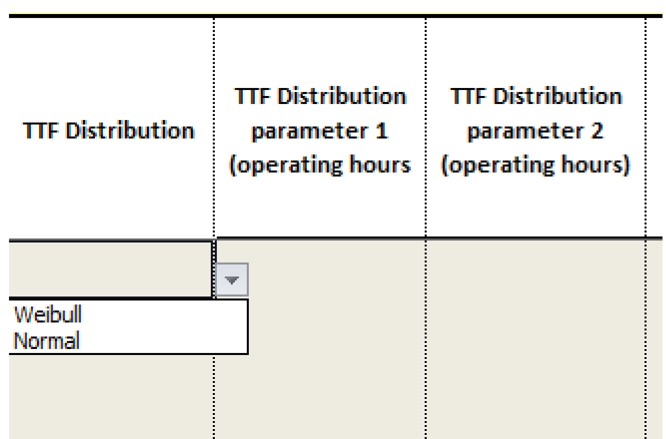


Figure 33: TTF Distribution

Table 29: Time To Failure Distribution and its distribution parameters

Distribution	TTF distribution parameter 1 (operating days)	TTF distribution parameter 2 (operating days)
Weibull	Beta (β)	Eta (η)
Normal	Mean (μ)	Standard Deviation (σ)
Exponential	1	*1/lapda (λ)*

Note: the exponential distribution can be modelled by the Weibull Distribution. If this is the case the time the Weibull distribution should be selected in the column "TTF distribution".

When the distribution is selected the values of the distribution parameters should be filled in in columns "TTF distribution parameter 1 (operating days)" and "TTF distribution parameter 2 (operating days)". Table 29 gives an overview of the distribution and its first and second parameter.

The operating time to failure data can be fitted to the Normal, Weibull or Exponential distribution by LS Tool File explained in section 5 of this appendix or Minitab software available within the organisation of Philips. The one that passed the goodness of fit test with the highest R^2 should be selected. For further details of the fitting process I would like to refer you to chapter 5..

The calendar time to failure data of FDV can be transformed to operating time to failure data with the use of utilization data logged in iCube. More information about these data techniques can be found in document Appendix O.

The tool does also consist of a feature which may help you to get more insight in the time to failure distribution by generating the graph of the distribution. This feature is described in section 4 of this appendix.

1.2. Downtime Distribution

After the time to failure distribution, the downtime distribution of the component should be indicated.

Note: Downtime is the time the system is down when the component fails.

Figure 34 shows the four required downtime input parameters of the component.

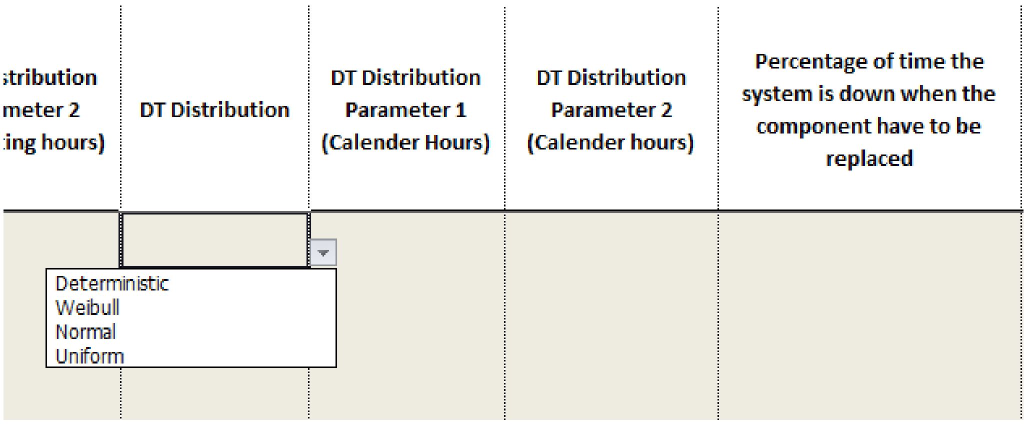


Figure 34: Downtime input parameters

By clicking the fold down arrow in the column “DT Distribution”, “Deterministic”, and three distributions “Weibull”, “Normal”, and “Uniform” appear. Deterministic means that only one constant or fixed value (expected downtime) without a distribution should be modeled. Either Deterministic or one of the distributions should be selected for the component. To complete the distribution the values of the distribution parameters should be given in the columns “DT distribution parameter 1 (Calendar hours)” and “DT distribution parameter 2 (Calendar hours)”. Table 30 gives the downtime distribution and its parameters.

Note: The unit of the downtime distribution is calendar hours!

Table 30: Downtime Distributions and its parameters

Distribution	TTF distribution parameter 1 (Calendar hours)	TTF distribution parameter 2 (Calendar hours)
Weibull	Beta	Eta
Normal	Mean	Standard Deviation
Exponential	1	*1/λ*
Uniform	Lower Limit	Upper limit
Deterministic	Expected value	*empty*

The downtime distribution can be estimated based on downtime data or estimation with LS Tool or Minitab. More information about the LS tool can be found in section 5 of this appendix.

The last required downtime parameter is the percentage of time the system is down when the component fails. It could be that the component causes an intermitted problem which does not result in system downtime. The failure data consists of component replacements at intermitted problems and at system down problems. For instance the percentage of time that the system is down at a failure of component A1 is 100%, and at replacement of component B2 is about 70%. For this reason the percentage of time the system is down when the component has to be replaced should be filled in. For more information about this I would like to refer you to Appendix L

Note: Decimal number should be used to indicate the percentage of time that the system is down when the component have to be replaced. For instance 70% = 0.7.

Note: Non critical components never cause downtime. Thus, the percentage of time that the system is down when the component have to be replaced is equal to 0.

1.3. Costs

In case the purpose of the simulation is to determine the life cycle costs of the component, the corrective maintenance costs at a failure, preventive maintenance costs at a preventive replacement/repair, and the purchasing of the component should be filled in in the columns "CM Costs (Euro)", "PM Costs (Euro)", and "Purchasing Price (Euro)". These costs are also required to determine the optimal preventive maintenance interval as described in section 1.4.

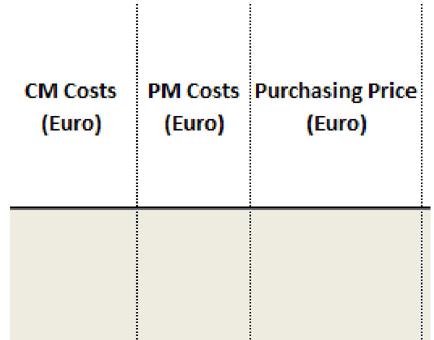


Figure 35: Cost input of the component

Note: the purchasing price is the total price of the component including possible backup and switch

1.4. Preventive maintenance interval

In this availability calculation tool the preventive block replacement is considered. For more information about this preventive maintenance policy I would like to refer you to chapter 2.

In the column "PM interval (operatingdays)" the time between two preventive maintenance replacements of the components should be filled in if preventive maintenance is performed. The optimal preventive replacements interval with respect to the maintenance costs can also be determined by another feature in the tool. More information about the determination of the optimal preventive maintenance interval can be found in section 3 of this appendix.

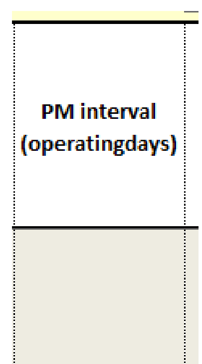


Figure 36: Preventive maintenance interval input

Note: In case no preventive maintenance is performed the cell should be left empty

Note: Preventive maintenance is defined as the action to restore the component in as goods as new condition. Thus preventive maintenance is not the same as the definition of planned maintenance.

1.5. Backup

The backup input parameters are the final required input parameters of the component before the simulation can be launched. A back up is defined as a component that is installed in the system which can take over the functionality of a critical component at a failure. This backup can prevent system downtime. Figure 37 gives the five input parameters of the backup.

First, in column "Backup Yes or No", it should be determined whether or not a backup is installed for the component by selecting "Yes" or "No" in the fold down list.

Note: In case it is indicated that no backup is available, the other input parameters in Figure 37 *can be left empty.*

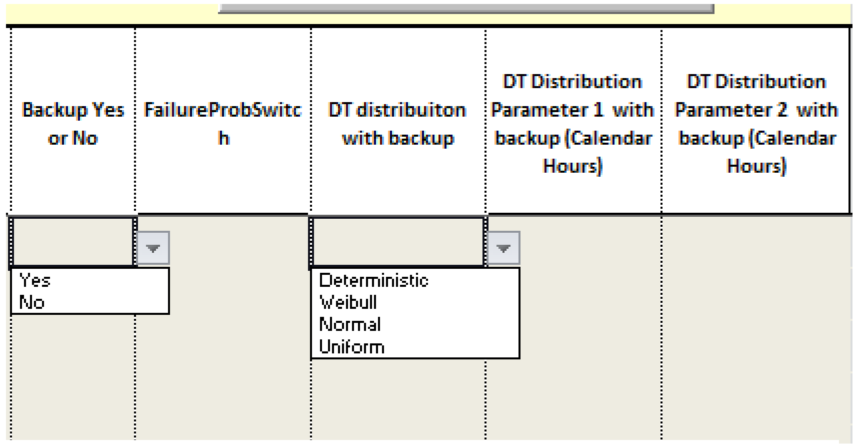


Figure 37: Backup input parameters

Second, the failure probability of the switch, which is used to trigger the backup to take over the functionality of the component, should be filled in.

Note: The failure probability should be filled in for the switch. For instance if the reliability of the switch is determined to be 99%, the failure probability is equal to 1%, where 1% is filled in as 0.01.

Third, the downtime that occurs when backup takes over functionality should be filled in. The majority of the backups prevent system downtime completely. This means that the downtime is 0 when the backup takes over functionality. There might be backups that are only able to shorter the downtime at failure of the component. For this reason the downtime distribution with backup can be selected in column “DT distribution with backup” and its parameters can be filled in in columns “DT distribution Parameter 1 with backup (Calendar hours)” and “DT distribution Parameter 2 with backup (Calendar hours)”.

Note: In case no backup is installed the columns “FailureProbSwich”, “DT distribution with backup”, “DT distribution Parameter 1 with backup (Calendar hours)” and “DT distribution Parameter 2 with backup (Calendar hours)” should be left empty.

Note: In case the downtime is 0 when the backup takes over functionality, the downtime distribution should be deterministic, the distribution parameter 1 should be 0, and the cell of distribution parameter should be left empty.

2. Run Monte Carlo Simulation

When the input list of the components to simulate is complete, the simulation can be launched by pressing the purple button "Run MonteCarloSimulation" as shown in Figure 38.

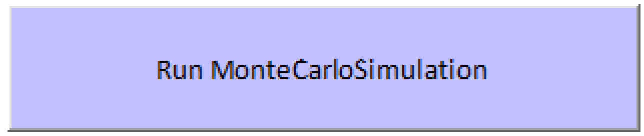


Figure 38: Button to launch the simulation

2.1. Customer data input

By pressing the purple button, a screen pops ups as shown in Figure 39. This screen requires data of the customer where the system/components should be installed. The first field is the warranty length for the specific customer, which is normally 1 year. The expected number of contract years should be given in the second field. The first and second field together determines the total simulation period. E.g. the warranty length is 1 year and the expected number of contract years is 10 years, the availability and life cycle costs will be simulated from year 1 until year 11. The expected number of contract hours and scan hours of the customer should be filled in in respectively the third and fourth field of Figure 39.

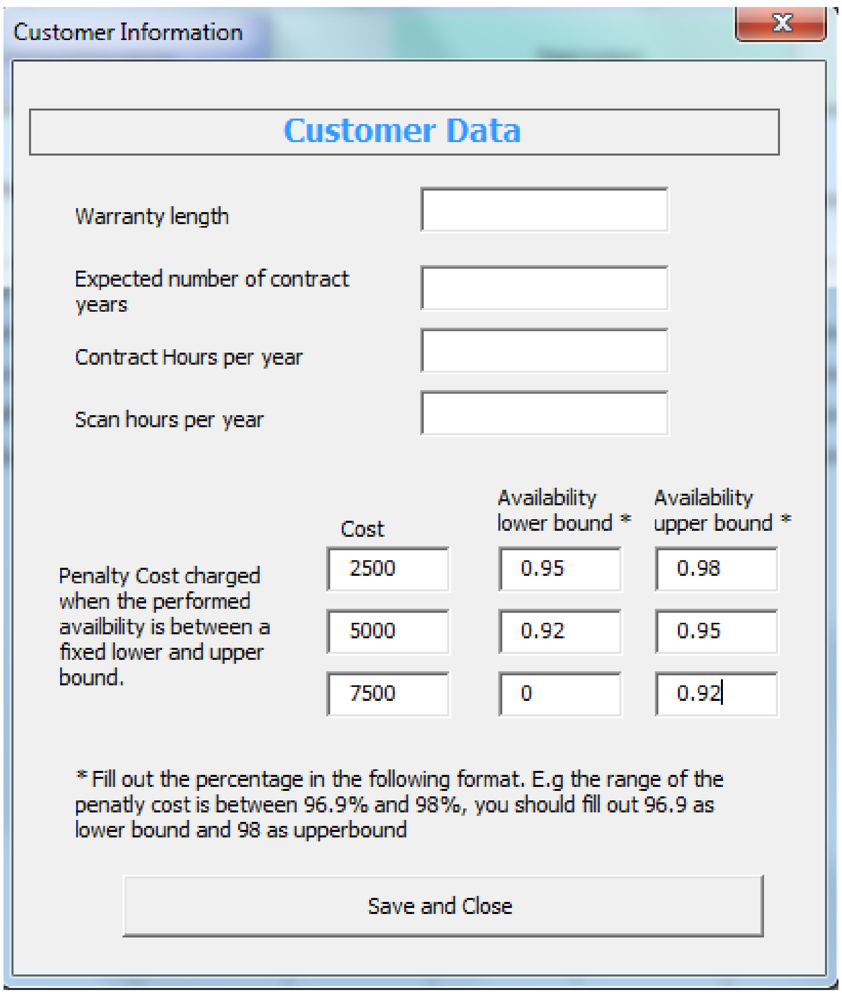


Figure 39: Customer data input field

Note: The first four fields must be filled in to run the simulation.

In order to determine the penalty costs of the service contract, the 9 fields of the lower part of Figure 39 should be filled in. The penalty costs between an upper and lower availability bound should be given. Figure 39 gives an example of the costs for a 98% service contract.

When the fields are filled in, the input can be saved by the button "Save and Close".

Note: When you would like to perform more simulation with the same customer input data, you only have to fill in this screen once. At the second simulation this screen can be ignored when it appears by pressing the cross in the right top. The saved information will be used again in the next simulations.

After the button "Save and Close" is pressed, the second customer input data screen pops up as shown in Figure 40. This input screen consists of two fields: The coolant loss per year (liter) and the current coolant price per liter (Euro). By filling in these fields the coolant costs are incorporated in the life costs for the specific customer.

By pressing "Save and Close", your input is saved.

Note: The information regarding coolant is only updated when the "Save and Close" button is pressed. By clicking the cross button, the previous data is used. If never before data have been put in the coolant costs are not taken into account in the life cycle cost output.

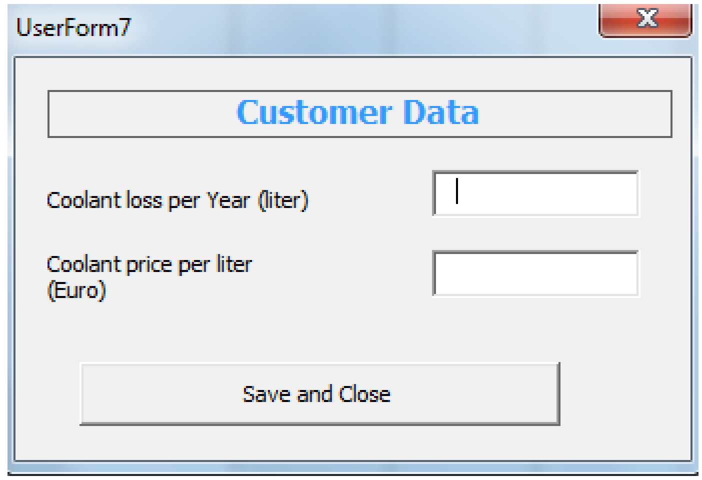


Figure 40: Coolant input screen

After the screen of Figure 40, the warning message as shown in Figure 41 appears. This message gives you the warning that it might be that your computer is busy for a while due to the simulation. By pressing "No", you can abort the simulation.

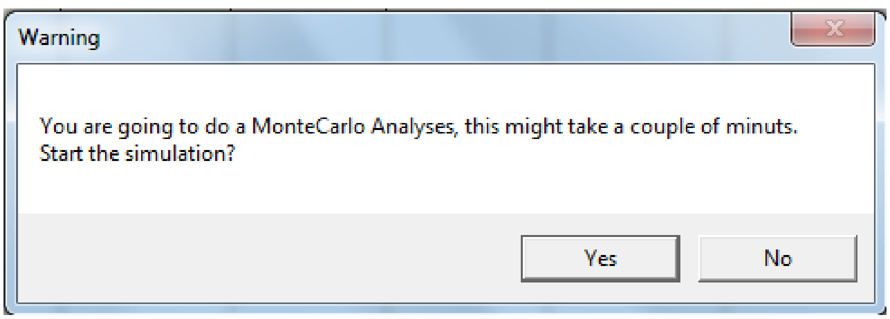


Figure 41: Finally screen before the simulation starts

In case "yes" is selected the simulation starts and the windows command processor (CMD) box appears as shown in Figure 42

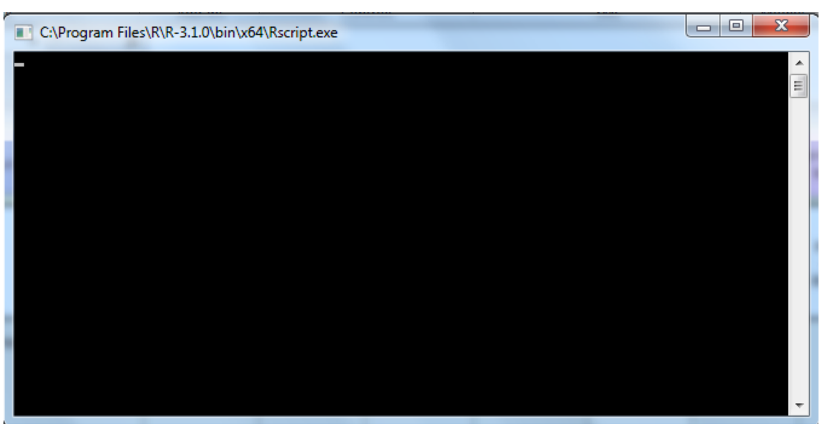


Figure 42: Windows command processor box

When the simulation is finished the CMD box disappears and Figure 43 pops up. This message shows both that you can read the output and the number of runs that has been simulated.

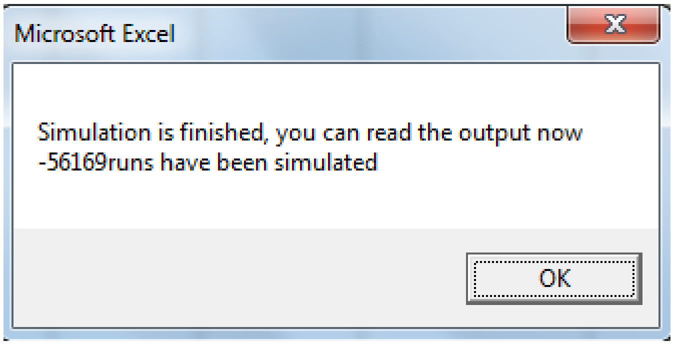


Figure 43 Simulation finished

2.2. <u>Read output</u>

After the message of Figure 43 has been closed by "OK", the output can be read by pressing the green button "Read output". After a few second the output is loaded in the Excel File.

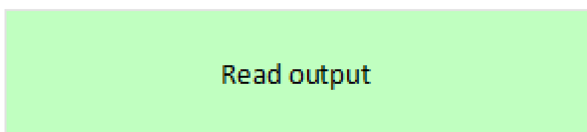


Figure 44: Read output button

The Excel file provides five sheets with output of the simulation: "LCC output", "Average Availability Output", "Variation Availability Output", "Average Cost Output", and "Variation Cost Output".

2.2.1. <u>LCC output:</u>

This sheet gives the values of cost elements of the life cycle costs over simulated period. The design costs are the sum of purchasing prices of the simulated components. The total coolant costs over the simulated period are given in the field "Coolant costs". Furthermore, the corrective maintenance costs during warranty and service are given. In case preventive maintenance is performed, these costs are given in "PM warranty costs" and "CM warranty Costs". Finally the contract penalty costs over the total service period are given in "Contract Penalty Costs".

Cost Bucket	
Design costs	€ 145,103
Coolant Costs	€ 45,550
CM Warranty costs	€ 1,373
PM Warranty costs	€ 0
CM Service costs	€ 12,451
PM Service costs	€ 0
Contract Penalty costs	€ 27
Total Life cycle costs	€ 204,504
LCC per year	€ 20,450

Figure 45: Life cycle costs output

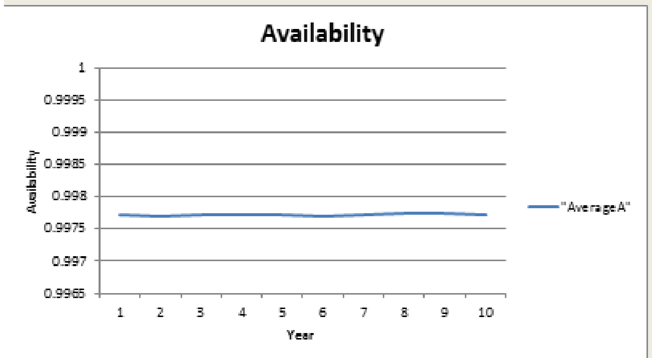
The sum of all the costs elements determines the "Total Life cycle costs". In addition to the total life cycle costs, the life cycle costs per simulated year are given in "LCC per year".

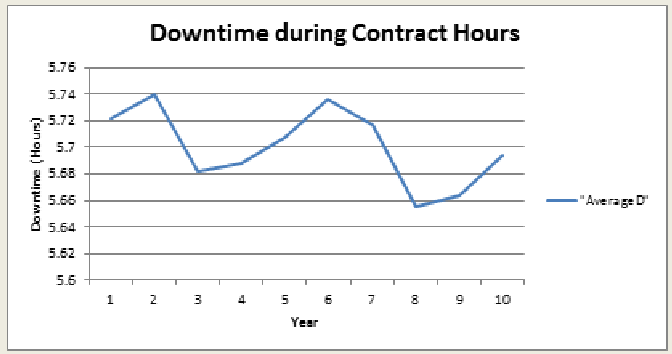
2.2.2. Average availability output

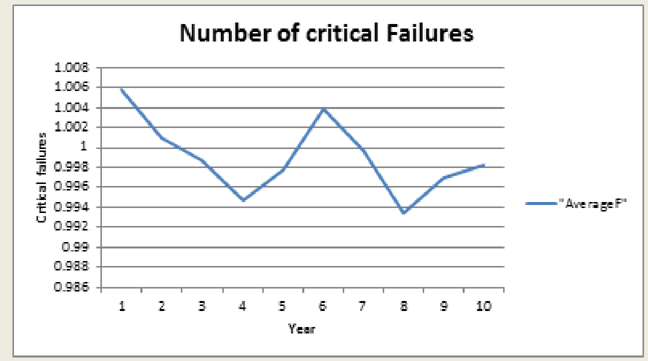
The second output sheet consists of the average availability of simulated components in year n, the average downtime in year n, and the average number of failures in year n. The results are given for each year within the simulated period. In addition to the average number, the minimum and maximum values of all the runs are given for the availability, downtime and number of failures.

Note: The availability is defined as the fraction of time that a system is in condition to perform its intended function during contract hours

Figure 46 shows the average availability output screen.







Availtability			
"year"	"AverageA"	"MinimumA"	"MaximumA"
0	0	0	0
1	0.997711343	0.96782448	1
2	0.997704163	0.966076598	1
3	0.997727097	0.968164931	1
4	0.997724654	0.967444879	1
5	0.997716981	0.96346213	1
6	0.997705763	0.96314804	1
7	0.997713021	0.951985948	1
8	0.997737808	0.961846396	1
9	0.997734586	0.968467374	1
10	0.997722262	0.968436787	1

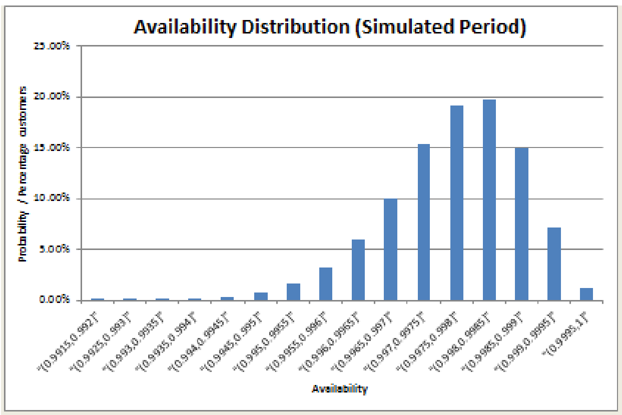
Downtime			
"year"	"AverageD"	"MinimumD"	"MaximumD"
0	0	0	0
1	5.72164167	0	80.43880097
2	5.739593255	0	84.80850382
3	5.682257916	0	79.58767328
4	5.688364698	0	81.38780322
5	5.70754718	0	91.34467621
6	5.735593644	0	92.12990055
7	5.717448631	0	120.03513
8	5.655480454	0	95.38400883
9	5.663535496	0	78.83156557
10	5.694345382	0	78.9080315

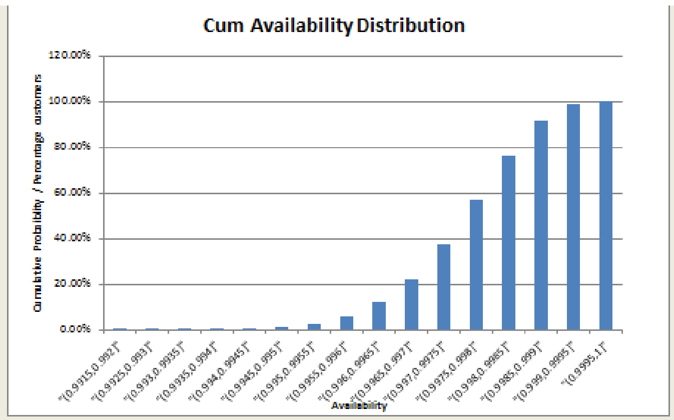
Number of critical Failures			
"year"	"AverageF"	"MinimumF"	"MaximumF"
0	0	0	0
1	1.0057683	0	7
2	1.0010504	0	7
3	0.998736	0	7
4	0.9947302	0	8
5	0.9977924	0	8
6	1.0038633	0	7
7	0.9996795	0	9
8	0.9934661	0	7
9	0.9969022	0	9
10	0.9982553	0	9

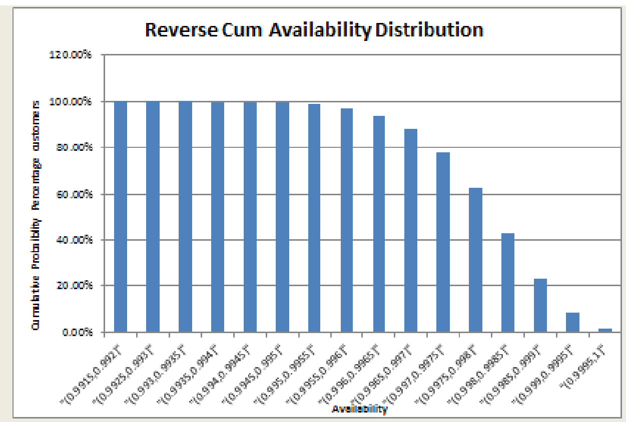
Figure 46: Average availability output screen

2.2.3. Variation availability output

In addition the average availability, the shapes of the availability over the total simulated period are given by histograms with equal class width. Three shapes are given: the shape of the probability density function, the shape of the cumulative density function, and the shape of the reverse cumulative density function. Figure 47 shows the variation output of the availability. In the column “factorx”, the lower and upper bound of the availability classes are shown. Column “Freq” represents the number of runs in given class. The cumulative number of runs is given in column “CumFreq”. Based on the number of runs in given class the relative probability is calculated for each individual class. The cumulative probability and reverse cumulative probability are calculated based on the column “CumFreq”.





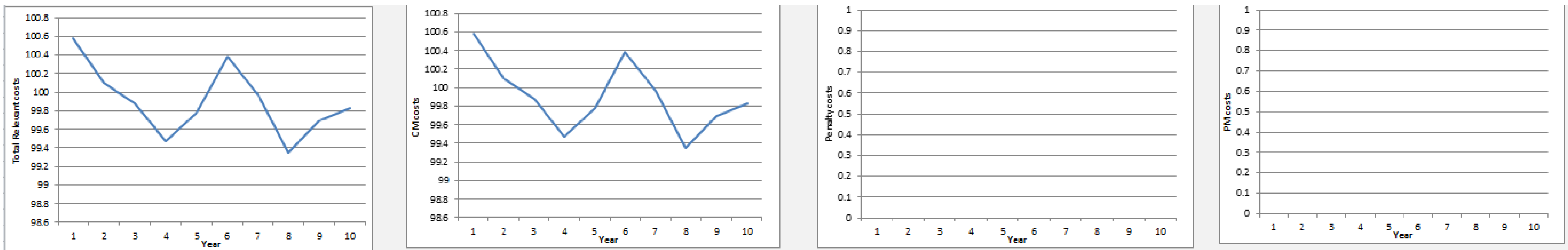


Availability in the first 10 years					
"factorx"	"Freq"	"cumFreq"	"relative"	"Cum r	"Inverse Cum relative"
"(0.9915,0.992]"	4	4	7.12E-05	7.1E-05	1
"(0.9925,0.993]"	11	15	1.96E-04	0.00027	0.999928786
"(0.993,0.9935]"	28	43	4.98E-04	0.00077	0.999732949
"(0.9935,0.994]"	59	102	1.05E-03	0.00182	0.999234453
"(0.994,0.9945]"	208	310	3.70E-03	0.00552	0.998184052
"(0.9945,0.995]"	420	730	7.48E-03	0.013	0.994480941
"(0.995,0.9955]"	913	1643	1.63E-02	0.02925	0.987003507
"(0.9955,0.996]"	1832	3475	0.03261586	0.06187	0.97074899
"(0.996,0.9965]"	3350	6825	0.05964144	0.12151	0.938133134
"(0.9965,0.997]"	5633	12458	0.10028663	0.22179	0.878491695
"(0.997,0.9975]"	8659	21117	0.15415977	0.37595	0.77820506
"(0.9975,0.998]"	10766	31883	0.19167156	0.56763	0.624045292
"(0.998,0.9985]"	11099	42982	1.98E-01	0.76523	0.432373729
"(0.9985,0.999]"	8455	51437	1.51E-01	0.91575	0.23477363
"(0.999,0.9995]"	4016	55453	7.15E-02	0.98725	0.084245758
"(0.9995,1]"	716	56169	0.01274724	1	0.012747245

Figure 47: Variation output of the availability.

2.2.4. *Average cost output*

In order to give more insights in the life cycle costs over the years, the average values of the cost elements per year are given. For each year, the average corrective maintenance costs, penalty costs, and preventive maintenance costs are given. In addition to these individual costs elements the total costs are given. Moreover, the minimum, maximum value, and the cumulative of the average are given. Figure 48 shows the average costs output screen of the Excel file.



Total Costs				
"year"	"AverageTl	"MinimumTl	"MaximumTl	"Cumulative"
0	0	0	0	0
1	100.57683	0	700	100.5768306
2	100.10504	0	700	200.6818708
3	99.873596	0	700	300.5554665
4	99.473019	0	800	400.0284855
5	99.779238	0	800	499.8077231
6	100.38633	0	700	600.1940572
7	99.967954	0	900	700.1620111
8	99.346615	0	700	799.5086258
9	99.690221	0	900	899.1988463
10	99.825527	0	900	999.0243729

Corrective Maintenance Costs				
"year"	"AverageC	"MinimumC'	"MaximumC	"Cumulative"
0	0	0	0	0
1	100.57683	0	700	100.5768306
2	100.10504	0	700	200.6818708
3	99.873596	0	700	300.5554665
4	99.473019	0	800	400.0284855
5	99.779238	0	800	499.8077231
6	100.38633	0	700	600.1940572
7	99.967954	0	900	700.1620111
8	99.346615	0	700	799.5086258
9	99.690221	0	900	899.1988463
10	99.825527	0	900	999.0243729

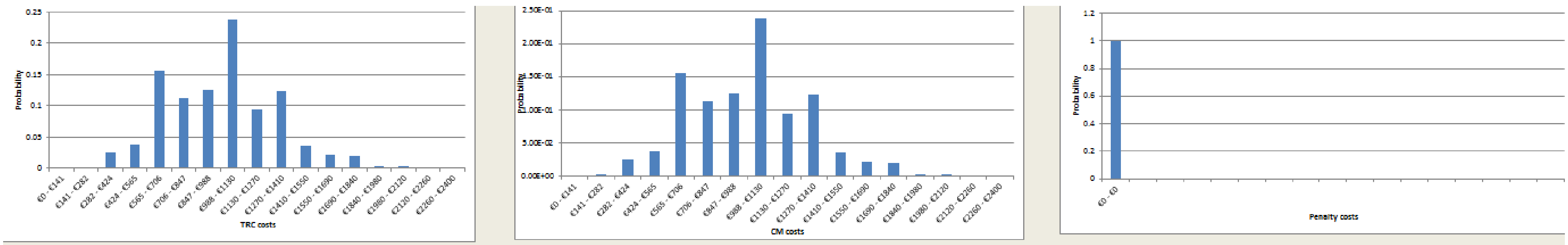
Penalty Costs				
"year"	"AverageP	"MinimumP	"MaximumP	"Cumulative"
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0

Preventive maintenance Costs				
"year"	"AveragePm	"MinimumPm	"MaximumPm	"Cumulative"
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0

Figure 48: Average costs outputs

2.2.5. *Variation cost output*

In the variation cost output sheet, the shape of the distributions of the corrective maintenance costs, penalty costs and total costs over the simulated period are given by histograms with equal class width. Figure 49 shows output screen of the costs variation. The first four columns in the tables have the same structure as the column of the availability variation output screen. Lower bound and upper bound column give the lower and upper bound in euros.



Total Costs						
"factorx"	"Freq"	"cumFreq	"relative"	LowerBound	UpperBound	
"[-2.4,141]"	30	30	5.34E-04	0	141	I0 - I141
"[141,282]"	130	160	2.31E-03	141	282	I141 - I282
"[282,424]"	1469	1629	2.62E-02	282	424	I282 - I424
"[424,565]"	2095	3724	3.73E-02	424	565	I424 - I565
"[565,706]"	8765	12489	1.56E-01	565	706	I565 - I706
"[706,847]"	6373	18862	1.13E-01	706	847	I706 - I847
"[847,988]"	7002	25864	1.25E-01	847	988	I847 - I988
"[988,1.13e+03]"	13336	39200	2.37E-01	988	1130	I988 - I1130
"[1.13e+03,1.27e+03]"	5306	44506	9.45E-02	1130	1270	I1130 - I1270
"[1.27e+03,1.41e+03]"	6943	51449	1.24E-01	1270	1410	I1270 - I1410
"[1.41e+03,1.55e+03]"	2004	53453	3.57E-02	1410	1550	I1410 - I1550
"[1.55e+03,1.69e+03]"	1196	54649	2.13E-02	1550	1690	I1550 - I1690
"[1.69e+03,1.84e+03]"	1112	55761	1.98E-02	1690	1840	I1690 - I1840
"[1.84e+03,1.98e+03]"	203	55964	3.61E-03	1840	1980	I1840 - I1980
"[1.98e+03,2.12e+03]"	166	56130	2.96E-03	1980	2120	I1980 - I2120
"[2.12e+03,2.26e+03]"	26	56156	4.63E-04	2120	2260	I2120 - I2260
"[2.26e+03,2.4e+03]"	13	56169	2.31E-04	2260	2400	I2260 - I2400

Corrective Maintenance Costs						
"factorx"	"Freq"	"cumFreq"	"relative"	LowerBc	UpperBound	
"[-2.4,141]"	30	30	5.34E-04	0	141	I0 - I141
"[141,282]"	130	160	2.31E-03	141	282	I141 - I282
"[282,424]"	1469	1629	2.62E-02	282	424	I282 - I424
"[424,565]"	2095	3724	3.73E-02	424	565	I424 - I565
"[565,706]"	8765	12489	0.15605	565	706	I565 - I706
"[706,847]"	6373	18862	0.11346	706	847	I706 - I847
"[847,988]"	7002	25864	0.12466	847	988	I847 - I988
"[988,1.13e+03]"	13336	39200	0.23743	988	1130	I988 - I1130
"[1.13e+03,1.27e+03]"	5306	44506	9.45E-02	1130	1270	I1130 - I1270
"[1.27e+03,1.41e+03]"	6943	51449	1.24E-01	1270	1410	I1270 - I1410
"[1.41e+03,1.55e+03]"	2004	53453	3.57E-02	1410	1550	I1410 - I1550
"[1.55e+03,1.69e+03]"	1196	54649	2.13E-02	1550	1690	I1550 - I1690
"[1.69e+03,1.84e+03]"	1112	55761	1.98E-02	1690	1840	I1690 - I1840
"[1.84e+03,1.98e+03]"	203	55964	3.61E-03	1840	1980	I1840 - I1980
"[1.98e+03,2.12e+03]"	166	56130	2.96E-03	1980	2120	I1980 - I2120
"[2.12e+03,2.26e+03]"	26	56156	4.63E-04	2120	2260	I2120 - I2260
"[2.26e+03,2.4e+03]"	13	56169	2.31E-04	2260	2400	I2260 - I2400

Penalty Costs						
"factorx"	"Freq"	"cumFreq"	"relative"			
0	56169	5.62E+04	1.00E+00	0	0	I0 - I0

Figure 49 Costs variation output screen

3. *Optimal Preventive Maintenance Interval*

Another feature of the Excel tool is to determine the optimal preventive maintenance interval with respect to corrective maintenance costs and preventive maintenance costs for components with an increasing failure rate. After the time to failure distribution and the costs for corrective and preventive maintenance costs are filled in, the determination of the optimal preventive maintenance interval can be started by pressing the light purple button as shown in Figure 50.

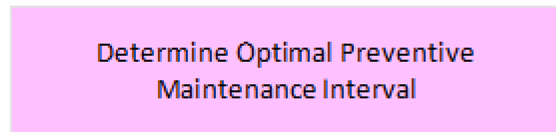


Figure 50: Button to determine the optimal preventive maintenance interval

3.1. *Input screen optimal preventive maintenance interval*

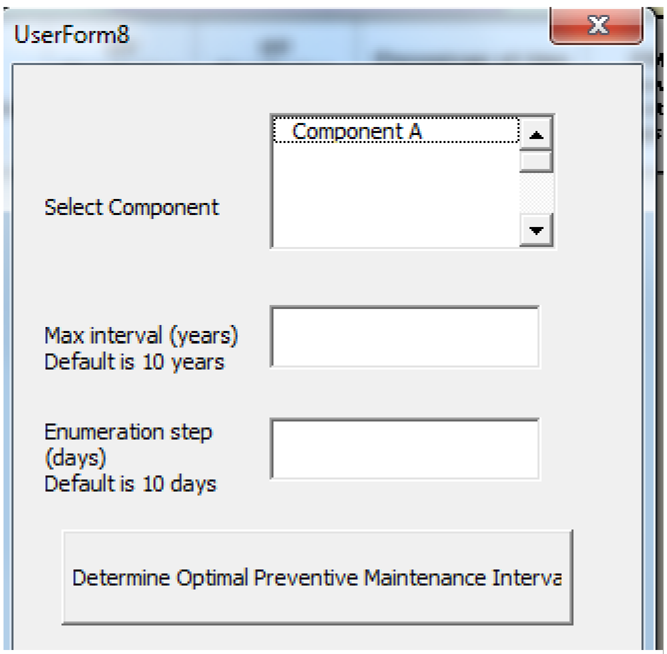


Figure 51: Input screen determine optimal preventive maintenance

When you press this button, a screen pops up as shown in Figure 51. In the list select component, the component of interest can be selected.

In order to determine the optimal preventive maintenance interval, the simulation does an enumeration. This enumeration is done for the preventive maintenance interval in a range between 0 and given max. This max should be filled in by you in the field “Max interval (years)”.

Note: In case you leave this field empty the default of 10 years is selected by the simulation.

Secondly, the enumeration requires the step between two numbers to enumerate. For instance if the enumeration range is between 0 and 100 days, and the step is equal to 10 days, the numbers that will be used by the enumeration are: $\{0,10,20,\ldots,100\}$.

The smaller the step the more precise the preventive maintenance interval will be determined.

Note: In case you leave this field empty the default of 10 days is selected by the simulation.

Note: Decreasing the step leads to increasing computational time!

By pressing the button “Determine optimal preventive maintenance interval”, Excel gives you the confirmation of the component that you have selected.

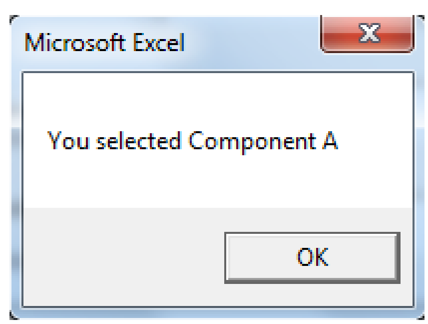


Figure 52: Confirmation of selected component

After pressing “OK”, you get again the simulation warning message as shown in Figure 41. In case you start the simulation, the CMD pops up.

When the simulation is finished the message as shown in Figure 53 is shown.

By pressing “OK” you are sent to the output screen.

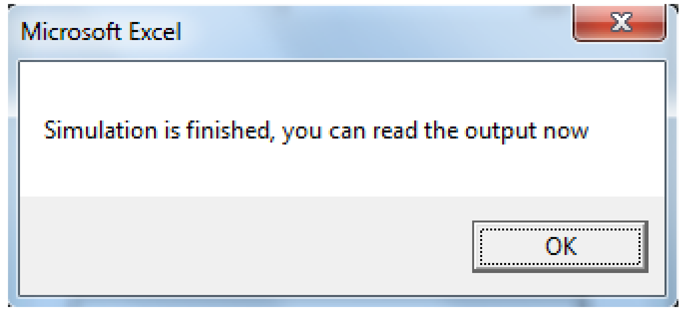


Figure 53: Simulation finished

3.2. Output screen optimal preventive maintenance interval

The output screen of the optimal preventive maintenance interval is shown in Figure 54. The output consists of a table and a graph. In the table the enumerated preventive maintenance intervals in operating days are given together with the sum of preventive and corrective maintenance cost per day. The optimal preventive maintenance interval with respect to these costs is highlighted in purple. In the graph, the preventive maintenance interval is shown on the X-axes and the preventive maintenance cost plus the corrective maintenance cost per day is shown on the Y-axis.

Note: In case the first or last row of the table is highlighted it may be that either the preventive maintenance interval is outside your predefined range, the step is too large, or failure based policy is optimal instead of preventive block replacement policy.

"PM+CM costs per day"	"PM interval operating days"
€ 381.47	10
€ 205.84	20
€ 150.58	30
€ 124.78	40
€ 110.23	50
€ 101.43	60
€ 95.39	70
€ 91.72	80
€ 89.40	90
€ 87.57	100
€ 86.41	110
€ 85.58	120
€ 85.26	130
€ 85.18	140
€ 85.27	150
€ 85.34	160
€ 85.64	170
€ 85.98	180
€ 86.31	190
€ 86.70	200
€ 87.16	210
€ 87.57	220
€ 88.12	230
€ 88.50	240
€ 88.94	250

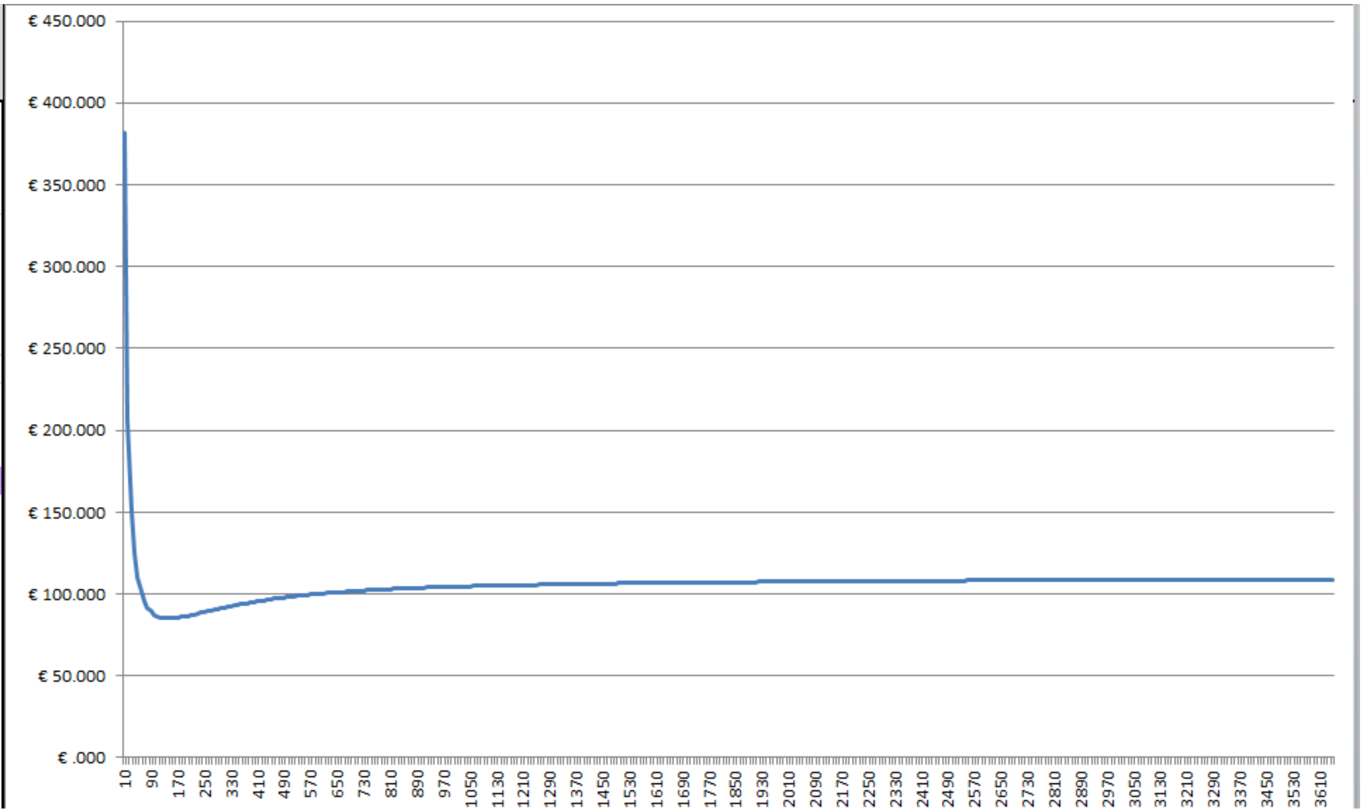


Figure 54: Output screen optimal preventive maintenance interval

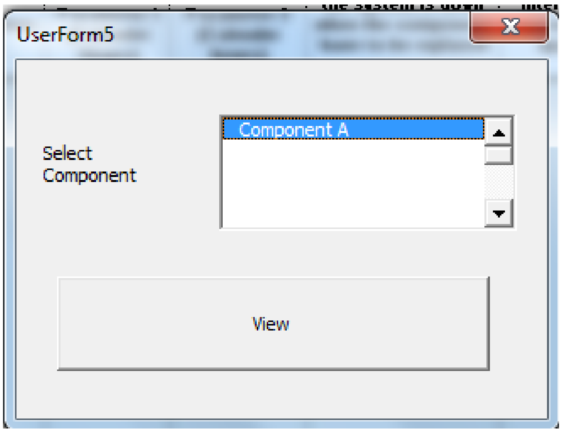
4. *Graphical representation of distributions*

The excel tool consist of two buttons which may help you in understanding the time to failure and downtime distribution. The red button (Figure 55) can be used to view the time to failure distribution and the grey button (Figure 56) can be used to view the downtime distribution of the component.

Figure 55: Button to view the time to failure distribution

Figure 56 Button to view the downtime distribution

By pressing one of these buttons, a screen appears where you can select a component. This screen is shown in Figure 58. When a component has been selected the distribution can be viewed by pressing the button "View". Before the graph appears, Excel gives you the confirmation that you selected the particular component as shown in Figure 58.



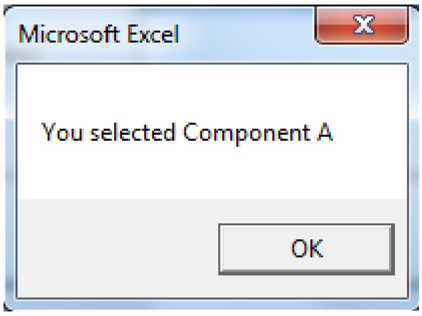


Figure 57: Component selection confirmation

Figure 58: Selection of component

After you pressed "OK", the time to failure distribution (Figure 60) or downtime distribution appears (Figure 59).

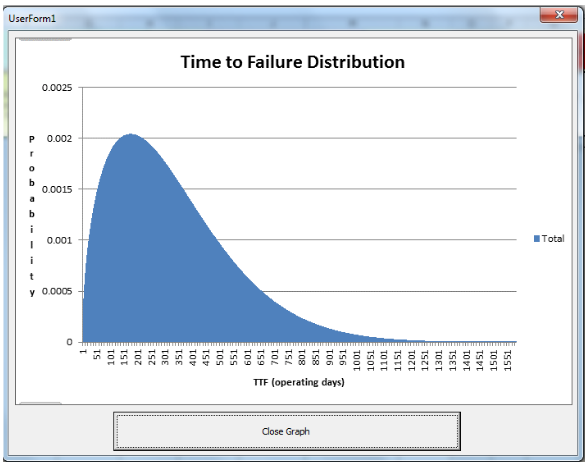


Figure 60: Graph of time to failure distribution

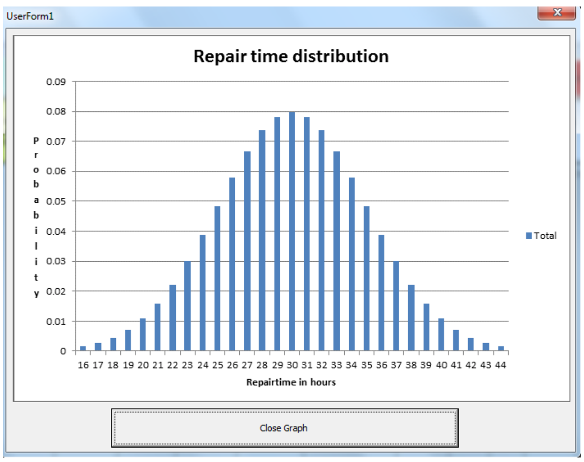


Figure 59 Graph of downtime distribution

5. *Error messages and Error codes*

Due to the fact that the simulation does not work if the input parameters are not correct or missing, error messages and error codes have been constructed.

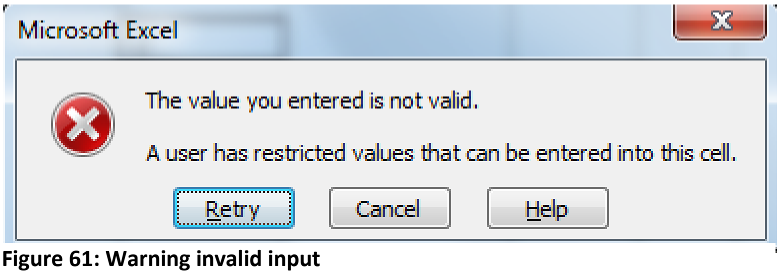


Figure 61: Warning invalid input

Error messages

In case one of the input value as described in section of this appendix is not correct a warning is given as shown in Figure 61.

It is also not allowed to use the cut function of Microsoft excel since this will screw up the Excel file. In case you use this function accidently, an error pops up as shown in Figure 62

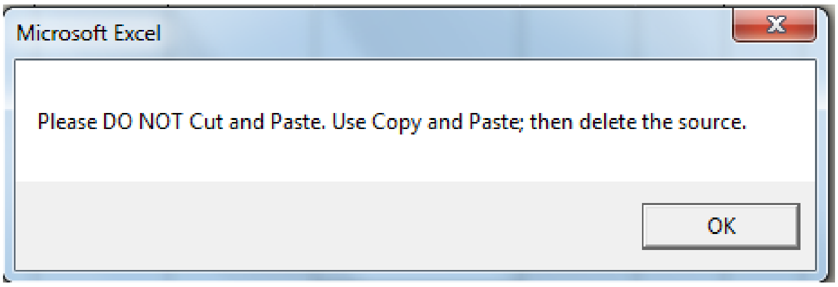


Figure 62: Cut copy error

Error codes

For missing data four error codes have been created. Error code 101 is given when some data is missing of the component input for the availability simulation. The error message, as shown in Figure 63, shows both which componenID has missing data and which data is required.

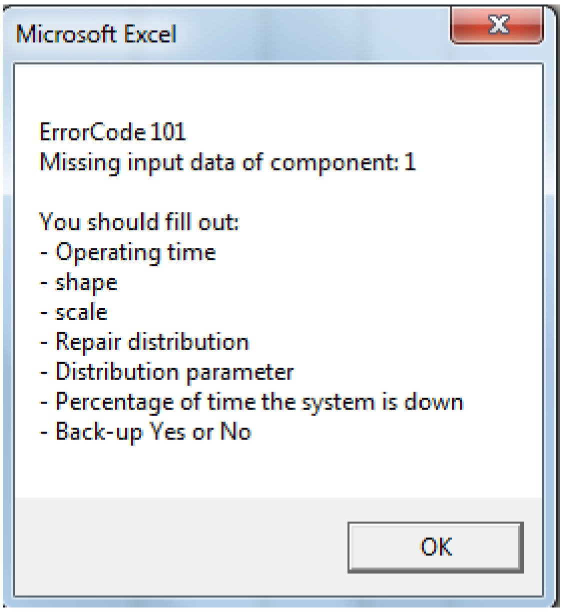


Figure 63: Error code 101

When input data is missing of the backup, error code 201 is given. The error message shows who which component has missing information of the backup and which data is required.

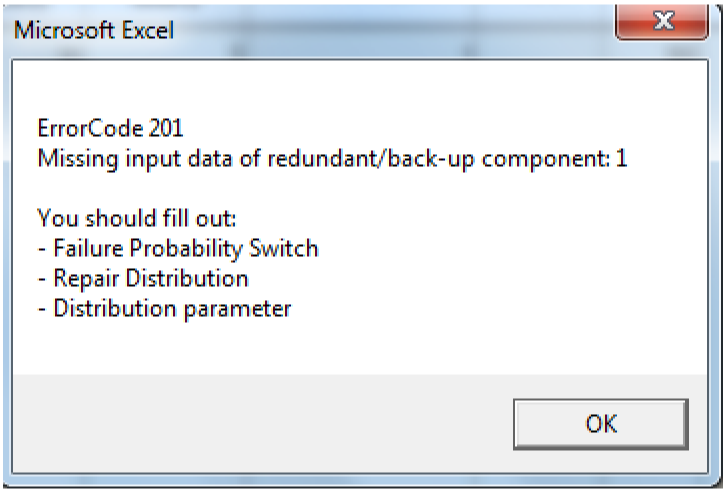


Figure 64: Error Code 201

If you launch simulation to determine the optimal preventive maintenance interval without filling in all the required input data, Error code 301 appears as shown in Figure 65. This error message shows you which input data are required to determine the optimal preventive maintenance interval.

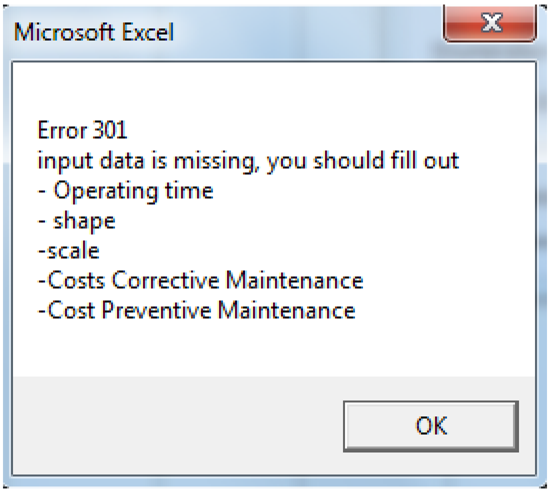


Figure 65: Error Code 301

6. *The distribution parameter estimation tool*

The LS tool can be used to fit either the operating time to failure data or the downtime data to the theoretical distributions: Exponential, Weibull, and Normal. The spread sheet of the tool is shown in Figure 66.

The green part is the output data, and the grey part is generally the input of the time to failure data. In this grey part the observed time to failures should be given as well as the censored time to failures, denoted as t_i in the tool. The censored time to failures should be given as negative values. For instance if a component has been survived for 22 operating days and is still working at the moment of fitting the data, the time to failure input is equal to -22 as shown in Figure 66

Moreover, all the time to failures and censored time to failures should be sorted ascending in absolute t_i.

Distribution Fitting								
				Exponential	Weibull	Normal		
	b			0.00017	0.88846	0.00131		
	a			n/a	-8.023	-2.239		
	R-sqd =			0.954	0.986	0.866		
	parameter1			0.000	0.888	765.869		
	parameter2			n/a	8356.115	1714.701		
enter number at risk n =				1058				
sample	t_i	Rank increment	Adjusted rank	F(ti)	ln[1/(1-F(ti)]	ln ti	ln Col D	normz
1	3	1.0000	1.0000	0.0007	0.0007	1.0986	-7.3209	-3.2110
2	4	1.0000	2.0000	0.0016	0.0016	1.3863	-6.4331	-2.9466
3	11	1.0000	3.0000	0.0026	0.0026	2.3979	-5.9700	-2.8005
4	14	1.0000	4.0000	0.0035	0.0035	2.6391	-5.6544	-2.6972
5	14	1.0000	5.0000	0.0044	0.0045	2.6391	-5.4147	-2.6166
6	16	1.0000	6.0000	0.0054	0.0054	2.7726	-5.2213	-2.5500
7	-22	1.0010	6.0000					
8	22	1.0010	7.0010	0.0063	0.0064	3.0910	-5.0591	-2.4931
9	24	1.0010	8.0019	0.0073	0.0073	3.1781	-4.9194	-2.4433
10	28	1.0010	9.0029	0.0082	0.0083	3.3322	-4.7967	-2.3989
11	33	1.0010	10.0038	0.0092	0.0092	3.4965	-4.6874	-2.3587
12	36	1.0010	11.0048	0.0101	0.0102	3.5835	-4.5887	-2.3221
13	-36	1.0019	11.0048					
14	-51	1.0029	11.0048					

Figure 66 The LS tool to fit data to the Exponential, Weibull, or Normal distribution

When the input data has been filled in, the output is directly given in the green area. The output consist of parameters a, b and R^2 (denoted as " R-sqd" in Figure 66) as explained in Table 2 of chapter 5. In addition to these three parameters, the value of the first and second parameter of the distribution is given as used in the availability simulation tool. Table 31 shows specific distribution parameters that are represented by parameter 1 and parameter 2.

Table 31: Distribution parameters represented by parameter 1 and parameter 2

	Exponential	Weibull	Normal
Parameter 1	Lapda (λ)	Beta (β)	Standard deviation (σ)
Parameter 2		Eta (η)	Mean (μ)

The brown cells in figure 66 are the rank adjustment steps and median rank steps (chapter 5), which are generated by the LS tool. For instance, the column " Adjusted Rank" is generated by the Rank increment. Next, the adjusted rank is used to estimate the cumulative distribution function $\hat{F}(t_i)$. More information can be found in chapter 5.

Invalid or no data available

In case invalid or no data is available of either the downtime or time to failure, the distribution can be estimated based on expectation of experts. For the downtime distribution, the expert should fill in the downtimes (t_i) in the grey column and the expected value of the cumulative distribution ($\hat{F}(t_i)$) in the yellow column, which is the percentage of cases the downtime will be shorter than the defined downtime. Table 32 shows an example.

Table 32: Example downtime distribution estimation

Downtime hours	$\hat{F}(t_i)$
10	0.12
14	0.33
18	0.50
22	0.80
30	0.95

Again, for the time to failure distribution, the expert should fill out the time to failures (t_i) in the grey column and the expected value of the cumulative distribution ($\hat{F}(t_i)$) in the yellow column. However, $\hat{F}(t_i)$ represent the percentage of cases that the component has failed before t_i.

Appendix L: Failure classification study

Philips gives priorities to the failures of a medical scanner: priority 1 up to 5. The explanations of these priorities are given in Table 33.

Table 33: Failure priorities with explanation

Failure Priority	Description	Explanation
1	Critical Need	The customer has a critical need for support that requires immediate action.
2	System Down	The system cannot be used for diagnostic purposes.
3	System Restricted	The system can only be used with limited functionality.
4	Intermittent Problem	Occasionally appearing problems.
5	Scheduled Activity	System is fully operational, normal maintenance is required.

Priority 2 and 1 should indicate no functionality failures. Priority 3 and 4 should indicate limited functionality failures. The lowest priority, priority 5 should not occur at a corrective replacement.

In a small study, 51 failures of different critical component over the entire world are examined line by line whether there was system downtime after the failure. The results are shown in Table 34

Table 34: System downtime results at failure priorities of critical components.

	Downtime		Percentage system down failure
Failure priority	**Yes**	**No**	**yes**
1	1		1
2	11	1	0.92
3	13	5	0.72
4	5	3	0.63
5	7	5	0.58

The result indicates that the percentage of no functionality failures is related to the failure priority. However, the data consist of a considerable amount of bias since only priority 1 and 2 should indicate no functionality failures. In order to take these bias into account, the percentage that the system is down at each critical component failure priority is estimated, which is shown in the last column of Table 34.

This percentage is multiplied by the number observed failure in each priority category and dived by the total number of observed failure, which gives the probability that the component is a "no functionality failure".

Appendix M: Reliability block diagram of Subsystem A designs

Subsystem A1

Only the power and component A1 are critical. The medical institute cooling, component B1, and component C1 are not critical for subsystem A1.

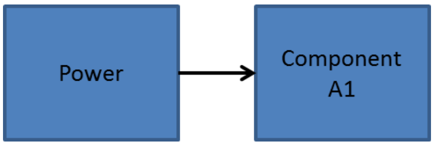


Figure 67 Reliability configuration of subsystem A1

Subsystem A2

The power, medical institute cooling, component B1, and component C1 are critical components for subsystem A2.

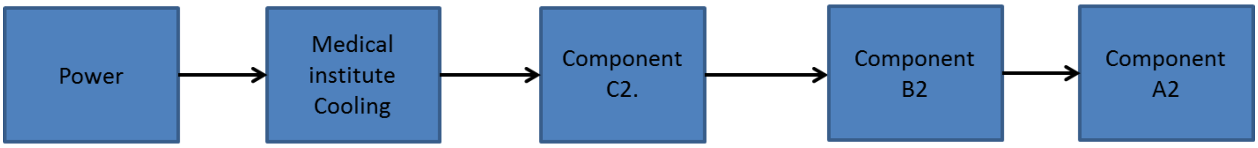


Figure 68: Reliability configuration of subsystem A2

Subsystem A2 with backup

Component D can take over the functionality of both component C2 and of the medical institute cooling

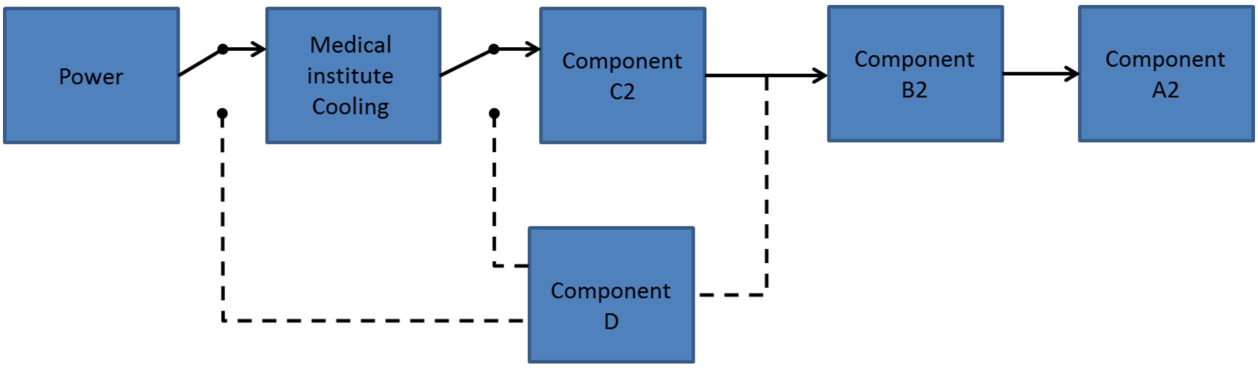


Figure 69: Reliability configuration of Subsystem A2 with backup

Appendix N Critical components System Design 1

Table 35: Subsystems with the critical components of system design 1

Critical component	Subsystem G	Subsystem C	Subsystem E	Subsystem D	Subsystem K	Subsystem F	Subsystem I	Subsystem J	Subsystem B	Subsystem H
452211797196	x									
452213257941			x							
452213257951			x							
452213258922	x									
452213258932	x									
452213301821		x								
452213301831		x								
452213301841		x								
452213301851		x								
452213301861		x								
452213301871		x								
452213301881		x								
452213301901		x								
452213301911		x								
452213301921		x								
452213301931		x								
452213301941		x								
452213301961		x								
452213301971		x								
452213301991		x								
452213302001		x								
452213302031		x								
452213303173	x									
452213303201	x									
452213303212	x									
452213303222	x									
452213303231	x									
452213303241	x									
452213303251	x									
452213303271	x									
452213303281	x									
452213303291	x									
452213303301	x									
452213303341	x									
452213304571		x								
452213305711	x									
452213316381	x									
452213316391	x									

452215036471		x								
459800044941		x								
459800069821		x								
459800069831		x								
459800069841		x								
459800069851		x								
459800092351		x								
459800092821		x								
459800093531		x								
459800093541		x								
459800093551		x								
459800093561		x								
459800093571		x								
459800093581		x								
459800093591		x								
459800093601		x								
459800093611		x								
459800093631		x								
459800093641		x								
459800093661		x								
459800093671		x								
459800093701		x								
459800093711		x								
459800093801		x								
459800093811		x								
459800093821		x								
459800093831		x								
459800093841		x								
459800093851		x								
459800093861		x								
459800093881		x								
459800113981		x								
459800114011		x								
459800116021		x								
459800116031		x								
459800121731		x								
459800121741		x								
459800121751		x								
459800126691		x								
459800126712		x								
989603019913	x									
989603020134		x								
989603020463	x									
452209005851				x						

452211752057				x						
452211773553				x						
452211781557				x						
452211794255					x					
452211794452					x					
452211795873					x					
452211795897					x					
452211797254					x					
452211798123				x						
452213167513				x						
452213262671				x						
452213272052				x						
452213311271				x						
452213700393				x						
452215034241					x					
452215034253					x					
452215034261					x					
452215034271					x					
452215043471					x					
453567031325					x					
452213314441							x			
452213314451							x			
452213315331						x				
452213315581							x			
452213315591							x			
452213315611							x			
452213316041							x			
452213316061						x				
452213316071						x				
453567031384							x			
459800013771						x				
459800083911						x				
452211788753									x	
452211788772									x	
452211795755									x	
452213177013									x	
452213183603								x		
452213203243								x		
452215040461								x		
452215040471								x		
452211764145										x
452213206353										x
452213302871										x
452215021803										x

452215021821										x
452215021831										x
452215021841										x
452215021852										x
452215021861										x
452215021881										x
452215021901										x
452215021931										x
452215021961										x
452215021971										x
452215021983										x
452215034521										x
452215043101										x
452215043361										x
459800014631										x
459800064911										x
459800073194										x
459800111771										x
459800111791										x
459800111831										x
459800111783										x

Appendix O: Estimation steps of the parameters values for the case study

In this section, the steps that have been taken to estimate the values of the input parameters in the case study (chapter 6) are explained.

Operating time to failures distribution

Before the time to failure distributions have estimated, the operating time to failure data have been created. In order to determine the operating time to failures of the critical components several data mining step have been performed.

1. Critical component selection

Together with the product experts of Philips the critical subsystems of the system has been identified. After this, the critical components of the subsystem have been identified. The list of subsystem with their critical components can be found in Appendix N. In addition to the identification of the critical component, the operating hour category has been defined for each critical component by the product expert.

2. Selection of System Design 1 field data

The failure data of Philips consists of bias. The major causes of this bias have been identified by examining the failure data. It has been found that three data issues cause a considerable part of the bias. First, some systems appear in the data without having any failure. These systems are called outliers. Second, when the systems are going out of service the failures are not logged anymore. The date that the system is out of service is not always known. Third, the operational start date of the system is not always correct. Fourth, the failure data before 2010 consists of failures of old components which have been upgraded.

In order to reduce the bias caused by the second and third data issue, the first call and last call date are used to identify the period of time where the failures are known (i.e. failure time window). In other words, the failure time window denotes the period of time where the system is under the radar of Philips with respect to failures. One call represents a moment of contact between the customer and Philips with respect to service or warranty, which may be a corrective maintenance call or planned maintenance call. In order to reduce the bias due to the first data issue, outliers have been removed based on two criteria. First, system with a call rate less than 3 should be removed. Second, systems with a failure time window less than 50 calendar days should be removed. Based on sample tests, it has been found that these two criteria find most of the outliers. Finally system which an operational start date before 2010 have been removed from the analyses to reduce the bias caused by data issue four.

Moreover, it has been decided to use operating time to failure as failure predictor instead of calendar time to failure as described in chapter 2. In order to determine operating time failures of components that do not operate 24/7, the number of scan hours or contract hours should be known. Unfortunately, these hours are not known for all of the systems. Therefore, the data of the systems which do not have information about the scan hours and contract hours have not been taken into consideration.

All the System Design 1 in the field have been downloaded from the GDWH of Philips. In total 1148 systems have been downloaded. After removing the systems, which are excluded from the failure analyses, 898 systems has been left. For the failure analysis of critical components that operate during contract hours or scan hours 690 system has been left. For these systems the percentage scan hours per year and the percentage contract hours per year have been identified.

3. Determination of the utilization

The number of scan hours and procedure hours per day are logged in the database iCube. The procedure hours represent the contract hours in iCube. As explained in Appendix D, the iCube database is incomplete. For this reason, only the days with data have been taken into account.

The data before 2010 in iCube is less reliable than the data after 2010. For this reason, the scan hours and contract hours after 2010 are used. These scan hours and contract hours have been summed per system and dived by the number of days with data. This gives the average number of scan hours and contract hours per day. Due to the fact that most of the customers do not scan on Sundays and during week 51 and 52, the average number of scan hours and contract hours per day are multiplied by $\frac{300}{365}$.

Systems with less than 10 data points (days) does not give a good representation of the number of scan and contract hours. For this reason the data of these systems have been removed from the failure analyses. This leads to data of 672 systems for the failure analyses of critical components that operate 24/7.

4. Failures

From FDV the corrective maintenance replacements of the critical components have been extracted. These corrective maintenance replacements represent failures. In addition to the failure dates, the systems where the component is installed have also been downloaded from FDV. It might be that a component is not installed in all the System Design 1 systems in the field due to small upgrades[4]. Finally the failure dates of the critical components have been aggregated to failure dates of critical subsystems. This has been done since it occurs that more critical components have been replaced at the same time.

5. Generate Time To Failure

For each critical subsystem the first call data and the last call date of the considered systems, where the critical subsystem is installed, have been listed. In case that the critical subsystem has been failed during this time frame, the failure date(s) has/have been added between the first and last call date. The dates are ordered from old to new per system per component. The time between two consecutive dates has been calculated, which is called time to failure. These time to failures have been classified as censored or failure as explained in table 36

.

[4] For this failure analysis the latest upgrades have been selected.

Table 36: Time to failure classification

Time interval	Censored/Failure
First Call data – Last Call date	Censored
First Call date – failure date	Failure
Failure date – Failure date	Failure
Failure date – Last call date	Censored

In order to consider the scan hours and contract hours, the calendar time to failures should be adapted to operating time to failures. The calendar time to failures have been multiplied by the percentage of time the component was operating in the system. As mentioned before the percentage of time that the component was operating could be either percentage scan hours, percentage contract hours or 100% (always) as shown in chapter 2

The number of data points (failures and censored) of each individual critical component/ subsystem used in the scenario analyses are given in table Table 37.

Table 37: Number of failure and censored data points

Component/Subsystem	Failures	Censored
Sub system B	28	675
Sub system C	120	681
Sub system D	150	676
Sub system E	25	629
Sub system F	36	854
Sub system G	73	673
Sub system H	102	680
Sub system I	47	663
Sub system J	118	674
Sub system K	109	676
Component C1	56	899
Component C2	103	1007
Component B1	106	825
Component B2	46	1014

After the operating time to failures have been created, the operating time to failure distributions have been estimated by the least square method followed by the goodness of fit test as explained in section 5.1.

Expected Downtime

As explained in chapter 2, it has been decided to use one downtime parameter. Unfortunately, the downtime is not measured at the moment.

In order to determine this downtime parameter it has been identified what the downtime elements are at failure and how the downtime should be calculated. This has been done for each individual critical component/subsystem per system design since it depends on the critical component/subsystem and system design how the system downtime should be calculated.

For instance, the system downtime due to a failure of the subsystem J depends on the time the FSE needs to diagnose the failure, the replenishment time of the new component, travel time and the time the FSE needs to replace the component. This does not hold for the downtime of the critical component A. The downtime of the critical component A depends on how fast critical component A can recover itself. For instance critical component A2 can recover faster than the critical component A1.

The identified downtime elements can be estimated based on either data or experience of experts. The critical components with their individual downtime calculations are shown in table 38

Table 38 critical components with their downtime calculations

Component / subsystem	Design	Downtime calculation
Component A1-2	System Design 1 with subsystem A1,A2,A2 with backup	Recovery time
Component B1-B2	System Design 1 with subsystem A1,A2,A2 with backup	(Diagnose time + Replenishment time + Travel time + Replacement time -4)*2
Component B1-B2	System Design 1 with subsystem A1	0
Component C1-C2	System Design 1 with subsystem A2,A2 with backup	(Diagnose time + Replenishment time + Travel time + Replacement time -4)*2
Component B1-B2	System Design 1 with subsystem A1	0
Sub system B-K	System Design 1 with subsystem A1,A2,A2 with backup	Diagnose time + Replenishment time + Travel time + Replacement time
Medical institute cooling	System Design 1 with subsystem A1	0
Medical institute cooling	System Design 1 with subsystem A2,A2 with backup	(Alarm 1-4)*2

The recovery times of the critical components have been estimated based on experience of service experts since no data is available about the recovery time.

The diagnose time together with the replacement time is called the corrective maintenance labour hours. These hours are recorded in FDV per corrective maintenance action. Based on the historical data of System Design 1, the average time the FSE needs to diagnose and replace a subsystem at a failure has been determined. Furthermore the travel times at a failure are recorded in FDV. However, the travel time depends on the location of the system instead of the subsystem itself. For the scenario analyses, the average travel time per area have been calculated from the historical data of System Design 1. The replenishment time of the critical components does not depend on the component itself. It also depends on the location of the system. The replenishment times are recorded in SAP MM01. For the scenario analyses, the average replenishment time per country have been calculated from historical SAP data of System Design 1.

Due to the fact that the diagnose time , replenishment time, travel time, and replacement time are not known for an individual failure, it was not possible to fit a downtime distribution.

For the medical institute cooling a certain alarm is measured. The alarm goes on when the medical institute cooling does not work properly. After the alarm has last for four hours the system is down. Each hour that the alarm is on after four hours, the system is down for two hours. For example, if the alarm has been on for 10 hours, the system has been down for 12 hours. Thus, the downtime due to a medical institute cooling failure is equal to two times the measured alarm time minus four. The historical alarm data points of system design 1 in Area A and Area B have been adapted to system downtime data due to medical institute cooling failures. Only the alarms that lasted for more than four hours have been counted as failures. Based on the downtime data point the downtime distributions have been fitted for the countries used in the scenario analyses by the least square method.

Costs

1. Purchasing price

The purchasing prices for each component are stored in the enterprise information system of Philips Healthcare (i.e. SAP MM03)

2. Repair costs for one corrective maintenance action

Historical data is available about the costs to repair the component at the repair shop in FDV. These costs contain the cost for buying repair components, labour costs, administration costs, spare component supply costs and the costs for stocking the component. Based on the historical data of System Design 1, the average repair cost of all corrective maintenance actions have been calculated for the component of the subsystem A

3. FSE Labour costs for one corrective maintenance action

The travel time of the FSE, diagnostic time and the replacement time determines the labour hours for an individual corrective maintenance job. These labour hours have been multiplied by the labour cost per hour. The travel time of the FSE, Diagnostic time and the replacement time have been estimated as explained in the section downtime of this appendix.

4. Repair costs for one preventive maintenance action

The same procedure as used to estimate the repair costs for one corrective maintenance action can be used to estimate the repair cost for one preventive maintenance action. However, no historical data is available about preventive maintenance repair cost.

For this reason, the repair cost for one corrective maintenance action has been estimated by a product expert based on the repair cost for one corrective maintenance action. The reason for this is that the repair costs elements for one corrective maintenance action are the same as the repair cost elements for one preventive maintenance action. However, it is expected by the product experts that one preventive maintenance action requires less repair components than one corrective maintenance action, since the component is in better working condition at a preventive maintenance action than at a corrective maintenance action. Thus, the repair costs for one preventive maintenance action are expected to be less than one corrective maintenance action.

5. FSE Labour costs for one preventive maintenance action

The same procedure as used to estimate the FSE labour costs for one corrective maintenance action can be used to estimate the FSE labour costs for one preventive maintenance action. However, no historical data is available about preventive maintenance FSE labour hour.

For this reason the FSE labour costs for one preventive maintenance action have been estimated by service experts based on the FSE labour costs for one corrective maintenance action. The travel time of a corrective maintenance action is equal to the travel time of a preventive maintenance action, since it only depends on the location of the system. However, it is expected that the time that is needed to perform a preventive maintenance action is less than the time that is needed to perform a corrective maintenance action due to the fact that the FSE does not need time to diagnose the failure. For this reason, it is expected that the FSE labour costs for one preventive maintenance action is less than the FSE labour costs for one corrective maintenance action.

Appendix P: Parameters Critical Components System Design 1

In this appendix the value of the input parameters of the System Design 1 critical components apart from the subsystem A can be found.

Table 39: Downtime input of the subsystems

Critical Component	Mean system downtime at a failure of subsystem i in Area B(Calendar hours)	Mean system downtime at a failure of subsystem/component i in Area A(Calendar hours)	Downtime Percentage	Operating class
Subsystem B	30.28	50.15	0.72	C
Subsystem C	19.92	39.79	0.73	B
Subsystem D	21.25	41.12	0.76	C
Subsystem E	19.67	39.54	0.70	C
Subsystem F	23.05	42.92	0.71	B
Subsystem G	22.47	42.34	0.78	C
Subsystem H	20.89	40.76	0.72	C
Subsystem I	19.89	39.76	0.73	B
Subsystem J	20.92	40.79	0.80	C
Subsystem K	21.41	41.28	0.75	C

Table 40: Time to failure distributions of the subsystems

Component	Distribution and values of the parameters (days)	R^2	Goodness of fit test	Selected distribution
Subsystem B	Exponential λ = 0.000379 Weibull: β = 0.673, η= 11366 Normal: μ = 465, σ = 196	0.949 0.984 0.827	Accepted Accepted Accepted	Weibull: β = 0.673, η= 11366
Subsystem C	Exponential λ =0.000777 Weibull: β = 0.846, η= 1638 Normal: μ = 472, σ =241	0.954 0.977 0.745	Accepted Accepted Rejected	Weibull: β = 0.846, η= 1638
Subsystem D	Exponential λ = 0.001845 Weibull: β = 0.907, η= 596 Normal: μ = 249, σ = 133	0.987 0.971 0.796	Accepted Accepted Rejected	Exponential λ = 0.001845
Subsystem E	Exponential λ = 0.000480 Weibull: β = 1.986, η= 749 Normal: μ = 461, σ = 170	0.696 0.977 0.946	Rejected Accepted Accepted	Weibull: β = 1.986, η= 749
Subsystem F	Exponential λ = 0.000071 Weibull: β = 0.974, η= 13819 Normal: μ = 1985, σ = 799	0.884 0.968 0.684	Rejected Accepted Rejected	Weibull: β = 0.974, η= 13819
Subsystem G	Exponential λ = 0.000986 Weibull: β = 0.794, η= 1479 Normal: μ = 317, σ = 158	0.823 0.950 0.677	Rejected Accepted Rejected	Weibull: β = 0.794, η= 1479
Subsystem H	Exponential λ = 0.001274 Weibull: β = 0.741, η= 1319 Normal: μ = 320, σ = 170	0.910 0.985 0.690	Accepted Accepted Rejected	Weibull: β = 0.741, η= 1319
Subsystem I	Exponential λ = 0.000411 Weibull: β = 0.787, η= 4620 Normal: μ = 494, σ = 218	0.837 0.944 0.676	Rejected Accepted Rejected	Weibull: β = 0.787, η= 4620
Subsystem J	Exponential λ = 0.001453 Weibull: β = 0.818, η= 934 Normal: μ = 283, σ = 150	0.961 0.991 0.760	Accepted Accepted Rejected	Weibull: β = 0.818, η= 934
Subsystem K	Exponential λ = 0.001407 Weibull: β = 0.911, η= 651 Normal: μ = 272, σ = 144	0.803 0.928 0.614	Accepted Accepted Rejected	Weibull: β = 0.911, η= 651

Appendix Q Corrective maintenance costs distributions scenario 1-6

The bars in these figures represent the percentage of observations (Y-axis) within the corrective maintenance bin/class (X-axis). On the X-axis only the corrective maintenance cost (euro's) of the upper bin/class is given, the upper bin/class of the previous bar is lower bin/class of the class.

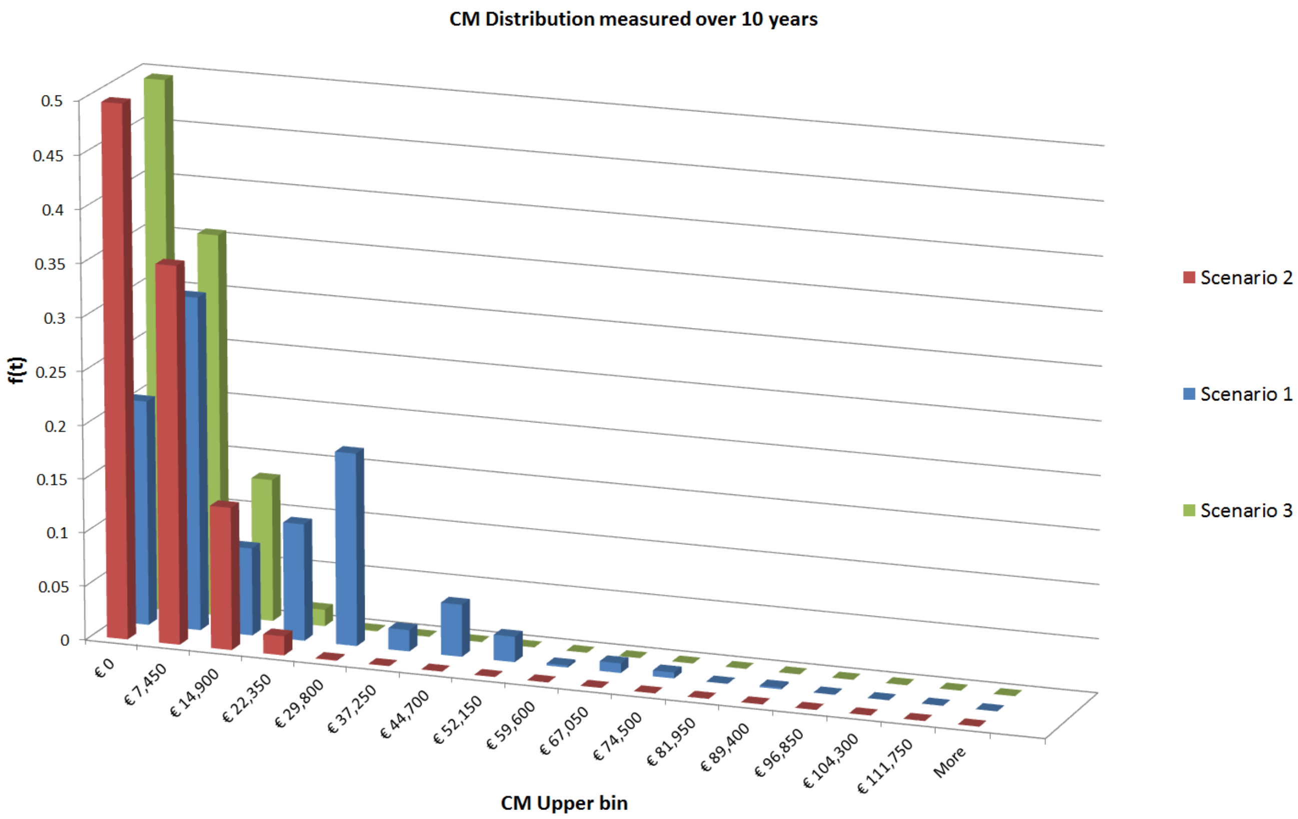


Figure 70: Distribution of the corrective maintenance costs over 10 years for scenario 1-3

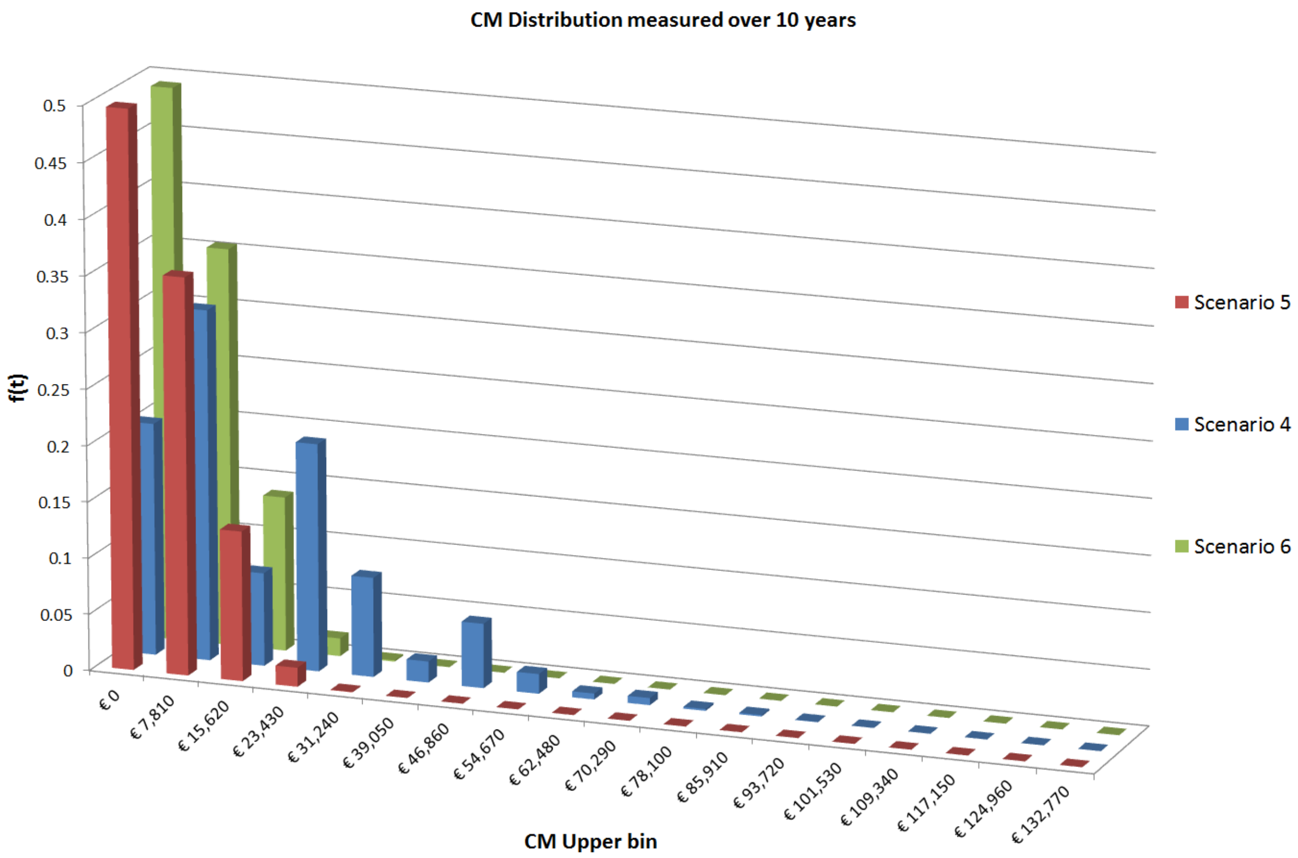


Figure 71 Distribution of the corrective maintenance costs over 10 years for scenario 4-6

Appendix R Availability distributions scenario1-6

The bars in these figures represent the percentage of observations (Y-axis) within the availability bin/class (X-axis). On the X-axis only the availability of the upper bin/class is given, the upper bin/class of the previous bar is lower bin/class of the class.

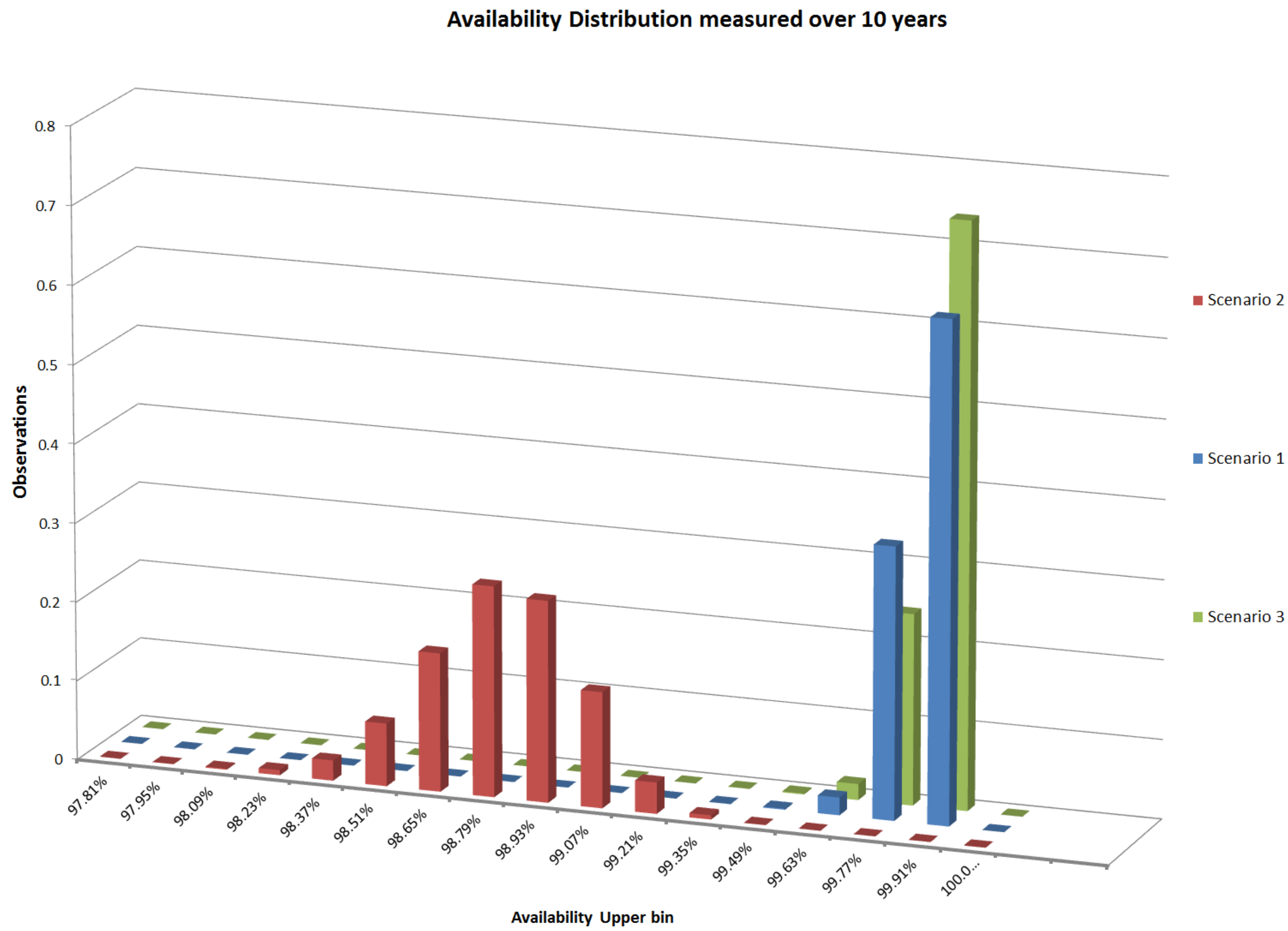


Figure 72 Distribution of the availability over 10 years for scenario 1-3

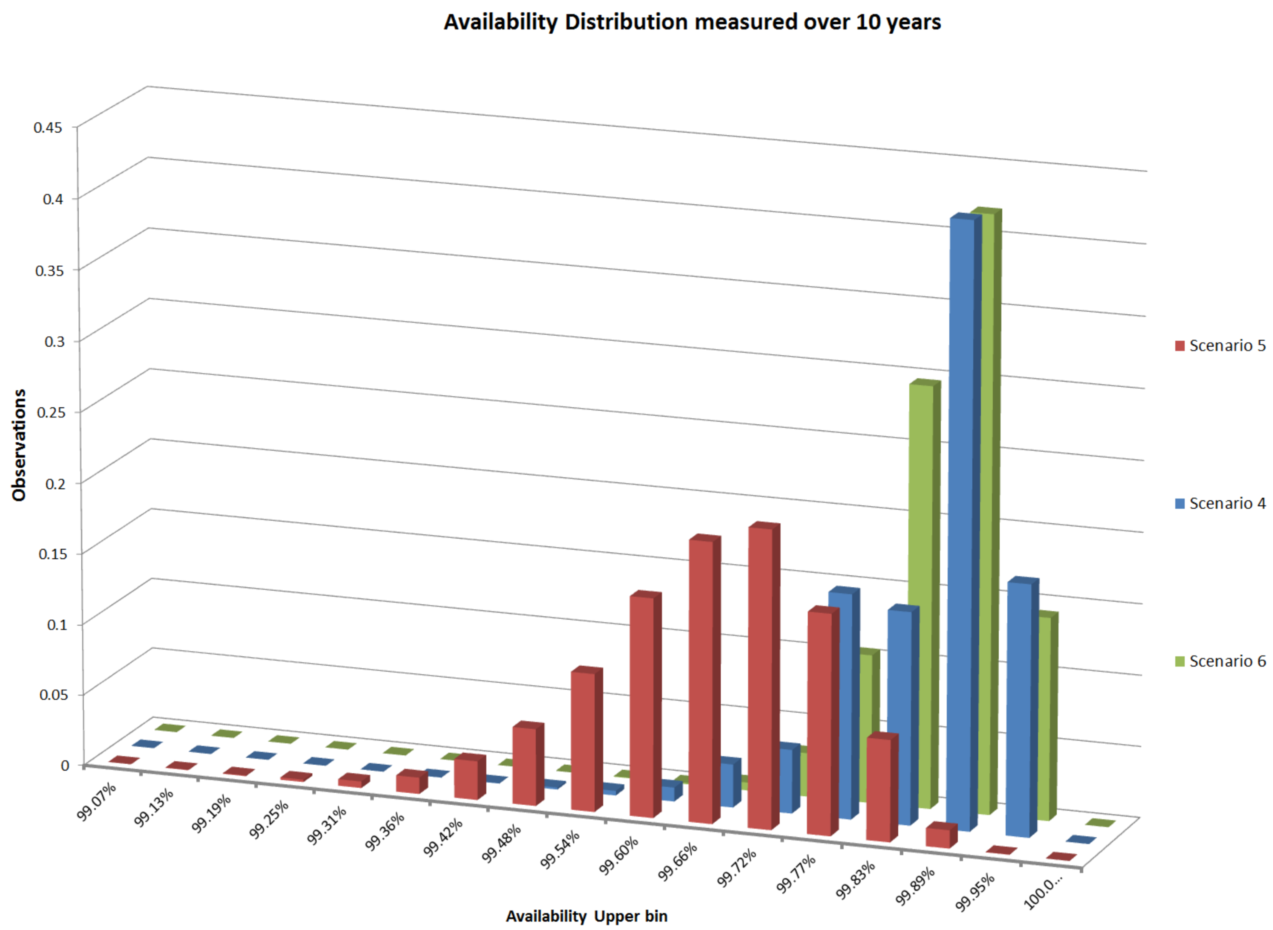


Figure 73 Distribution of the availability over 10 years for scenario 4-6

Appendix S: Availability distribution of scenario 7-12

The bars in these figures represent the percentage of observations (Y-axis) within the availability bin/class (X-axis). On the X-axis only the availability of the upper bin/class is given, the upper bin/class of the previous bar is lower bin/class of the class.

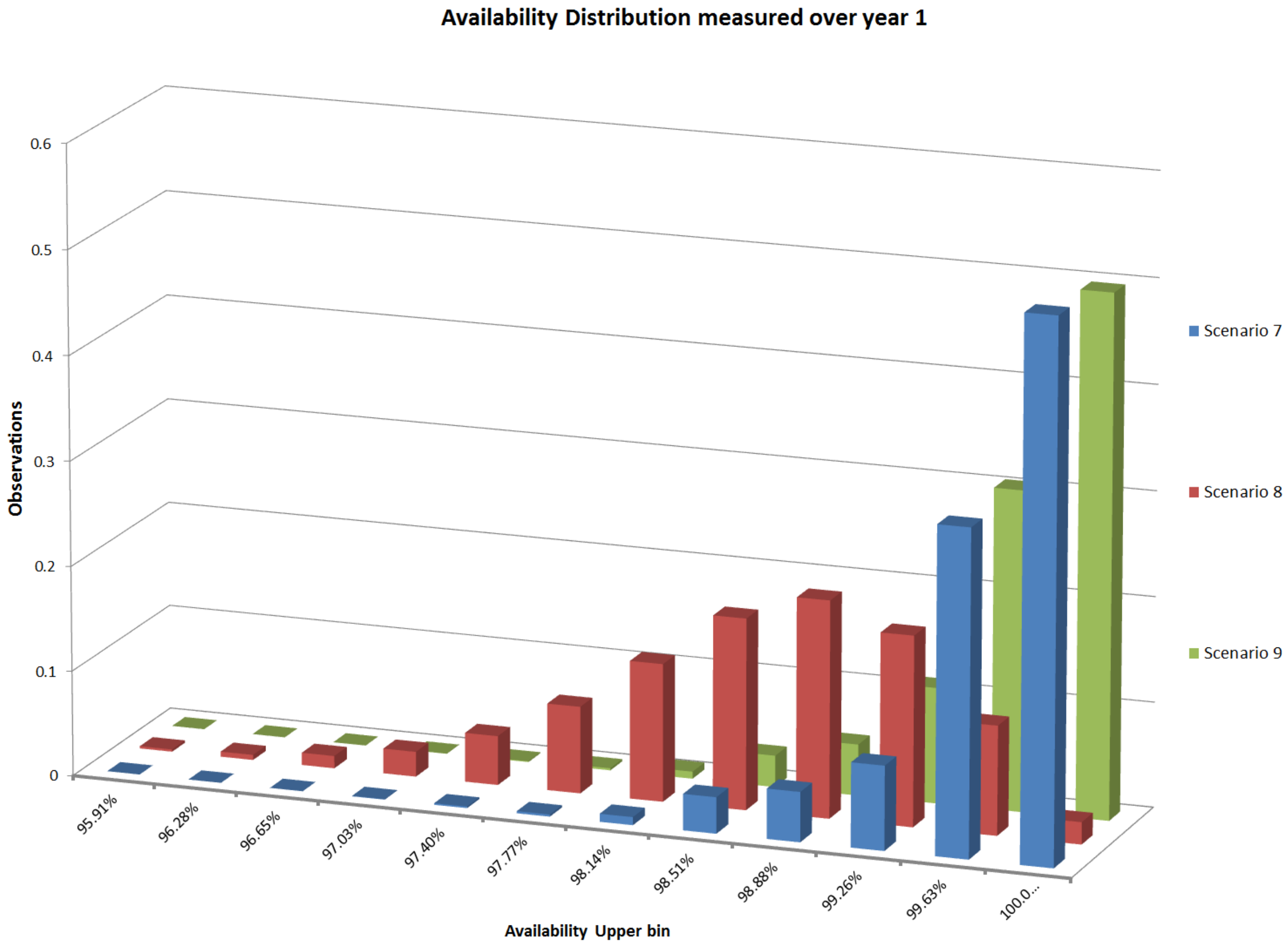


Figure 74 : Distribution of the availability over the first year for scenario 7-9

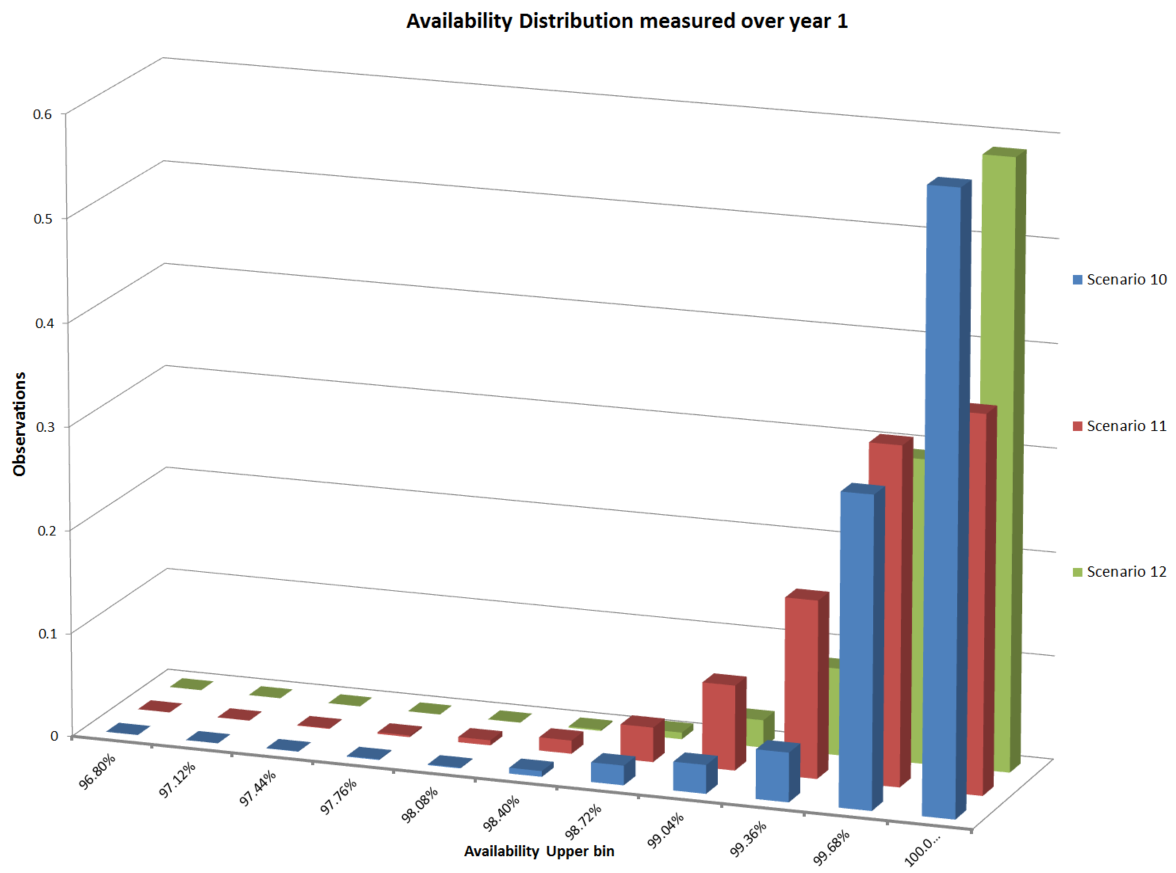


Figure 75 Distribution of the availability over the first year for scenario 10-12

Appendix T: Availability distribution of scenario 13-14

The bars in these figures represent the percentage of observations (Y-axis) within the availability bin/class (X-axis). On the X-axis only the availability of the upper bin/class is given, the upper bin/class of the previous bar is lower bin/class of the class.

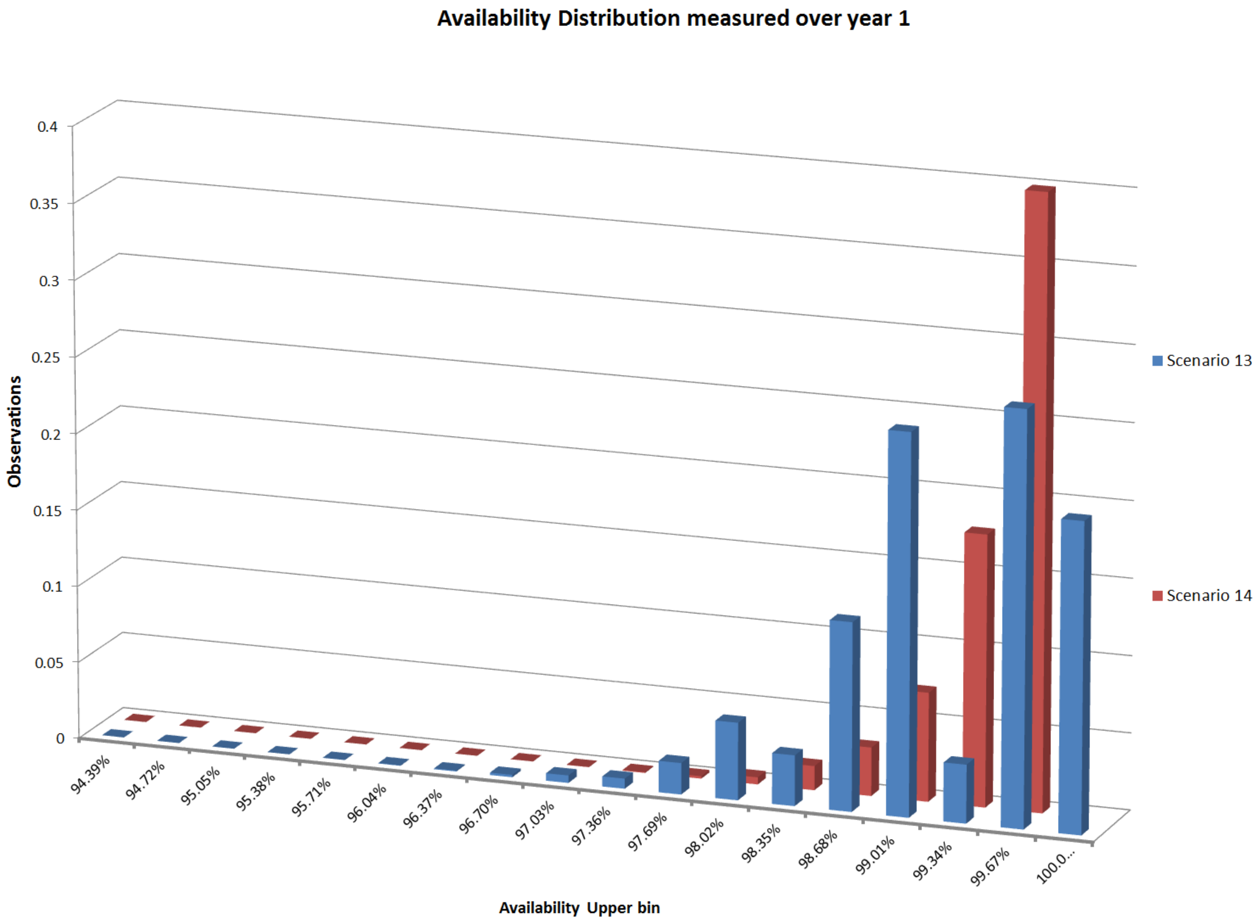


Figure 76 Distribution of the availability over the first year for scenario 13-14