Bachelor thesis Industrial engineering and management

PREVENTIVE MAINTENANCE AND INVENTORY MODEL USING FAILURE RATES

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Preventive maintenance and inventory model using failure rates

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Preface

Dear reader,

This report contains the research that I have done for my bachelor thesis of Industrial Engineering and Management at the University of Twente. The research has been executed at the company IMD in Apeldoorn from February to July 2021.

At IMD I have had the pleasure of meeting new people and even in these strange times be able to be in contact with my colleagues. So I would like to thank IMD and all my colleagues for this opportunity and the experiences that I gained. It was exciting to apply my knowledge from my studies in practice. I especially want to thank my supervisor Dennis Zwart for helping me complete my research and guiding me through the company.

I also would like to thank my first supervisor from the university, Engin Topan. Thank you for the feedback and guiding me through my research. Also, thanks to Ipek for providing the last pieces of feedback and checking up on the students during module 11 and 12. Finally, I want to thank my friends and family for their support and interest in my research.

Hanna Sturm

Apeldoorn, July 2021

Management summary

Introduction

This report describes the research done at IMD B.V. as part of the study Industrial Engineering and Management at the University of Twente. The company IMD performs water measurements and analyses for other companies and water authorities in the Netherlands. The systems that measure the wastewater are very complex because they consist of many components that should all function together. With the measurements from the wastewater and the analyses, clients' production processes are improved. The materials from the water measuring systems can show failure after a particular time. This failure causes downtime for the system and is repaired by doing corrective maintenance in the current situation. The corrective maintenance takes up unnecessary time and costs. From this problem, we come to the following main research question: "How can the preventive maintenance of the materials be planned to minimise the downtime and costs of materials?"

Approach

To solve this question, we found the optimal preventive replacement times, and from this, optimal inventory levels were determined. The problem was approached by first analysing which items of the company could best be focused on. For this, the failure data and costs were gathered. The missing information was supplemented by performing interviews with employees. From this, the item UV-vis sensor was chosen. The sensor was chosen for two reasons: the failure rates have been increasing during the past years, and the costs of the UV-vis sensor are reasonably high, 8000 euros for a new sensor, and therefore relevant to consider.

From the data and the interviews with employees, the failure rates per year were established. These failure rates were used to determine the parameters for the distribution, which is a Weibull distribution in our case. This distribution was chosen based on the literature.

The Weibull distribution that we determined, was used as input function for the replacement age. The equation for the cost per unit of time (CPUT) is filled in with the corresponding costs for planned and unplanned maintenance. With the optimal age and time to failure of the UV-vis sensor, the demand rate was determined for the sensor. The review period was set at one month, and the mean and standard deviation were determined from the demand rate. Other parameters were calculated, and finally the safety stock and order-up-to level (OUL) were determined.

Findings

The optimal replacement age is calculated to be 7 years for a total estimated lifetime of 15 years for the UV-vis sensor. The final safety stock is set at 5 sensors per year, and the OUL is advised to be 8 per replenishment order. We also tested on the replacement age model and safety stock model. The parameters costs, failure rates, downtime costs and safety stock were changed to see the influence on other values. Also, the impact of the model is tested, and an internal view is tested against a customer view.

The difference between the optimal age and current situation is 1469 euros costs and 1860 hours of saved downtime. Figure 0.1 shows this difference of costs and downtime between the current situation and the use of the optimal replacement age. This is the result of the model in our case, but other companies could also benefit from it by implementing their items. To start using the model, a few steps have to be followed, which are shown in figure 0.2.

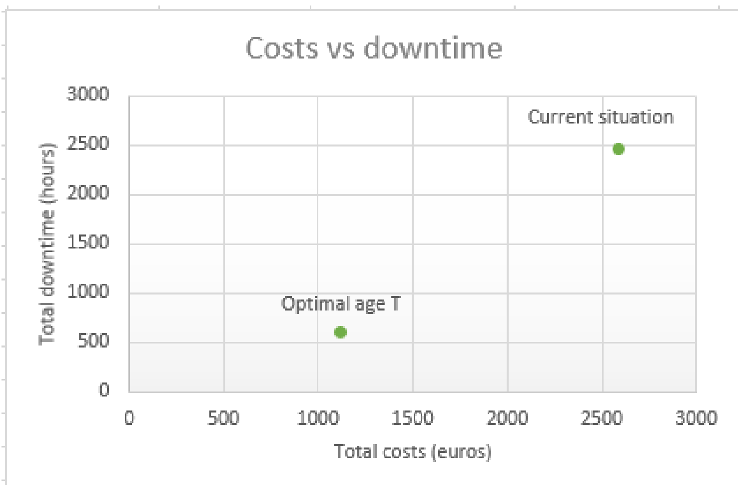

Figure 0.1: The current situation against the optimal replacement age

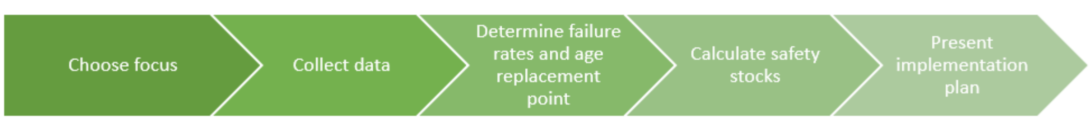

Figure 0.2: The research framework

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The introduction part of this thesis can be found in chapter 1. In this chapter, the problem is introduced, and also the approach is explained.

Chapter 2: Context analysis

In chapter 2, the context analysis can be found. The focus of the research is explained.

Chapter 3: Literature review

The literature review of this research can be found in chapter 3. The prior knowledge that is needed and the used theories are elaborated in this chapter.

Chapter 4: Solution design

In this chapter, the model for our solution is set up.

Chapter 5: Solution test

In chapter 5, the model is evaluated and tested on different aspects.

Chapter 6: Conclusions and recommendations

This chapter provides the conclusions and the recommendations of this research. In addition to this, possible further research is explained.

List of acronyms

MPSM Managerial Problem-Solving Method
ERP Enterprise Resource Planning
ARP Age replacement policy
MTBF Mean time before failure
MTTR Mean time to repair
TTF Time to failure
PM Preventive maintenance
CM Corrective maintenance
PDF Probability density function
CDF Cumulative distribution function
OUL Order-up-to level
CSL Cycle service level
KPIs Key performance indicators
ESC Estimated shortage per cycle

1 Introduction

This research is done for the company IMD b.v. The focus of this research is on providing a preventive maintenance policy to reduce downtime. Section 1.1 will introduce the company. Section 1.2 specifies the problem and how this problem was derived. In section 1.3, the research design for this thesis is described.

1.1 *Company*

IMD is situated in Apeldoorn, the Netherlands. First, IMD was part of another company, but in 2002 the company split off and became independent. It only consisted of 6 employees in the beginning. During the past 20 years, the number of employees has grown to the 34 employees there are now. The work is done by collaborating with three teams within IMD: the water chain, technology, and company team. The first team takes care of the measuring at water authorities and municipalities. The technology team is accountable for installing, maintaining and controlling the measuring equipment. Lastly, the company team checks and reviews the processes of the companies. The key activities of the company are:

- Measuring of wastewater for the water authorities and companies in the Netherlands
- Monitoring of the values that are gathered from the wastewater and performing analyses on the data
- Advising the company about their wastewater and the corresponding production processes that could need optimisation

IMD: *"Driven by water"*

Figure 1.1: An example of wastewater measuring equipment of IMD

1.2 ***The problem***

In this section, we establish the problem within the company. The section 1.2.1 describes the action problem. Then the current situation and core problem are defined with the corresponding problem cluster in sections 1.2.2 and 1.2.3. Based on this problem, the approach and given deliverables are explained. Section 1.2.5 explains the research questions.

1.2.1 *Action problem*

To identify the possible action problem within the company, firstly, interviews were conducted. These interviews are individual interviews and semi-structured. A list of structured questions is prepared, but also follow-up questions are asked, depending on the interviewee's answers. There are four sections distinguished for the different types of questions: personal questions, collaboration, problems, 4PS, the Enterprise Resource Planning (ERP) system of IMD, and the ending questions. The questions of the interviews can be found in Appendix A.

The main findings of the interviews can be divided into four different categories: inventory, maintenance, purchasing and ERP system. First, there is no inventory policy for inventory management, and the inventory levels are tracked by hand, and most of the time, not accurate. Then for the maintenance, no planned maintenance takes place, only corrective maintenance. In purchasing, the costs of new items are not calculated over their lifetime but always priced for the project that it is bought for. When item X is bought for project Y, then all costs of item X are written down for project Y. So for IMD, some projects make a high profit and others a loss even though the amount of work done was the same. Then the last problem within the company, the ERP system. A new ERP system is in use for a year, but there are many difficulties for the employees, which also causes inefficiency and communication problems in all departments.

To perform the water measurements and monitoring, the company uses many different materials. It happens that items break down occasionally. Employees can spend hours repairing an item that is not worth repairing. Also, it can be confusing if an item is still worth repairing or if it should be thrown away. This repairing of the items takes up unnecessary time and costs. The costs consist of the maintenance costs, repair costs of items and the inventory holding costs. In addition to these costs, also the machines cannot work when materials break down. So this results in high downtime of the machines, which is not ideal for IMD and for the company they work for. This also generates extra costs that could be avoided. These costs are not what the company wants, and therefore this is identified as the action problem. Figure 1.2 shows the action problem in the problem cluster that is explained in section 1.2.3.

1.2.2 *Current situation*

This section describes the current situation of the company. The situation is mapped by doing various interviews with employees. The interviews give insight into how the work is currently done.

Currently, no predictive or preventive maintenance takes place, only corrective maintenance. Every year, a check that is mandatory to perform, and this technical check (NEN3140) is performed once a year on all items. When something breaks down at the site, the customers call to inform IMD that the machine is not working. The other option is that IMD employees find that something is broken when they arrive to collect wastewater. Then they can immediately act to replace or repair it. The broken item is brought back to IMD to inspect if it is possible to repair. Another item is taken from the inventory to bring back to the customer if it is not already replaced. The broken item is waiting to be repaired or put away in storage, and the new item is placed back at the site for the customer. If the new item is not available at that time, it needs to be ordered and brought to the client as fast as possible. So the current logistics time can be high because there is the possibility that the employees drive back and forth to the customer.

1.2.3 *Core problem*

To identify the core problem, all possible problems are stated and connected to form a possible problem cluster. Then a problem needs to be selected as a core problem. A problem can only be a core problem if it can be influenced (Heerkens & Winden, 2017). Based on this, we select the core problem. Figure 1.2 shows the problem cluster. The problems that are in the cluster are all collected by conducting interviews with employees of the company.

Firstly, on the top left, there is the problem that items break down unexpectedly. From this comes the problem that the failure has to be noticed by the clients and they have to alert the company which can take up time. It can also be observed by employees when they visit the company. Then the corrective maintenance happens to solve the failure at the company. From this corrective maintenance, two problems occur. The first is that items are brought back to IMD and are kept in inventory to wait for a repair. The other problem is that because of corrective maintenance results in high logistics time and high downtime. This together finally results in high total costs and downtime.

On the top in the middle, there is the problem of non-optimal inventory management. Because of this, the availability of items is low, and again, the items are kept long in inventory waiting for repair. This results in a full inventory because items are kept long in inventory.

On the left bottom, there is our final problem, it is not clear when an item can be preventively replaced and when it should be replaced correctively. This results in two problems, first, only corrective maintenance happens; thus no preventive or predictive maintenance takes place. This leads again to only corrective maintenance and then that this causes high logistics times and high downtime. This all results in high total costs and high downtime.

The second problem is that much time is spent on repairing items that could have been replaced easily. This causes high costs for repairing and finally high costs and downtime. So the most left bottom problem in the problem cluster is identified as the core problem. Thus the core problem is:

It is not clear whether and when an item can be preventively replaced and when it should be replaced correctively.

The last problem of the problem cluster is the action problem as mentioned before. The core problem is coloured green and the action problem is red in figure 1.2.

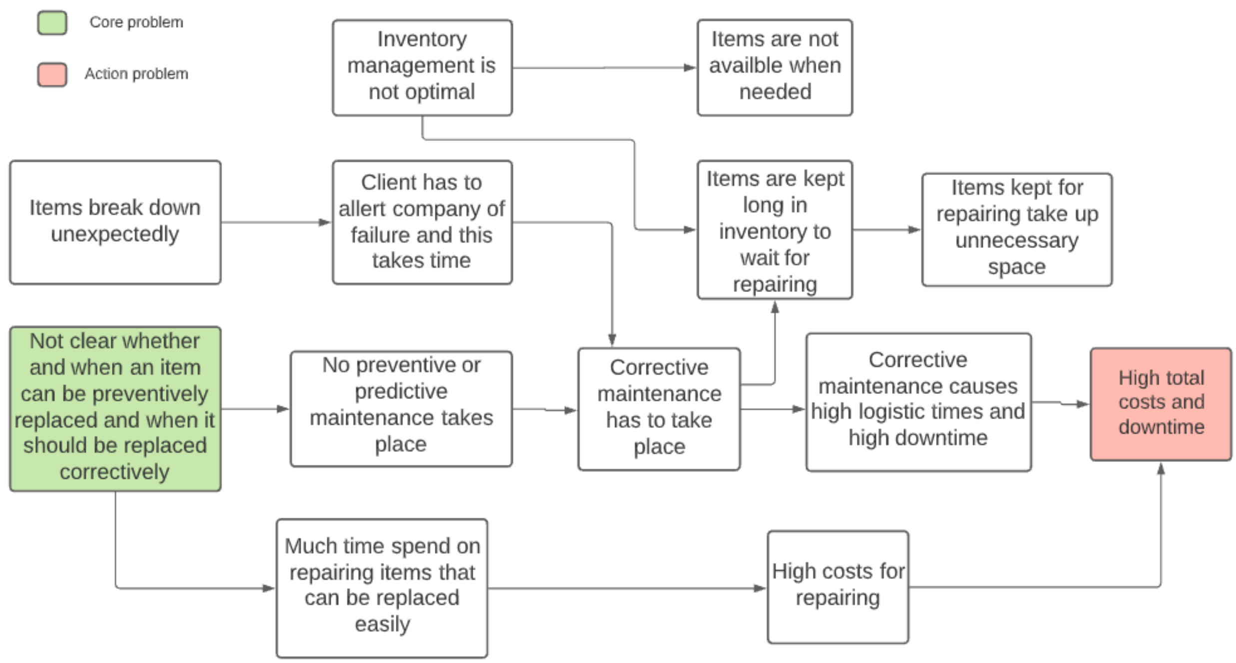


Figure 1.2: Problem cluster

1.2.4 *Norm and reality*

An action problem is defined as a problem where the reality differs from the norm that is set by the company (Heerkens & Winden, 2017). In our case, the difference between norm and reality considers the costs and the amount of downtime. The company has a specific budget that can be spent on repairing and replacing items. In reality, the downtime of the machines is far from optimal, and there are also higher costs than expected. So based on this, IMD wants to reduce the downtime and costs that are wasted on repairs. The costs also come from the downtime of the machines that cause the company to lose profit. Thus the difference between norm and reality can be measured by the costs and downtime due to repairs of items.

For the costs, the target is to reduce costs by at least 20%. As for the downtime, a reduction of 25% is aimed for. These values are set in consultation with the company and what the company aims for. Costs can be mainly saved on employee time and materials that need to be delivered fast. The downtime can be improved by doing preventive maintenance and therefore avoiding failure as much as possible. This will narrow the gap between norm and reality.

1.2.5 *Research questions*

To solve the core problem of this research the following main question has to be answered:

"How can the preventive maintenance of the materials be planned to minimise the downtime and costs of materials"

To solve this main question, the following sub research questions are asked:

1. *What items can be best focused on regarding the cost-profit and the downtime that could be improved?*

At IMD, employees use many materials and considering all these materials would be a too big scope for this thesis. Therefore, we need to make a selection of a few materials to focus on. This selection is made based on the items where the most can be improved for a specific group of items or item. This is concerning the costs that can be saved, the downtime that can be improved. So data will be gathered of costs and downtime that an item causes. This data will be gathered from previously done observations and completed with information of employees. The research for this question is descriptive research. The study gives an accurate profile of the situation and the corresponding failures of the items.

2. *What are the corresponding failure rates for each item?*

A failure rate is the rate at which failure occurs for a specified item within a specific time period (Greeff & Ghoshal, 2004). This rate is determined by analysing data from the previous failures. If this data is not available, it can be gathered by asking employees and observing items. The research for this question is exploratory. Insights are gained about the failures of the item. Then a part explanatory study is done because the Weibull distribution is determined.

3. *What is the optimal age at which to replace the used items?*

To calculate the age replacement for an item, the associated costs and downtime also have to be known. The costs of buying a new item should be less than the costs of failure of the item (Glasser, 1967). Also, the failure rates of the previous question need to be taken into account. To come to the replacement age, the model needs failure rates as input and the corresponding Weibull distribution. This question uses a explanatory research, as the Weibull function is used to determine the optimal replacement age, also using the costs.

4. *How can the safety stocks of the inventory be adjusted based on the maintenance policy?*

When it is clear at what age an item needs to be replaced, this also has an influence on the inventory. If an item has to be replaced often, higher safety stocks need to be kept. This also works the other way around for items that last very long. This can be a slight adjustment that has a significant impact on the availability of the materials. If the availability is higher than in the old situation, the downtime is also reduced. This research is a explanatory study. Based on the optimal age, a demand rate and safety stock are derived, thus the relationship between the variables is determined.

5. *What would the implementation plan for this maintenance policy look like?*

To start using the made policy, an implementation plan has to be set up. This will present how the policy can be best introduced and used within the company. To gather information on how to implement the policy best, we talked with employees and used their opinion. This is a exploratory research, as the focus is on what the best implementation plan for the company could be.

1.2.6 *Problem-solving approach*

The Managerial Problem Solving Method (MPSM) is a problem-solving approach that combines creativity and systematic. The MPSM consists of seven different phases. The phases are represented in figure 1.3 (Heerkens & Winden, 2017).

The first step of the Managerial Problem Solving Method (MPSM) is to define the problem (Heerkens & Winden, 2017). To solve the maintenance problem, first, the current situation has to be mapped. This is done by interviews, as is explained in the previous sections. These interviews will give insight into how people view the current situation and what its status is. This shows the employee side of the problem. Then the side of the item of the problem needs to be looked at. So data needs to be analysed to understand how often items break down and how much time is spent on the repair of items. Also, it is essential to select the items where the most can be improved.

Based on the definition of the problem, a problem-solving approach can be formulated. This is the second and next step of the MPSM. The approach is set up in agreement with the company and their needs. Also, the problem needs to be analysed (Heerkens & Winden, 2017). The data from the breakdowns and failures will be analysed. Statistical analysis will be done on this data to acquire the failure rates.

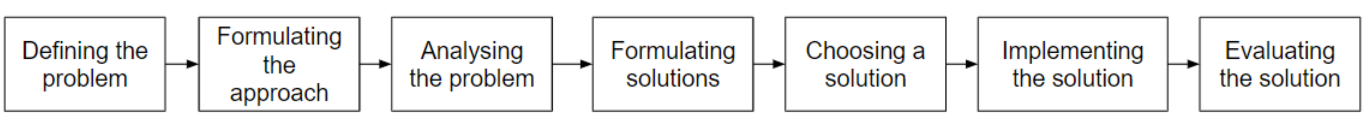


Figure 1.3: The seven different steps of the MPSM

The maintenance policy will be made to minimise the costs for repairing or replacing materials. This will be partly done by analysing previously gained data of the company and collecting new data if necessary. In addition to this, the outcomes of the model will be analysed and tested.

Then solutions are generated and chosen. From the statistical analysis, a maintenance policy will be proposed. Based on this maintenance policy, the inventory policy can also be adjusted as these two concepts are interrelated strongly. The adjustments to the inventory policy will be minor, as the focus of this research is mainly on the maintenance policy. The inventory will be adjusted on the safety stocks that are kept. Other elements of the inventory could be adjusted in further research.

Lastly, an implementation plan for the policies will be given to the company. With this plan, the company can continue the implementation on its own. As implementation is very time-consuming, it will only stay at a plan in this research. After the implementation, the company should be satisfied with the outcomes and the solving of the problem.

To form this approach, we made some assumptions. When employees collect items from the site then the question arises if an item should be repaired or a new one has to be bought. This question is left for further research because of time constraints on this research. So in this research, we assume that 50% of the items that fail will be repaired in the repair shop and the other 50% will be new buy.

1.2.7 *Deliverables*

The chosen approach will give several outcomes. The first deliverable is the statistical predictions for the breakdown of items which will be done using Excel. This is based on the analysed data from the company. A model will be provided which can calculate the replacement age and the safety stock accordingly. Then, a maintenance policy will be provided for the employees to regulate at what age the items need to be repaired or replaced based on the model. Also, there will be adjustments made to the safety stocks of the inventory policy. The new possible levels for the safety stocks will be calculated and proposed to the company. Lastly, advice on the implementation of the maintenance policy will be given to the company.

1.3 ***Research design***

In this section, the research design for this thesis is discussed. First in section 1.3.1, the type of research and subjects are discussed. Then the key variables are stated in section 1.3.2. Lastly, is the theoretical perspective in section 1.3.3.

1.3.1 *The research type and subjects*

The type of research that will be done is prescriptive research because a policy will be recommended from this research. The research comes up with a solution for the identified problem. In this research, there are two research subjects. Firstly, the materials that experience failure are the main research subjects. The data that is used in this research is data about the failure of the materials. Secondly, the employees that use the materials. The employees play an essential role in how the materials are handled. How the materials are handled has an influence on the lifetime of an item thus, the number of failures of items. Therefore the employees are asked about their work and how they handle the different materials.

1.3.2 *The key variables*

- Costs of failure per item, measured by the costs of buying a new item, downtime and time spent on replacing or repairing.
- Failure rates calculated per item using available data.
- Availability of resources, measured by the percentage of time that the item is on stock, and the percentage of downtime on a project.

1.3.3 *Theoretical perspective*

For this research, a theoretical perspective of preventive maintenance, more specifically age replacement, is chosen. An age replacement policy suggests replacing an item at the time of failure or at a specific age, whichever occurs first (Chien & Chen, 2007). To be able to provide this policy, failure rates are used. A statistical analysis of data will be done, and from this, failure rates can also be calculated. The age replacement theory is chosen because it fits the problem the best. Also, it is a systematic approach and to use the failure rates for this. The framework for this research can be seen in figure 1.4. In the first step, the focus of the items has to be chosen. This is done by analysing data on costs and the availability of resources per item. From this, a group of items can be chosen where the most can be approved, this is described in chapter 2. Secondly, the data of past failures for this group of items have to be collected. Then the failure rates and age replacement point can be calculated using statistical analysis. The calculations and methods for this are explained in chapter 4. From this maintenance policy, the safety stocks can be improved to keep more inventory for items that need replacement more, this is in chapter 5. Lastly, an implementation plan for the maintenance policy has to be provided, this is described in section 5.8.

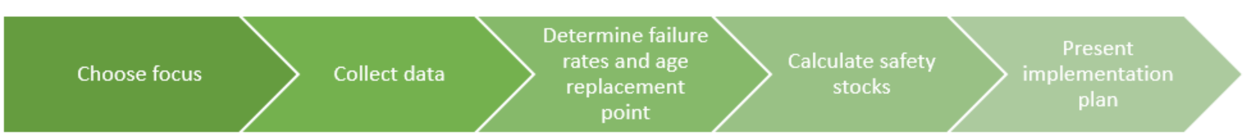


Figure 1.4: The research framework

2 Context analysis

In this chapter, the context analysis for this bachelor thesis is described. This is done by answering the first research question: Which items can be best focused on regarding the cost-profit and the downtime that could be improved? In the first section, the choice for the component selection is explained. Then the zero measurements are explained. This means that the values are measured in the current state before any adjustments are made. Then an explanation of the component is given.

The input for this chapter is provided mainly by analysing data and data gathering. The data is gathered from the company's database and completed with information gathered from employees. To gather information from employees, informal interviews were performed. The main goal of the interviews is to gather information on what product groups could need preventive maintenance and if the data says the same.

2.1 *Component selection*

It is not possible to focus on all components of the company so therefore a selection of components is made. The selection is made based on consulting the employees and making an analysis of the materials. The company uses many materials and some items are so small that it is not relevant to even consider preventive maintenance, for example on small rubber bands. It is also the case that a rubber band is non-repairable and thus it could only be replaced and not repaired. The item, UV-vis sensor was chosen based on advice from the company and talks with employees. Figure 2.1 shows an example of a UV-vis sensor.

Figure 2.1: An example of a UV-vis sensor

2.2 *UV-vis*

The UV-vis sensor was selected for this research. This is because the sensors have shown an increasing number of failures during the last years. The development of the failures per year is found in figure 2.2. UV-vis is a quantitative method to measure how much light is absorbed by a substance (Edingburgh Instruments, 2019). The sensor measures the intensity of light that passes through the substance. This intensity can be compared to a previously measured sample. With a UV-vis sensor, the concentration of a chemical substance can be determined. The concentration depends on the amount of absorbed light at a specific wavelength.

At IMD, this sensor is used to measure the pollution degree of the wastewater for the companies. The pollution degree is measured in comparison to purified water. IMD owns a total of 75 UV-vis sensors which are not always all in use. Figure 2.1 shows a picture of a UV-vis sensor. The sensor consists of two parts, the analyser and the measuring part. The part that shows the most failure is the measuring part.

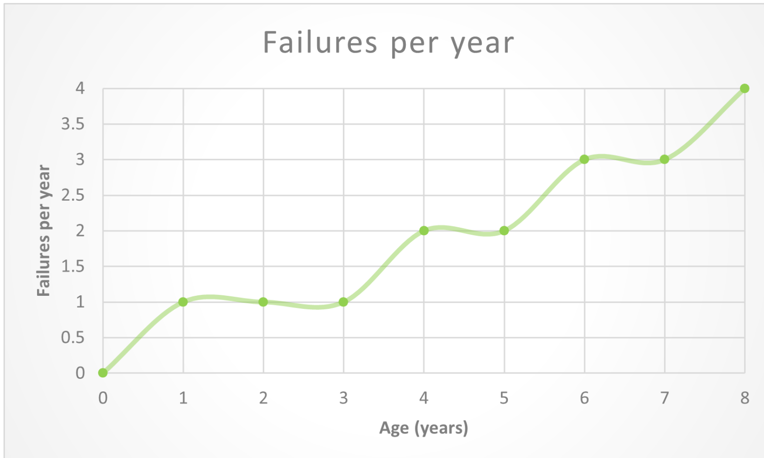


Figure 2.2: Failures of the UV-vis per year

2.3 *Zero measurement*

In this section, the current situation for the sensor is described. In the section before this, the increasing failure rates are already shown. When a failure occurs, it takes about two days for IMD to visit the company and review the failure. The sensor is a very complex item, thus a specialist is needed to judge the state of the system. The cost of buying a new sensor is 8000 euros. This is only done when the company sees what is broken and knows that it is not possible to repair it. When a sensor breaks down, there are two options for repairing it. The company sends the sensor to a repair shop in Germany where the sensor is repaired. The German company judges if a small or big revision needs to happen. A small revision only repairs the measuring part and costs 1230 euros. The big revision replaces the measuring part and the optical fibre that is inside the sensor and costs 4805 euros. We do not know in what ratio the two options are used and therefore we assume a fifty-fifty ratio. If this ratio changes, the costs for the unplanned maintenance variate which has an influence on the age replacement policy.

3 Literature review

When it was clear what item we needed to focus on, we moved on to researching the literature. In this chapter, we will look into the literature and terminology needed to answer research questions 2, 3 and 4. In the following chapters, the questions will be answered but here the literature for the questions is reviewed. Also the needed terminology for answering the questions is explained.

3.1 *Failure rates*

In this section, the second research question is considered: What are the corresponding failure rates for each item? The answer to this question is given later in chapter 4, but here the literature is reviewed. The terminology that is needed for the question is the topics failure, statistics and other relevant concepts like regression and least-squares method.

The definition of maintenance is the "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function" (British Standards Institution (BSI), 2010). Maintenance is an essential aspect of ensuring that items and machines remain in good condition. Maintenance aims to reduce downtime that is caused by failures and also unplanned and planned downtime. This is performed by choosing the right maintenance policy for the problem and needs. In this thesis, there is chosen for an age replacement policy, which is explained further in section 3.2, based on what the company wants and fits their needs.

3.1.1 *Failure*

First, we look into the definition of failure. Generally, there are two types of failure considered. The first is the type of failure that is considered a minor failure. This failure can be removed by performing small repairments on the item. The second type of failure is considered a catastrophic failure, where the failure can only be removed by replacing the item for a newly bought item (Jhang & Sheu, 1999).

The lifetime of an item and the failures during it can be represented as a bathtub curve. In the first phase of using an item, the item is in its early life phase and can experience high failure rates. The first phase is the start-up period of an item. The failure rates start to decrease with time and then start the next phase. In the useful life of an item, minimal failure occurs and thus the failure rate is at its lowest. The last phase of the lifetime is referred to as the wear-out phase. In this phase, the failure rates increase until a catastrophic failure occurs. The last phase, the wear-out, is the phase that is most interesting for this thesis. In figure 3.1 a bathtub curve is shown (Ahmad & Kamaruddin, 2012). The bathtub curve represents the lifetime of an item through the number of failures.

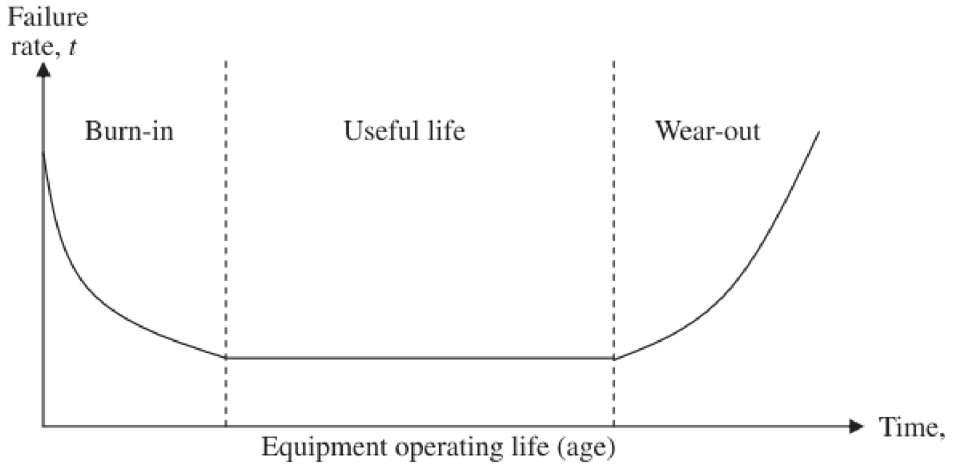


Figure 3.1: Bathtub curve, adapted from Ahmad and Kamaruddin (2012)

With previous failure data, it can be shown that an item will break down after a specific given time on average. This is called the failure rate and is represented with the λ. To calculate the failure rates some things have to be known. The T is defined as 'the first time to failure given that a system is on operation at time 0'. This is a product-specific value thus is calculated per item. With this T value, the cumulative probability distribution (CDF) can be calculated with equation (1). With equation (2) the probability density function (PDF) can be calculated. From equation (1) and (2), equation (3) can be derived. Lastly, the failure rate can be calculated with equation (4) (Famous et al., 2019). In this equation the N stands for the number of failures and the T is the total time.

$$\begin{aligned} F(t) &= P(T \leq t) \\ &= \int_{-\infty}^{t} f(s)\, ds \end{aligned} \tag{1}$$

$$f(t) = F'(t) \tag{2}$$

$$R(t) = 1 - F(t) \tag{3}$$

$$\text{Failure rate } \lambda = N/T \tag{4}$$

3.1.2 *Statistics*

To calculate the failure rates and finally determine the optimal age, statistical methods are needed. There are three types of distributions that are relevant here, the normal, exponential and Weibull distribution.

First, there is the normal distribution. This is a distribution that is symmetric in the mean value. At the mean value is the peak and then the value slowly decreases as it turns away from the mean. The normal distribution looks like a bell curve when it is graphed (Chen, 2021).

Secondly, there is the Poisson distribution. "A Poisson process is a model for a series of discrete events where the average time between events is known but the exact timing of events is random." Koehrsen (2019). The arrival time of an event is independent of the event before or after that current event. The arrival rate of the Poisson process is constant, otherwise it cannot be modelled as a Poisson process. An example of a Poisson process, is customers visiting the checkout of a shop.

Then there is also the Weibull distribution. The Weibull distribution can be represented by a cumulative distribution function (CDF) or a probability density function (PDF). In section 3.2.2, the Weibull distribution is explained further. A PDF is a continuous function that is larger than or equal to 0. As the name already suggests, it is the function of the density of all the probabilities. A cumulative distribution function (CDF) can be used to describe all types of random variables. The CDF is the primitive of the PDF.

Another statistical method is regression. This is used to find possible trends in the data. It estimated the relationships between the independent and dependent variables. This also provides a prediction for the values in the future. There is also the least-squares method. This is a type of statistical regression that aims to derive the line of best fit for the data (Kenton, 2021). The method provides a line that is the best fit around the data points that were used. The line is the minimum of the sum of the squares of the errors that are determined with the equation (Cooper & Schindler, 2014) (Winston, 1971).

3.2 ***Optimal age replacement***

In this section, the literature of the third research question is reviewed: What is the optimal age at which to replace the used items? The answer to this question is given in chapters 4 and 5.

3.2.1 *Age based policy*

Figure 3.2 shows all types of maintenance. In this research, a preventive maintenance policy was chosen. An age replacement policy (ARP) is a preventive replacement model. It aims to replace an item at age T or when a failure occurs, whichever of the two happens first (Chang, 2014). The ARP was first proposed by Barlow and Proschan (1965) and since then variations of this policy have been researched. Many case-specific policies have been derived.

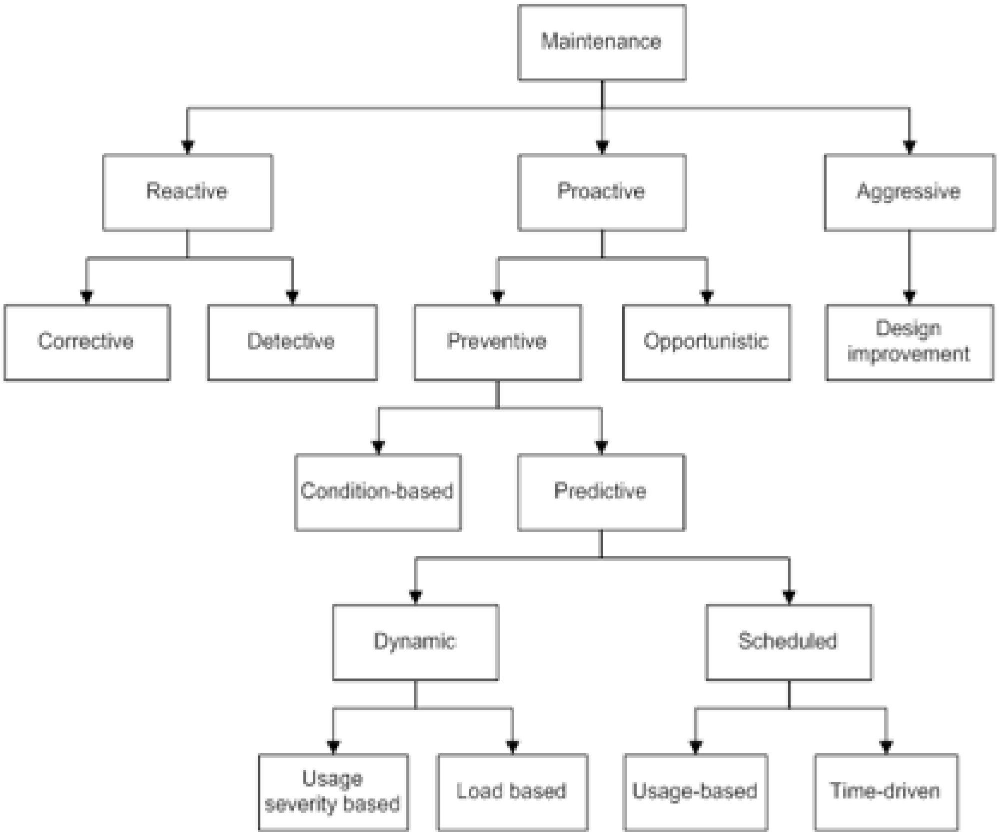


Figure 3.2: Overview of the types of maintenance policies, Topan (2015)

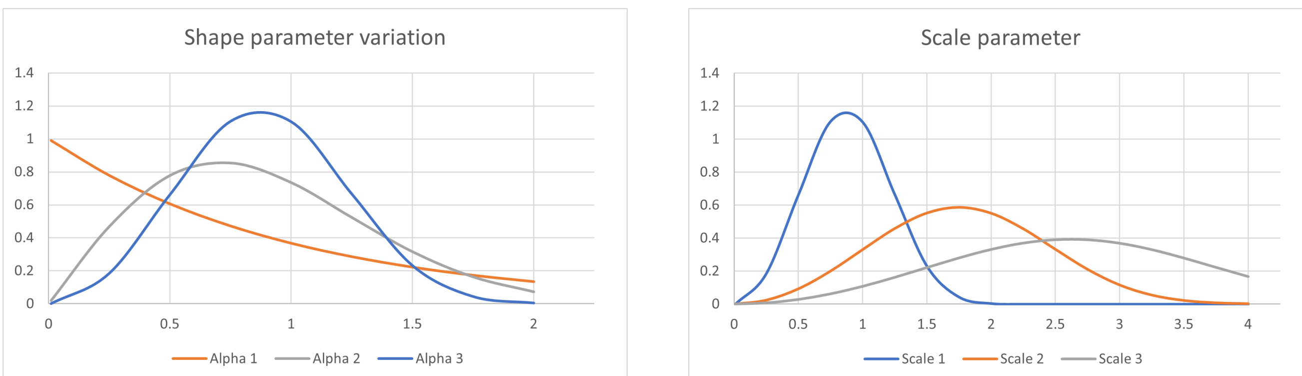
In this research, the age replacement policy will be derived for the selected item group. The age T at which the item needs to be replaced will be determined using the failure rates. The optimal T will be derived with the failure rates and a Weibull distribution. This Weibull distribution is then used in combination with the costs for planned and unplanned maintenance. The replacement age can be calculated by calculating the cost per unit of time (CPUT(t)). The optimal T can be derived from equation (5). In equation (5) the CPUT is calculated, this equation combines the Weibull distribution and the costs for maintenance. Here the C_P is the cost for planned maintenance and C_U the cost for unplanned maintenance (Reliability Engineering Resources, 2014). The specific costs for our case for C_P and C_U, are elaborated in chapter 4. The $F(T)$ in equation (5) is the function of the Weibull distribution that will be determined with the failure rates.

$$\begin{aligned} CPUT(T) &= \frac{Total\ expected\ replacement\ cost\ per\ cycle}{Expected\ cycle\ length} \\ &= \frac{C_U \cdot F(T) + C_P \cdot [\bar{F}(T)]}{\int_0^T [\bar{F}(t)]\, dT} \end{aligned} \tag{5}$$

3.2.2 *Weibull distribution*

The Weibull distribution is a model that is commonly used for representing failure data and describing failure times (Sgarbossa et al., 2020). The Weibull distribution uses three parameters, the shape (β), scale (η) and location (τ) parameter (Quality-one, 2020). In our case, we assume that the location parameter is zero and therefore not used in our calculations of the Weibull distribution.

The β indicates how many failures are occurring at that moment. If the β is lower than one, it indicates that failures will decrease over time. When the β is equal to one, this means that the failure rates are constant. Lastly, if the β is bigger than one, the failure rate will increase in time. This also means that it is not worth it to consider preventive maintenance if the β is lower than one. Figure 3.3a shows how the graph changes with a different β parameter. As shown, the whole graph type changes with the changing β, because it is the shape parameter.



(a) Weibull shape parameter (b) Weibull scale parameter

Figure 3.3: Influence of a parameter on the distribution

The η is the scale parameter, this determines how stretched out the graph is. Figure 3.3b shows how the graph changes with the η parameter. The peak of the graph is the sharpest and highest with a low scale parameter, so equal to one here. The higher the scale parameter is, the lower and more stretched out the peak of the graph is.

To perform a Weibull analysis, first the data of the materials need to be gathered. This data concerns the failures that occur per year or another time unit. Then the parameters need to be estimated so that the data fit the distribution. Lastly, plots and graphs can be generated. With the Weibull distribution, the failure of items can be predicted. The mean value of the Weibull distribution can be determined using equation (6). In this equation, the t_0 is the location parameter, which is zero in our case. The Γ in the equation can be determined using equation (8). The Variance of the Weibull distribution can be determined with the equation (7). In our case, the parameters β and η are estimated by doing regression and least-squares method, which are explained in section 3.1.2.

$$E(T) = t_0 + \eta\Gamma(1 + 1/\beta) \tag{6}$$

$$Var[T] = \eta^2(\Gamma(1 + \frac{2}{\beta}) - \Gamma^2(1 + \frac{1}{\beta})) \tag{7}$$

$$\Gamma(r) = \int_0^\infty x^{r-1}e^{-x}\,dx \tag{8}$$

3.2.3 *Preventive and corrective costs*

The corrective costs consist of the time that employees spend on repairing the item. This is the time for driving to the site and back, and repairing or replacing the item. The costs for downtime also fall within the corrective costs. These costs consist of the costs per hour for the company.

Preventive costs concern the costs for the hours to repair the items, thus the driving hours and repairing or replacing hours. Also, the costs for the total hours of downtime are part of the preventive maintenance costs.

3.2.4 *Downtime costs*

The costs for the downtime can be calculated by estimating the profit that is lost because of the downtime. Usually, IMD earns money per hour that the item is working but because of downtime, this profit is lost. Thus, the lost profit is estimated per hour and then multiplied with the number of hours that downtime is caused.

3.3 ***Safety stocks***

This section reviews the literature of the fourth research question: "How can the safety stocks of the inventory be adjusted based on the maintenance policy?" For this, we looked into safety stocks in general but more specifically into optimal stocks in combination with an age replacement policy.

The safety stocks concern the spare parts that are necessary for repairing the failed items. A spare part is defined as a part that is identical to the part of a machine that needs to be replaced due to failure (Shi et al., 2016). Wang (2012) discusses three types of inventories. Spare part inventory is not the same as work-in-process and final inventories. There are two main differences between the types of inventory, concerning the functionality and the policy. The main common thing between the inventories is that a decision should be made about the optimal stock levels. A work-in-process inventory is the stock of items that are being repaired or almost ready to be used again. Final inventory is the stock of finished products that are ready to be used.

When there are excessive spare parts kept in inventory, this gives high holding costs. The holding costs are the costs for keeping one spare part on stock for a unit of time. On the other hand, when there are limited spare parts kept in inventory this can result in more extended downtime (Wang, 2012), which can result in unsatisfied customers. For these reasons, optimal stock levels need to be determined.

In this research, the safety stocks are determined in combination with the preventive maintenance policy. The stock levels are thus dependent on how often and what type of failures occur. ARP replaces items when a failure occurs or the age T is reached, whichever occurs first. If an item has a low age T at which it will be replaced, the need for spare parts is high. On the other hand, an item with a high optimal T can generate more replacements because of failure. Therefore the spare parts inventory and the ARP are strongly connected.

If an item is replaced because of failure, time is needed to repair the item before it can re-enter the inventory system. Therefore, it is helpful to have items on stock that are ready to use. Also, spare parts for fixing the items should be available. Otherwise, the repairing takes up more time.

The safety stock is often referred to as $r - E(X)$, the inventory level at which an order is placed, r the reorder point, minus the expected demand. The expected demand is the demand that is expected for the determined cycle. The expected annual holding costs for the safety stock is $h(r - E(X))$ which is equivalent to the holding costs multiplied by the safety stock level (Winston, 1971).

All of the above-stated literature is a combination of preventive maintenance and spare parts inventory planning. This is indeed relevant literature for our subject but in this case, it is not used. Mainly because the inventory planning is not only dependent on the maintenance policy. Therefore, the following section explains the literature we will use.

In our case, a periodic review policy fits the best. With a periodic review policy, the inventory levels are reviewed periodically and a new order is placed. The size of the replenishment order depends on the current inventory level. In a periodic review policy, the inventory is filled up to a predefined level, the order-up-to level (OUL). Therefore, the size can differ per replenishment order (Chopra & Meindl, 2016). The variable R is defined as the review interval, which is the time between successive orders. The average demand per period is expressed with variable D. In our case, the period for the average demand is the review period and the lead time, thus D_{R+L}, equation (9). The corresponding standard deviation of demand per period is σ_D. The variable L represents is the lead time of the replenishment order. The standard deviation of demand during the review period and lead time is calculated with equation (10). Then there is the desired cycle service level which is shortened to CSL. A possible equation for determining the CSL is equation (11).

$$\text{Mean demand during R + L periods}, D_{R+L} = (R + L)D \tag{9}$$

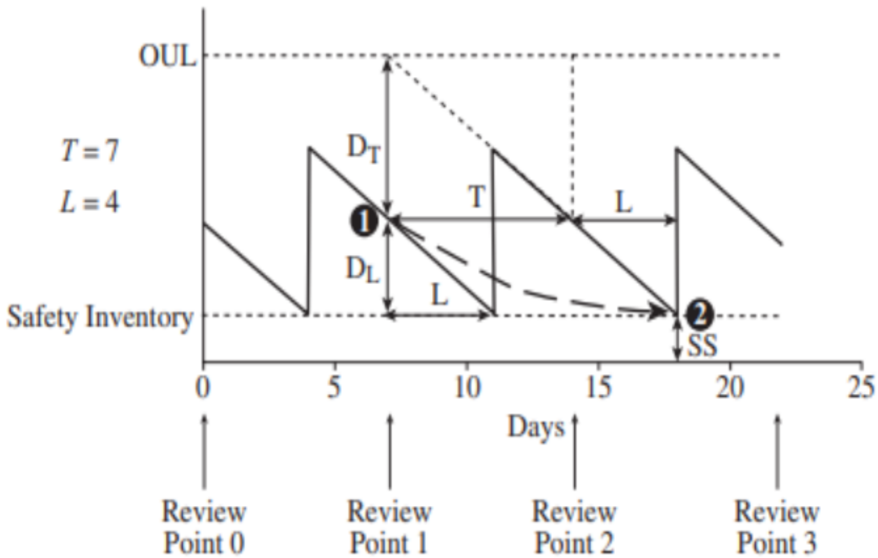


Figure 3.4: Example of inventory level in a periodic review policy from Chopra and Meindl (2016)

$$\text{Standard deviation of demand during R + L periods}, \sigma_{R+L} = \sqrt{(R+L)} \cdot \sigma_D \tag{10}$$

$$\text{Probability(demand during } R + L \leq OUL) = CSL \tag{11}$$

In figure 3.4, an example of the inventory levels in a periodic review system is shown. The x-axis shows the number of days that have gone by and the y-axis is the inventory level. The T is the review period and the L is the lead time, these variables should be expressed in the same time unit. The D_T is the demand during the review period and SS stands for the safety stocks. To determine the desired safety stocks, equation (12) is used. The variable k in the equation (12) is the safety factor and is determined with equation (13) (Silver et al., 1967). In this equation, Q represents the predefined order quantity in units. The σ_L is the standard deviation of demand during the lead time. Then, r stands for the carrying charge of the inventory, expressed in euros per unit of time. Lastly, B_3 is the downtime cost per unit of time. The parameter r is the inventory carrying charge, expressed in euros per year. The safety stock and demand rate are used to determine the OUL, in equation (14).

$$ss = k \cdot \sigma_{R+L} \tag{12}$$

$$G_u(k) = \frac{Q}{\sigma_{R+L}} \cdot \frac{r}{B_3 + r} \tag{13}$$

$$OUL = D_{R+L} + ss \tag{14}$$

Fill rate is the fraction of the demand that is met. A high fill rate means that almost all demand can be delivered from inventory, a low fill rate results in lost sales or backorders. The fill rate can be determined using equation 17. In this equation the ESC is written, the Estimated Shortage per Cycle. The ESC is calculated with equation (16). In this formula, the F_s function is the normal distribution used. The average lot size Q is calculated in equation (15), with the demand rate during the review period.

$$Q = D_R = D \cdot R \tag{15}$$

$$ESC = -ss(1 - F_s(\frac{ss}{\sigma_{R+L}}) + \sigma_{R+L} \cdot F_s(\frac{ss}{\sigma_{R+L}}) \tag{16}$$

$$Fillrate = 1 - \frac{ESC}{Q} \tag{17}$$

4 Solution design

In this chapter, the model for our solution is designed. It is explained how the model was realised with all the various steps and elements included. First off, the failure rate and the failure distribution are established in section 4.1. Using the distributions, the replacement policy is set up in section 4.2 and the optimal age T can be calculated. Lastly, the demand rate and the demand rate distribution are determined in the last section 4.3. How all of these different elements are combined together, is shown in figure 4.1.

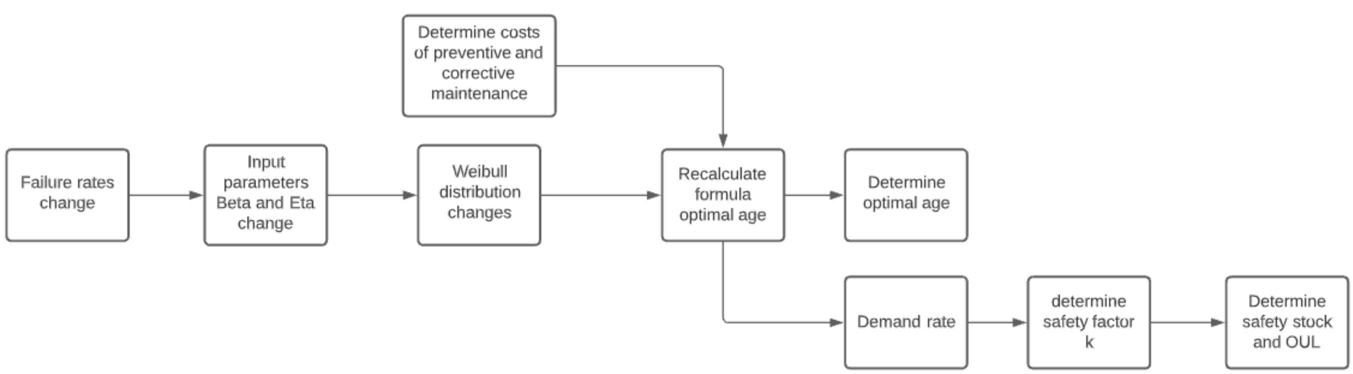


Figure 4.1: Flowchart of how the model parts are connected

4.1 *Failure distribution*

The failure rates can be calculated using equation (4) from chapter 3. In our case for the UV-vis sensors, the failure rate is estimated per year and based on the oldest sensors that are currently in use. The oldest sensors are around eight years old and the sensors start showing increased failures from year four. When the sensors fail, the downtime is around two days before the sensor runs again. The failure rate is already known but now the failure distribution has to be defined. For the distribution, we assume a Weibull distribution with its corresponding parameters. As is described in (Sgarbossa et al., 2020), the Weibull distribution shows when a time-based maintenance policy can be suitable and if components are affected by degradation or not. The distribution is especially relevant to estimate the optimal maintenance interval and corresponding costs. In our case, the location parameter is assumed to be zero. Therefore, we use a two-parameter Weibull distribution thus the shape (β) and scale (η) parameters should be estimated. The equation for the failure distribution is given by equation (18). To estimate the parameters for the failure distribution, the least-squares method is applied in Excel using a coordinate transformation and regression. The calculations and explanations for this are stated in the following section.

$$z(t) = \frac{\beta}{\eta}(\frac{t - t_0}{\eta})^{\beta-1} \tag{18}$$

Table 4.1, shows the Excel file with the calculations. First, the failure rates that are given, are shown in column A. This failure rate is given for eight years, as is indicated by 'i' in column B. Then the Ln function is taken from the failure rate. Then the F(t(i)) function is calculated. Then the value is calculated for 1- F(t(i)).

Table 4.1: Input Weibull distribution calculation

	A	B	C	D	E	F
1	TTF	i	ln(t)	F(t(i))	1-F(t)	
2	1	1	0	0.005	0.995	-5.29581
3	1	2	0	0.015	0.985	-4.19216
4	1	3	0	0.025	0.975	-3.67625
5	2	4	0.693147	0.035	0.965	-3.33465
6	2	5	0.693147	0.045	0.955	-3.07816
7	3	6	1.098612	0.055	0.945	-2.87227
8	3	7	1.098612	0.065	0.935	-2.69995
9	4	8	1.386294	0.075	0.925	-2.55154

Then with using the Excel data analysis, a regression is performed. The outcomes of the regression are specific values, which can be seen in table 4.2.

Table 4.2: The regression output of the failure rates

	A	B	C	D	E	F	G	H	I
1	SUMMARY OUTPUT								
2									
3	*Regression Statistics*			ß	1.40526039				
4	Multiple R	0.862625107		η	21.87299159				
5	R Square	0.744122074							
6	Adjusted R Square	0.701475754							
7	Standard Error	0.500030506							
8	Observations	8							
9									
10	ANOVA								
11		*df*	*SS*	*MS*	*F*	*Significance F*			
12	Regression	1	4.3627027	4.3627027	17.44868159	0.005831871			
13	Residual	6	1.500183041	0.250030507					
14	Total	7	5.862885741						
15									
16		*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
17	Intercept	-4.335583293	0.273734632	-15.83863633	4.01831E-06	-5.00538781	-3.665778777	-5.00538781	-3.665778777
18	X Variable 1	1.40526039	0.336415112	4.177161906	0.005831871	0.582082266	2.228438514	0.582082266	2.228438514

From this, the X variable coefficient is equal to the β parameter of the Weibull distribution. The η parameter is calculated by dividing the intercept coefficient by the x variable coefficient, then the exponential function is powered by that number. Thus the final values of the β and η parameters can be found in cells E3 and E4. Then the Weibull distribution is determined with the Excel function and the parameters. The Weibull distribution and the age T are used as input for the graph of the Weibull distribution. With the determined β and η parameter, we can compute a Weibull function. The parameters are the input for the function and a variable t is made. Figure 4.2 shows the graph that this Weibull distribution produces.

t	Weibull
0	0
1	0.018161
3	0.027013
5	0.031154
7	0.033093
9	0.033641
11	0.033233
13	0.032153
15	0.030609
17	0.028756
19	0.026714
21	0.024578
23	0.02242
25	0.020294
27	0.018241
29	0.016292
31	0.014464
33	0.01277
35	0.011215
37	0.009802
39	0.008526
41	0.007384
43	0.006368
45	0.005469
47	0.004679

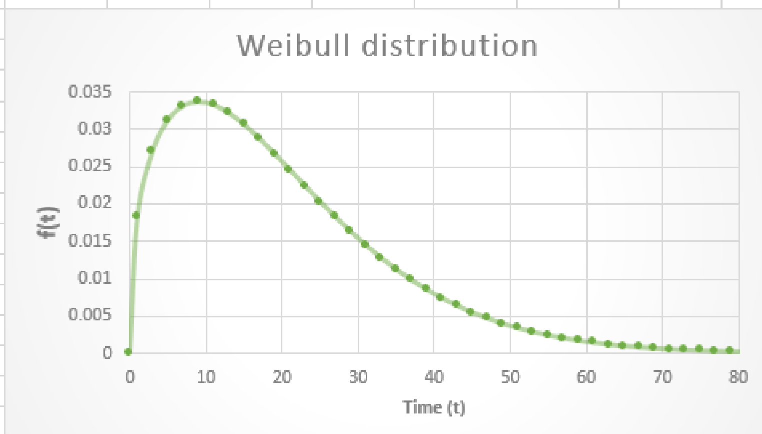


Figure 4.2: Weibull graph

4.2 *Optimal age calculation*

To calculate the replacement age, the equation (5) is used. For this the C_U and C_P need to be known. The C_U is the cost of unplanned maintenance and consists of the costs per downtime hour (h_D), multiplied with the total hours of time (h_t), plus the hours needed for repair (h_R) multiplied by the employee costs (E). This is expressed in equation (19). The variable (h_D) is the costs that are caused because of one hour of downtime. (h_t) is the total hours of downtime that are caused by the failure of the item. (h_R) is the total amount of hours that are needed for the employee to resolve the failure. Lastly, E is the costs for the company of paying the employee. The C_P is the cost of planned maintenance and consists of the costs per downtime hour (h_D) , multiplied with the total hours of time (h_t), plus the hours needed for repair (h_R) multiplied by the employee costs (E). This is expressed in equation (20). So the unplanned and planned maintenance costs use the same equation. The main difference between the costs is the amount of downtime that is caused and thus the costs for downtime.

$$C_U = (h_D * h_t) + (h_R * E) \tag{19}$$

$$C_P = (h_D * h_t) + (h_R * E) \tag{20}$$

The life time of an item is assumed to follow the failure Weibull distribution. The Weibull distribution has the following functions:

$$F(t) = 1 - e^{-(\frac{t}{\eta})^\beta} \tag{21}$$

$$\bar{F}(t) = e^{-(\frac{t}{\eta})^\beta} \tag{22}$$

$$\int_0^T [\bar{F}(t)]\, dt = t \cdot e^{-(\frac{t}{\eta})^\beta} \tag{23}$$

To calculate the replacement age T, equation (5) was used in Excel. First, the costs were determined with equations (19) and (20). The Excel sheet is shown in table 4.3, the values for this are explained in section 5.1. Then the equation (5) was filled in with the known information. The optimal T can be finally derived by determining the extreme value of the function.

Table 4.3: The cost parameters

	A	B	C	D	E	F
2						
3		**hd**	**ht**	**hr**	**E**	**Total**
4	Cu	1	60	11	105	1215
5	Cp	1	2	3	105	317
6						
7	Cu	Cp		ß	1.40526039	
8	4232.5	317		η	21.87299159	

To calculate the optimal age, Excel was also used. Figure B.3 in Appendix B shows the Excel sheet for this. First off, the costs were calculated with equations (19) (20). This is shown in table 4.3. Then, the equation for the replacement age is filled in. First, column A states the generated T values. The F(T) is calculated in column B and then in column C 1-F(T) is calculated. Then the integral is calculated for this in column D. Lastly, in column E, the value of the function is calculated with all the previously mentioned values. This is portrayed in a graph, that can be seen next to the calculations. From this figure, the minimum value is determined.

4.3 *Safety stocks*

We have a periodic review system (R,S) in our case. This means that the inventory is reviewed after a fixed period every time. The R in (R,S) stands for the review period. In this system, the period that no orders can be placed consists of R + L. When an order is placed at time t_0, the order will be received in t_0 + R + L. Therefore the inventory should be sufficient enough to cover the demand for the period R + L. The order amount will not be set but an order-up-to-level is used. This means that the order amount can differ every time but the inventory is filled up to a predefined level, the order-up-to-level (OUL).

The demand rate is determined using equation (24). In our case, the expected cycle length is the time until failure occurs or the item is replaced. This is the optimal replacement age T or failure time, whichever occurs first. To calculate the demand rate, equation (24) is used.

$$\text{Demand rate} = \frac{1}{\text{expected cycle time}} \tag{24}$$

The expected cycle length is equal to the minimum of the replacement age T or the time to failure.The demand rate is 1 over the expected cycle length. This gives the following equation (25).

$$\text{Demand rate} = \frac{1}{\min(\text{T or time to failure})} = \frac{1}{\int_0^T [\bar{F}(t)]\, dT} \tag{25}$$

For the demand rate distribution, a Poisson distribution is assumed. The Poisson parameters are estimated. In our case there is no seasonality, so we consider stationary parameters. If the parameters would change it would not be because of the seasonality.

Table 4.3 shows the Excel sheet with the demand rate calculations. In column A, on the left, what is calculated is written down. In column B, the actual calculated value is determined. Next to this, is the unit of that value written down, if it is calculated per year or per month. The last column shows the equation that is used for the calculation. On the top of the sheet, the demand rate is calculated. This calculation uses the function of the age replacement which is the Weibull distribution. The number corresponding to the optimal replacement age is filled in for the demand rate. To calculate the value of the safety factor k, equation (13) is used.

	A	B	C	D
1	**Name**	**Value**	**Unit**	**Equation**
2	demand rate	0.16	year	1/(integral (1-F))
3	R	1.00	month	
4	L	2.00	month	
5	Demand rate per time unit	0.04	6 months	R+L/12 * demand rate
6	demand rate all installations	2.91	per 6 months	demand rate * 75
7	yearly demand rate	11.63	per year	demand rate * 75
8				
9	**Assume normal**			
10	µ	11.63	per year	total average demand
11	σ	3.41		square root of Mu
12	√(R+L)	0.71	per year	square root of 0.5
13	σ_(R+L)	2.41	per year	σ* square root of 0.5
14	k	1.89		G_u(k)
15	ss	4.56		k * σ(R+L)
16	D_R	0.97		D * R
17	Q = D_R	0.97	per year	(R/12) * yearly demand rate
18	ESC	0.03		-ss(1-Fs(ss/σ_R+L)) + σ_R+L* Fs(ss/σ_R+L)
19	Fill rate	0.97		1-(esc/Q)
20	D_(R+L)	2.91		
21				
22	**Determining K**			
23	σ_(R+L)	0.985	per month	√(mean/12)
24	Q	0.081	per month	Q/12
25	Gu(k)	0.01132		(Q/σ_R+L) *(r/B3 + r)
26	r	120	per year	Holding cost per unit time
27	B3	750	per year	Downtime cost per unit time
28	cost price	8000		
29	CSL	0.97062		p_u>(k) = 1- P_1
30	Downtime	0.05876	Months	(1-CLS) * time to get part from supplier
31	downtime days	1.7628	days	
32				
33	OUL	7.47		D_(R+L)+ ss

Figure 4.3: Excel sheet with the demand rate calculations

5 Solution tests

In this chapter, the model will be discussed and tested. First, the parameters for this model are tested by varying the values. Then the impact of the proposed model is tested by comparing it with the old situation.

5.1 *Model implementation*

The previous chapter explains the set up of the model. Then in this model, the values corresponding to our item were filled in. Table 5.1a shows the values used for the failure rates. The failure rates are expressed as the number of failures of one sensor per year. The failure rates were collected by analysing the available data and where needed filling it in with information from employees. Then we used regression to calculate the Weibull distribution. Further explanations of the model can be found in section 4.1.

The cost function, equation (5), is filled in with the corresponding values. The downtime does not really incur any costs for IMD and therefore h_d is set at 1 for both planned and unplanned maintenance. Then, the hours of downtime for the unplanned maintenance is two and a half days so h_t has a value of 48 hours. For the planned maintenance, it will only take two hours to replace the sensor and therefore h_t is two. The h_r also includes the transport time because this is included in the payment. Therefore h_r for planned maintenance is 2 hours for replacement and 1 hour for transport. The transport hours are only 1 because if the maintenance is scheduled, the transport can also be connected to other locations which can be more efficient than riding to only one location. For the unplanned maintenance, it can take 2 hours for driving back and forth to the company. It takes 2 hours of replacing the sensor but an extra 7 hours that include inspecting the site, hearing out the employees of the company and also receiving the complaint and delegating the work. All of this comes together to a total of 11 hours h_r for the unplanned maintenance. The employee costs (E) are 105 euros per hour. Lastly, when the maintenance is only corrective, the repairing of the sensor is outsourced to Germany and can cost 1205 or 4830 euros, depending on the reparation. This is taken into account by half of the time one reparation and the other half of the time the other half. Thus a cost of (1205 * 0.5 + 4830 * 0.5) = 3017.5 is added. This is only added to the C_u costs, as the sensor then has to be repaired before it can be used again and for C_p another sensor can be used and the repairing or replacing of the old sensor can still be estimated. Using this as input for equation (5), gives a total of 4232.5 for C_u and 317 for C_p.

These costs together with the Weibull distribution are used to compute the CPUT. From this, an optimal age of 7 years is concluded. This is the number that generates the lowest value for CPUT, 160.07. The age of 7 and the corresponding Weibull function is used as input for the demand rate, which is 0.16 per year. The review period is set at 1 month and the lead time is 8 weeks so 2 months. This results in a yearly demand rate of 11.63, which is rounded to 12. All the values that were determined can be found in Appendix B. The advised safety stock is 4.56, so rounded to 5 sensors. The order-up-to level is 7.47 and this is rounded to 8.

5.2 *KPIs*

For testing the results and the model, it is necessary to use an important comparison for both cases. Therefore, Key Performance Indicators (KPIs) is selected. As our model is set up to minimise costs and downtime, the KPIs should cover this. The chosen KPIs are: total maintenance costs, total hours of downtime, availability of the sensors. The total maintenance costs consist of the costs of repair and the employee costs, which is calculated using the CPUT. The optimal age T is multiplied with the CPUT and this results in the final costs. The availability of the sensors is measured by the total uptime hours of the system minus the hours of downtime and this is all divided by the total hours of uptime of the system. Both situations will be tested on these KPIs and then the values will be compared.

5.3 *Parameters*

The used parameters are estimates and therefore the actual values can differ. So the parameters are varied to see the influence on the final results. The parameters that are changed are the failure rates which give the parameters for the Weibull distribution. Also the cost parameters are fluctuated and this has an influence on replacement age. Next, the downtime costs are changed to see the difference per downtime costs. Lastly, the safety stock values are varied to see the influence on the fill rate.

5.3.1 *Failure rates*

The failure rates that were used as an input for this model are shown in table 5.1a. Then the values of failures are changed and tested. Two different scenarios are made, one with lower failure rates and one with higher failure rates. This shows how the other values are influenced by the change of this input. One scenario is created with lower failure rates, the rates are shown in table 5.1b. With these failure rates as input the β turns out to be 0.60 This is lower than one and means that preventive maintenance is not profitable to be considered. The other scenario is with higher values for the failure rates, which are shown in table 5.1c. From this, results a β of 2.16 . Therefore, the Weibull distribution and the replacement age are calculated for the high failure rates.

Table 5.1: The failure rate scenarios

Failures	Year
1	1
1	2
1	3
2	4
2	5
3	6
3	7
4	8

(a) Input failure rates

Failures	Year
0	1
0	2
0	3
1	4
1	5
2	6
2	7
3	8

(b) Lower failure rate scenario

Failures	Year
2	1
2	2
2	3
3	4
3	5
4	6
4	7
5	8

(c) Higher failure rate scenario

5.3.2 *Costs*

The replacement age is dependent on the failure rates but also on the inserted costs. When fluctuating the costs, the replacement age changes with it. For the costs, the same procedure is executed as with the failure rates. First lower costs are considered and then higher costs are calculated. The costs and the corresponding downtime and maintenance cost, are shown in table 5.2. It shows how the total costs and the downtime change with the costs.

Table 5.2: The values for changing the costs parameters

Cu	Cp	T	1/int	CPUT	Costs	Downtime
4232.5	100	3	2.92	118.23	354.69	122
4232.5	200	5	4.75	142.43	712.17	302
5500	317	6	5.61	194.85	1169.08	422
5000	317	6.5	6.04	181.47	1179.54	482
4232.5	317	7	6.45	160.07	1120.49	602
4232.5	400	8.5	7.64	169.19	1438.10	902
3500	317	8.5	7.64	138.52	1177.45	902
3000	317	9.5	8.39	123.01	1168.62	1142
4232.5	500	10.5	9.10	177.88	1867.77	1382

5.3.3 *Downtime costs*

Next, there are the downtime costs, h_d are variated. For IMD the downtime costs are very meagre and therefore it is essential to see the influence of higher downtime costs. Table 5.3 shows the corresponding replacement age that is calculated under different downtime costs. The graphs that belong to the changed downtime costs, are shown in Appendix B.4. The replacement age is marked with a black dot in every graph.

Table 5.3: Input downtime costs

h_d	T
1	7
10	6.5
50	5
75	4
100	3.5
200	2.5

5.3.4 *Safety stock*

The last parameter is the safety stock. This is not a filled in value but a calculated one. Still, it is interesting to see what the safety stock does to the fill rate. The fill rate is the amount of demand that is met from inventory and is heavily dependent on the safety stock. Figure 5.1 shows how the fill rate changes with changing safety stock values. The graph shows that in the beginning, the slope is high and thus every change in the safety stock is a significant effect on the fill rate. The slope slowly decreases and with every higher safety stock value, the rise of fill rate decreases. In our case, the safety stock is set at 5 sensors per month, which is also the point where the slope is almost decreased to 0.

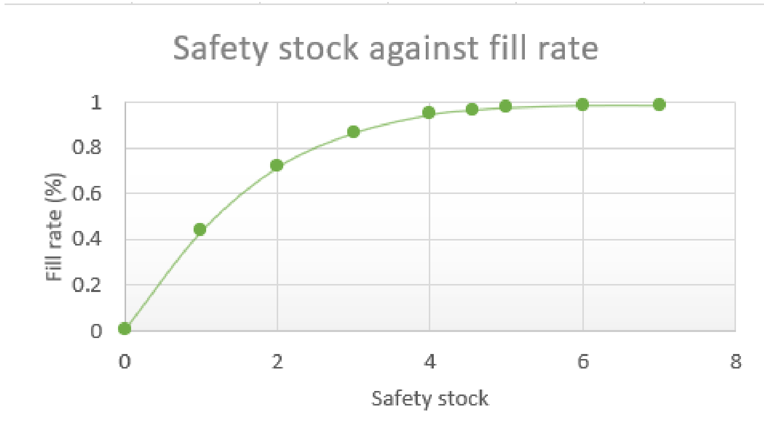


Figure 5.1: Different values of the safety stock against the fill rate

5.4 *Internal vs customer*

In our case for the UV-vis sensor, the downtime costs for the company are very low. However, the costs for the customer can possibly rise to a fine of thousands of euros. Because of this situation, a comparison is made between the costs for the company and the costs for the customer which is shown in table 5.4. The costs for the company are then mainly focused on maintenance costs as a cost obligation to avoid unnecessary costs. The customer costs could be considered as a new business opportunity for the company, to provide more personal service to the customer. This would contain preventive maintenance for the customer to avoid downtime of the sensor and therefore avoid possible fines of thousands of euros.

Table 5.4: The internal vs customer values

KPI's			Internal
T	8	70080	
CPUT	142.96	1143.69	
Total hours of downtime	782.00		
Availability of the sensors	0.99		
demand rate	0.14		
ss	4.38		
oul	7		

KPI's			Customer
T	3	26280	
CPUT	379.48	1138.44	
Total hours of downtime	122.00		
Availability of the sensors	1.00		
Demand rate	0.34		
ss	6.21		
oul	12.59		

5.5 *Model impact*

The proposed value of T is compared with the current situation. With this, the impact of the model can be tested. The steps that were followed, are represented in the flowchart in chapter 4 in figure 4.1. Here the steps can be seen for using the old and the new situation. In the old situation, there was no preventive maintenance done thus the replacement age is the time of failure. So the current situation is taken as a benchmark. In the current situation, there is no preventive maintenance done thus instead of the replacement age, the lifetime of the sensor is estimated.

Table 5.5: The optimal policy (left) and the current situation (right)

KPI's			Optimal T
T	7	61320	
CPUT	160.070	1120.493	
Total hours of downtime	602		
Availability of the sensors	0.990183		
Downtime	0.05876	Months	
downtime days	1.7628	days	

KPI's			Current situation
T	15	131400	
CPUT	172.6790978	2590.186467	
Total hours of downtime	2462		
Availability of the sensors	0.981263318		
Downtime	0.0455	Months	
downtime days	1.365	days	

In the current situation, the sensor is replaced when the lifetime is over, which is estimated at 15 years. So these 15 years is used as input and the CPUT is 172.679. This comes to a demand rate of 0.09 per year. Table 5.5 shows the calculated values. The yearly demand is equal to 6.44 which is rounded to 7. The advised safety stock is 3.59, or rounded to 4. Lastly, the order-up-to level is 5.20, which is rounded to 5. All values for calculating the OUL and more can be found in Appendix B. The current situation values and the values of the replacement age are represented in table 5.5. The CPUT for the current situation is much higher than for the optimal T, as is the total downtime. This is also shown in figure 5.2, the optimal T reduces costs and downtime. The difference between the optimal age and the current situation is 1469 euros costs and 1860 hours of downtime that are saved.

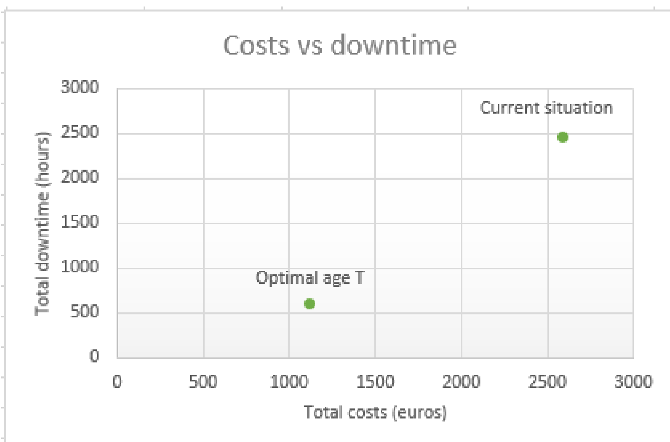


Figure 5.2: The costs and downtime of the current situation and optimal age T graphed

5.6 *Model relevance*

So far, the model is only explained and implemented in our case. Of course, the model can also be useful in other situations. Just as in our case, the model is beneficial for items with high downtime and high costs. In addition to this, the order-up-to level is also determined using the failure distribution and replacement age. The main benefits that this model can bring to other items is an advice on the replacement age. When this replacement age is considered by the company, the costs and downtime will decrease in comparison with the old situation. Another benefit is the inventory levels that will be more in control. The order-up-to level is also determined so this will result in fewer unnecessary inventory. This model is relevant for items that do not have any preventive maintenance or only scarcely.

5.7 *Validation*

Validation is "the process of ensuring that the model is sufficiently accurate for the purpose at hand." (Carson, 1986). There are two types of validation according to Robinson (2008), sufficient accuracy and models that are built for a specific purpose. No model is ever a hundred percent accurate because a model is a simplified version of reality. Still, a model should be as accurate as possible and at least accurate enough. To make sure the accuracy is high enough, there are many validation methods. In our case, a data validation is done. The source of the data should be checked to ensure that the data is as accurate as possible. The source of our data is mostly from observations that are written down and this is replenished with employee information. The information of employees is of course subject to human error and it is possible that this is not very accurate. Therefore, multiple employees are asked and the answers are compared with what the written down information shows.

The model is also discussed with the company experts to make sure that it follows what they know of the subject. Secondly, the data is tested. Other scenarios are used to test the influence on the output and to see what a difference in input would do. The input parameters do have a big influence on the output but it is especially about the ratio between the unplanned and planned maintenance costs. The input for the costs is fairly certain, as these are mainly collected from data. The failure data is all estimated by employees, so this is subject to human error. Again, for the data, multiple employees were asked. The answers were checked with the minimum data that was available on the failures.

5.8 *Implementation plan*

In this research, we have made suggestions about what preventive maintenance to do and how to manage the inventory for this. To start using this, could be a big step because the company did not have a maintenance policy before this. It can be challenging to start using a policy. Therefore, an implementation plan is necessary. First of, the maintenance policy should be clear to the employees. Secondly, the preventive maintenance has to be included in scheduling the visits to companies. A planning for this could be used inside the new ERP system, 4PS, that the company uses. This system could give reminders for when to schedule the maintenance and check what happens with the items.

The inventory policy should be integrated for the procurement employees. There are only a few employees that manage the buy-ins and therefore, this should be clear to them. The inventory should be first checked thoroughly before a new order is placed. Also, the size of the order should be calculated and thought about more than only order one sensor at a time.

6 Conclusions and recommendations

This section states the conclusions of the research in section 6.1 , the discussion in section 6.2, recommendations in section 6.3, in section 6.4 the contribution to theory and practice and lastly further research that could be conducted in section 6.5.

6.1 *Conclusion*

In this conclusion, we will give an answer to our main research question. To do this, we first look into the approach we used to solve this problem and the findings that came from this.

The first step was to gather failure data and costs. The missing information was supplemented by performing interviews with employees. From this, the item UV-vis sensor was chosen. The sensor was chosen for two reasons. The first being that the failure rates have been increasing during the past years. The second reason is that the costs of the UV-vis sensor are reasonably high, 8000 euros, and therefore relevant to consider. From the failure data and the interviews with employees, the failure rates per year were established. These failure rates were used to determine the parameters for the Weibull distribution by doing a regression in Excel. From this the Weibull distribution was determined.

The Weibull distribution that we determined, was used as an input function for the replacement age. The equation for the CPUT is filled in with the corresponding costs for planned and unplanned maintenance. In combination with the Weibull distribution, this results in an optimal replacement age of 7 years for the UV-vis sensor. The optimal replacement age, gave the input for the following part. First, the demand rate was determined with the minimum replacement age T and the time to failure. The review period was set at one month, and the mean and standard deviation were determined from the demand rate. Other parameters were calculated and finally, the safety stock and order-up-to level were determined. The final safety stock is set at 5 sensors per year and the OUL is advised to be 8 per replenishment order.

To start implementing the proposed model and policy, some changes need to be made. The maintenance policy needs to be supervised and implemented. The age of the sensors needs to be tracked, and if the sensor reaches the replacement age, it should be replaced. This replacement should be included in the scheduling of the employees. For the inventory part, the review period needs to be included in the scheduling of the replenishment orders. The size of the orders depends on the predetermined order-up-to level that we have calculated at 8.

So this all together answers our main research question: *"How can the preventive maintenance of the materials be planned to minimise the downtime and costs of materials?"*

The preventive maintenance of the materials can be planned such that the sensors are replaced at the replacement age, 7 years. In addition to this, the spare parts inventory needs to be reviewed every month and the replenishment orders should fill the stock up to the OUL of 8 sensors.

6.2 *Discussion*

In this section, the validity of the model is discussed. First the estimations of the model are elaborated and then the limitations of this research.

6.2.1 *Estimations*

In the implementation of our model, there were values, the failure rates and costs, that were estimated by employees of the company. The estimations were made by employees that have been working with the items for about years and therefore, the estimations will be close to reality. Of course, there is always the human error. The way that something is perceived is not always the same as how it really happens. Because of these estimations, the outcome of the model could differ from the actual values. This error can only be calculated if the company starts collecting data and comparing this with the estimations.

Aside from the estimations, there are many options to be explored on the side of inventory management. For now, only the safety stock and order-up-to level are included. This could be broadened in the future.

6.2.2 *Limitations of research design*

In doing this research, there were limitations to my research.
This research was not done for all the items of IMD but only for a selected group. So, this research could still be applied to many other items of the company as well but this is not included in this research because of time restrictions. This leads to the main restriction of this research, which is time. The research is designed to be completed within the given ten weeks but this of course limits the possibilities. It is also described in section 6.5, future research what could be further researched if there was more time.

6.3 *Recommendations*

The first advice is to start implementing the results of the model into the company. This starts with replacing sensors that are older than the advised replacement age. So first it the maintenance policy has to be applied to the current sensor. Then the policy has to be implemented to be used for future other sensors. The replacement of the item at the replacement age needs to be integrated into the scheduling.

Also, the results of the inventory part should be implemented. This mainly includes the predetermined order-up-to level and the advised safety stock. With this, the probability of a stockout is lower and the company can help the customer more accessible.

The following recommendation for the company is to start collecting data for other items as well. When the company collects data on other items, the model can be used for those items too. The primary data that should be gathered is the failure statistics. So the failures should be registered and also what kind of failures they are.

The model now only covers advice on the safety stock and order-up-to level but this can be extended. Many other elements of inventory management could be added to this model so that it covers more options. For example, the optimal order quantity can be added to minimise the costs for ordering replenishment orders.

Lastly, the advice is to implement the inventory and maintenance policy in the company's ERP system. For a year, the company uses an ERP system, which can help in organising the policies and keeping track of them.

6.4 *Contribution to theory and practice*

The most significant contribution to theory is the link between the age replacement policy and the safety stocks. The age replacement function is used as an input for the demand rate and from this, the safety stocks are calculated. In theory, there have been many connections made between a replacement policy and the inventory policy but not in the way it is done here. In most theory it is considered that the inventory policy solely depends on the maintenance policy but that is not the case for our situation.

In practice, the model can bring many benefits to a company. Aside from IMD, other companies that use materials to do their work can also use this model. It can be an easy solution if a company wants to use a maintenance policy but also want to look into using an inventory policy. The inventory part is currently very small, so this could be a good start for a company. Later on, this part can be expanded if it is necessary. By using the maintenance policy, the company will decrease corrective maintenance costs and also the downtime. The model is also a way to calculate if it would be profitable to use a maintenance policy in their company.

6.5 *Further research*

In the introduction, one assumption is made. When items are collected from the site, they are taken back to the workplace. Then at the workplace, it has to be decided if the item is discarded or repaired. In this research it is assumed that 50% of the items is repaired and the other 50% are discarded and bought new. This is an assumption made because of time restrictions. The process of the items should be researched and the state of the item has to be known or derived to solve this.

The inventory part of the model can be extended in further research. Currently, only the safety stock is determined. Other elements can also be determined in further research. The optimal order quantity could improve the lot sizes and the costs that come with this. As is mentioned before, the model is now only applied to one item. If the company starts collecting more data on other items, these can also be implemented in the model. The main thing that needs to happen before this is possible, is the selection of new items and the collecting of data of these items. This will be a time-consuming process but will give the company great benefits.

Lastly, the company could do more research on the new business opportunity that is mentioned. This business opportunity would include more personal service for companies to ensure that their sensor is not failing and they will not receive a fine. This could produce extra profit for IMD if they start offering this to companies.

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Appendix

A Interview questions

Personal questions
What is your job within IMD and what do are your daily activities?
How do you experience working at IMD regarding the ambience?
What are your responsibilities?

Collaborating
With who do you work together often?
How does the handover go-between colleagues?

Problems
What is going right?
Do you run into problems daily? Which problems? Are these often the same problems?
What would you point out as the biggest problem?

4PS
Can you tell me something about your activities with 4PS?
Is the system of 4PS clear for you? Is this the same for everyone?
What are the advantages of working with 4PS for you? And the disadvantages?
Does the system work? What would you like to see different in 4PS?
Do you run into steps that could be done automatically that are now done by hand?
When would you be totally satisfied with 4PS?
What should be changed or added?

Ending questions
Do you have any advice for my research? What do you think is for me the best to focus on?
What do you think of the interview and do you have any tips for me?

B Excel explanations

Name	Value	Unit	Equation
demand rate	0.16	year	1/(integral (1-F))
R	1.00	month	
L	2.00	month	
Demand rate per time unit	0.04	6 months	R+L/12 * demand rate
demand rate all installations	2.91	per 6 months	demand rate * 75
yearly demand rate	11.63	per year	demand rate * 75
Assume normal			
μ	11.63	per year	total average demand
σ	3.41		square root of Mu
√(R+L)	0.71	per year	square root of 0.5
σ_(R+L)	2.41	per year	σ* square root of 0.5
k	1.89		G_u(k)
ss	4.56		k * σ(R+L)
D_R	0.97		D * R
Q = D_R	0.97	per year	(R/12) * yearly demand rate
ESC	0.03		-ss(1-Fs(ss/σ_R+L)) + σ_R+L* Fs(ss/σ_R+L)
Fill rate	0.97		1-(esc/Q)
D_(R+L)	2.91		
Determining K			
σ_(R+L)	0.985	per month	√(mean/12)
Q	0.081	per month	Q/12
Gu(k)	0.01132		(Q/σ_R+L) *(r/B3 + r)
r	120		Holding cost per unit time
B3	750		Downtime cost per unit time
cost price	8000		
CSL	0.97062		p_u>(k) = 1- P_1
Downtime	0.05876	Months	(1-CLS) * time to get part from supplier
OUL	7.47		D_(R+L)+ ss

Figure B.1: All the calculated values with the optimal age T

Name	Value	Unit	Equation
demand rate	0.09	year	1/(integral (1-F))
R	1.00	month	
L	2.00	month	
Demand rate per time unit	0.02	6 months	R+L/12 * demand rate
demand rate all installations	1.61	per 6 months	demand rate * 75
yearly demand rate	6.44	per year	demand rate * 75
Assume normal			
μ	6.44	per year	total average demand
σ	2.54		square root of Mu
√(R+L)	0.71	per year	square root of 0.5
σ_(R+L)	1.79	per year	σ* square root of 0.5
k	2.00		G_u(k)
ss	3.59		k * σ(R+L)
D_R	0.54		D * R
Q = D_R	0.54	per year	(R/12) * yearly demand rate
ESC	0.02		-ss(1-Fs(ss/σ_R+L)) + σ_R+L* Fs(ss/σ_R+L)
Fill rate	0.97		1-(esc/Q)
D_(R+L)	1.61		
Determining K			
σ_(R+L)	0.733	per month	√(mean/12)
Q	0.045	per month	Q/12
Gu(k)	0.00842		(Q/σ_R+L) *(r/B3 + r)
r	120		Holding cost per unit time
B3	750		Downtime cost per unit time
cost price	8000		
CSL	0.97725		p_u>(k) = 1- P_1
Downtime	0.0455	Months	(1-CLS) * time to get part from supplier
downtime days	1.365	days	
OUL	5.20		D_(R+L)+ ss

Figure B.2: The calculated values for the current situation

	A	B	C	D	E	F	G
12				Expected cycle length			
13		1- e^-(t/n)^b	e^-(t/n)^b	(tn-tn-1) *(Fbar(tn)+Fbar(tn-1))/2 + area so far			
14	T	F(T)	1-F(T)	Int(1-F(t))	CPUT		
15	0	0	1	0	#DIV/0!		
16	0.5	0.005	0.995	0.499	674.281		#N/A
17	1	0.013	0.987	0.994	370.052		#N/A
18	1.5	0.023	0.977	1.485	273.747		#N/A
19	2	0.034	0.966	1.971	228.541		#N/A
20	2.5	0.046	0.954	2.451	203.379		#N/A
21	3	0.059	0.941	2.925	188.019		#N/A
22	3.5	0.073	0.927	3.391	178.125		#N/A
23	4	0.088	0.912	3.851	171.553		#N/A
24	4.5	0.103	0.897	4.303	167.131		#N/A
25	5	0.118	0.882	4.748	164.164		#N/A
26	5.5	0.134	0.866	5.185	162.217		#N/A
27	6	0.150	0.850	5.614	161.006		#N/A
28	6.5	0.166	0.834	6.035	160.335		#N/A
29	7	0.183	0.817	6.448	160.070		160.0705
30	7.5	0.199	0.801	6.853	160.113		#N/A
31	8	0.216	0.784	7.249	160.390		#N/A
32	8.5	0.233	0.767	7.637	160.849		#N/A

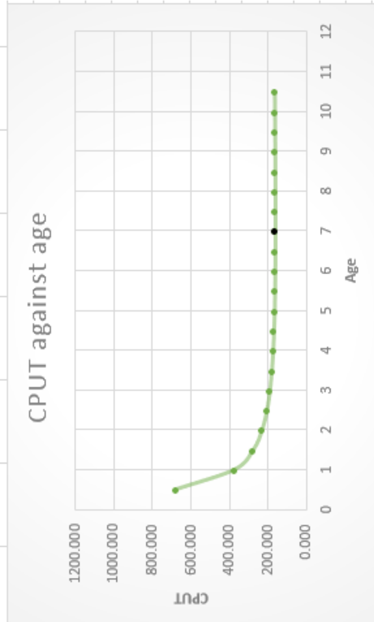

Figure B.3: Calculations for the replacement age

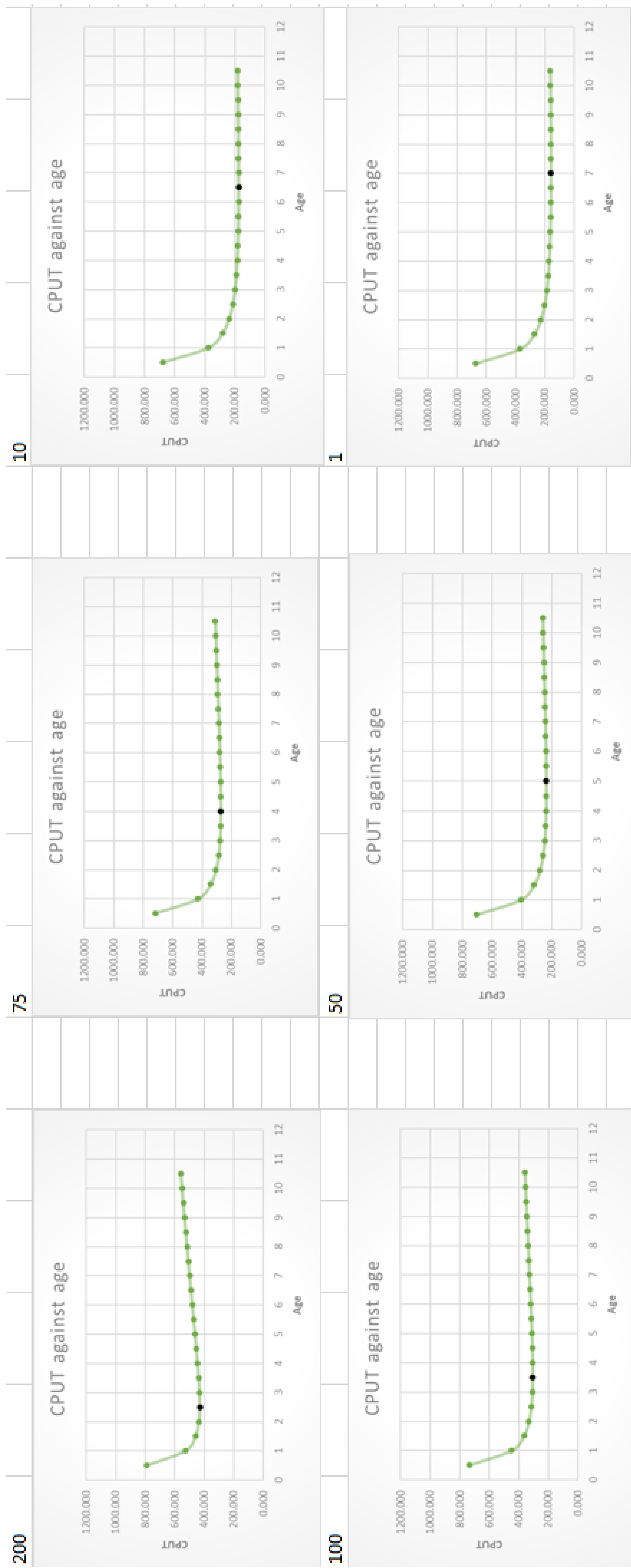

Figure B.4: Different graphs for varying downtime costs