MASTER

Selecting suitable components for multi-component heterogeneous systems
A case study on Lely's Collector

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Abstract

Lely is currently performing maintenance according to a corrective and preventive maintenance approach. However, Lely is changing its strategy to being a strategic business partner for dairy farmers. Therefore, Lely is changing its maintenance approach to a more proactive approach, where the emphasis of this research is focusing on the introduction of predictive maintenance (PdM). This research report considers an approach to select and rank suitable components for predictive maintenance (PdM), validated by a case study on Lely's Collector. The criticality of the components is determined by evaluating their importance with respect to the system based on the criteria downtime, costs, and output performance. These criteria rankings are combined and assessed by a multi-criteria decision-making approach. The component's accuracy is determined to understand whether PdM is more interesting than the currently used maintenance approach based on cost. Finally, the Collector tests the approach, where the components are selected and ranked based on the criteria downtime, costs, and output performance. The results show that for the Collector, eight components could be interesting for PdM, of which seven components are recommended to implement based on the accuracy.

Executive Summary

This thesis results from the internship at Lely for the master Operations Management and Logistics at the Eindhoven University of Technology. In this project, different methodologies are considered to identify and rank the components suitable for PdM, and the selected approaches are validated in a case study on the Collector. The outcome of this master thesis is an approach that could assess whether specific components are interesting for PdM for all the systems of Lely.

Introduction

Lely is traditionally an original equipment manufacturer for good functioning products. However, Lely is currently changing its strategy with the so-called "Route-25", which affects the entire organization. The maintenance department (TSS) is currently working according to a corrective and preventive maintenance approach, which needs to change to a more proactive maintenance approach. Lely aims to reach 100% uptime for all the systems. To reach this aim, changes have to be introduced in the maintenance approach. This research is, therefore, focusing on the start of the implementation of predictive maintenance. Predictive maintenance (PdM) can increase the uptime of the components by predicting a maintenance action just before the system or component would fail. Lely wants to consider PdM for its multi-component systems. Therefore, this research aims to define an approach that can identify and rank the interesting components for PdM and define the required accuracy bounds for these interesting components. This research aims to answers the following main question:

How to assess and rank the suitability of components for predictive maintenance within a multi-component heterogeneous system?

Research and main findings

The development of the identification and ranking of components interesting for PdM is divided into several research questions. The first step is to identify the components that are interesting for PdM. The literature review showed that the funnel approach of Tiddens et al. (2018) is most suitable to identify the possible candidates for PdM. However, some adjustments have been made in order to comply with research-specific differences. First, the criticality classification, where the authors select components by their number of failures and downtime of their failure mode. This research considers the selection of the failure frequency and cost of downtime of the components as described by Labib (1998). Second, the showstopper classification, where the authors use clustering and technical, organizational, and economical feasibility. However, this research focuses only on the technical feasibility and failure occurrence of the components. Last, the focused feasibility, where the authors use a detailed economical and technical study, where this research uses the same and focuses with the economical study on the influence on the total system maintenance costs.

The next step is to determine the criticality of the components that have been identified for PdM because the implementation of PdM involves high costs. For Lely, the criteria are downtime, costs, and output performance. Importance measures per criteria have been used to define the criticality of components with respect to a system performance indicator. First, the availability importance measure, where the approach of Barabady and Kumar (2007) is used. This importance measure defines the effect of the availability of one component with respect to the system's availability. Next, the cost importance measure, where the approach of Si et al. (2012a) is used. This importance determines the influence of one component on the system maintenance costs, where components with the highest influence on these costs are determined as most important for PdM. Last, the output performance importance measure, where the approach of Si et al. (2012b) is used. This importance measure ranks the components based on their contribution to the loss of system performance, where the component with the highest system loss is the most important for PdM.

As Lely wants to consider one ranking of components, a trade-off between the criteria has been used. The trade-off is considered with a multi-criteria decision-maker approach. The literature review conducted shows that the adjusted permutation method of Karimi and Rezaeinia (2011) is most suitable for the case of Lely. This approach proposes a rate per permutation and chooses the permutation with the highest rate as the preferable permutation.

Finally, component prediction accuracy is analyzed, as Lely wants to know what prediction accuracy for PdM per component is needed to outperform the current maintenance approach in terms of cycle cost. The approach of Mckone and Weiss (2002) has been used to determine the average cycle cost for both predictive maintenance and failure-based maintenance, which are compared with each other to see if predictive maintenance is performing better.

The approaches have been applied in a case study on the Collector. The results show that PdM is interesting for eight components of the Collector. From these components, component C has the highest influence on the availability and output performance, while component B has the highest influence on costs. A sensitivity analysis on the adjusted permutation method has been performed to understand the influence of different weight distributions on the permutations of components. These results show that component B and component C must first be considered when implementing PdM. However, it is shown that seven components are interesting to implement based on the average cycle cost of the eight selected components. Component A is not considered interesting since the current maintenance approach is less expensive on cycle cost than PdM.

Recommendations

From this research, several recommendations are formulated for Lely. The most important recommendations are highlighted below, where the complete list of recommendations can be found in Chapter 8.

Update FMEA and include the failure mode with failure data
In Section 3 the components could have been selected based on the failure modes of the components. However, within Lely, the Collectors' latest FMEA version dating from 2012, which was in the design phase of the Collector. When this information was known, a more accurate selection of components could have been made that could be interesting for PdM. Therefore, we recommend that Lely update their FMEA periodically to understand the valuable knowledge of the systems failure behavior. We refer to Chapters 2 and 3 of the PhD thesis of Braaksma (2012) for creating an FMEA in asset maintenance.

Deep learning methodology
When one of the components will be implemented for PdM, it is recommended that the model used to predict the Remaining Useful Life (RUL) of the component will be based on a deep learning methodology. The paper of Zhang et al. (2019) has done a survey comparing the results of different papers of machine learning with deep learning prediction methodologies. This paper shows that for RUL estimations, the deep learning methodologies have higher accuracy than machine learning.

Include comparison preventive maintenance for comparison accuracy
In this research, the model only compares the FBM with the PdM methodology because the majority of components are currently maintained by FBM. However, it could be the case for other systems within Lely that a component currently maintained by a preventive maintenance approach could be improved to a predictive maintenance approach. Therefore, it would be interesting to investigate how preventive maintenance is performing in comparison with predictive maintenance.

Contents

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List of Symbols

$(1-\alpha_i)$	Prediction accuracy of component i
$\lambda^i_{m,0}$	Transition rate from state m to state 0 for component i
$\Psi(X)$	System structure function
a_j	System performance level of state j
A_s	Availability of the system s
a_{*j}	Alternative * for criteria j

A_i	Availability of component i
c^{S-USD}	Setup cost unscheduled down
$c^{technician}$	Commercial rate service technician per hour
c_0	System maintenance cost for state 0
c_i^{part}	Cost of component i
c_i^{PM}	Cost of replacement of component i of preventive maintenance
c_m	System maintenance cost for state m
C_{kl}	Concordance set between alternatives k and l
D_{kl}	Discordance set between alternatives k and l
f_i	Failure likelihood of component i
I_A^i	Availability importance of component i
$I_l^C(i)$	Cost importance measure for state l for component i
K_i	Expected maintenance cycle cost for component i
L_i	Expected maintenance cycle length for component i
p_i	Prediction precision factor of component i
P_{im}	Probability of component i being in state m
$Pr(\Psi(l_i, X) = j)$	Probability of system X being in state j and component i being in state l
R_i	Permutation rate of permutation i
$t_i^{replacement}$	Time needed to replace component i (hrs)

1 Introduction

This thesis results from the internship at Lely for the master Operations Management and Logistics at the Eindhoven University of Technology. This chapter aims to clarify the background information needed to formulate the current opportunity at Lely. Section 1.1 explains the terminology used in this thesis. Section 1.2 describes the background of the company. Section 1.3 gives context of the project. Section 1.4 explains the problem description of the current problem. Section 1.5 gives an explanation of the Collector. Finally, Section 1.6 gives an overview of how maintenance is current performed.

1.1 Explanation of terminology

This section explains the terminology used in this thesis and gives a basic overview of the topic. This section describes the explanation of the terminology of maintenance and importance measure.

The definition of maintenance management is given as the; *"set of activities required to keep physical assets in the desired operating condition or restore them to this condition"* (Pintelon and Parodi-herz, 2008, p. 22). This terminology is used by Arts (2017) to define the three primary sorts of maintenance strategies, namely, modificative maintenance, corrective breakdown maintenance, and preventive maintenance, as shown in Figure 1.1.

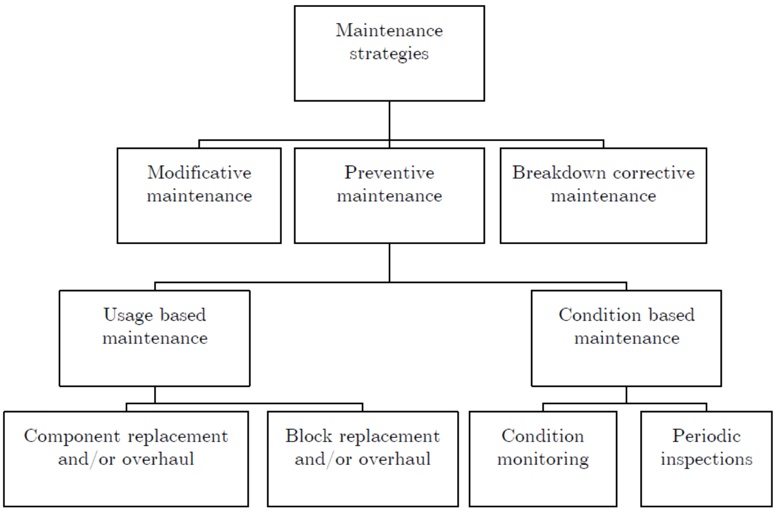


Figure 1.1: Maintenance strategies defined, from Arts (2017)

Figure 1.1 illustrates the different maintenance strategies indicated by Arts (2017). Under a modificative maintenance strategy, a maintenance action is performed to replace a components by a more technically advanced component to increase the system's performance. Under the breakdown corrective maintenance strategy, the components are replaced when they fail, while under the preventive maintenance strategy, the aim is to replace these components before failing. This preventive strategy is divided into usage-based maintenance (UBM) and condition-based maintenance (CBM), where for UBM, the usage of the component is measured, and maintenance is performed when certain thresholds are reached, while for CBM, the actual condition of the component is received and maintenance is based on that. CBM is divided into periodic inspections, where a mechanic measures the condition of the component, and condition monitoring, where the condition of components is continuously measured. Therefore, condition monitoring is also described as Predictive Maintenance (PdM). However, PdM goes further than CBM. The gap between CBM and Corrective Maintenance (CM) is bridged by PdM and enabled by Industry 4.0 (Lee et al., 2014a). Due to the Internet of Things (IoT), more data can be acquired from systems. PdM's value is created by using the collected data from intelligent systems that get transformed into predictions about the system's health, so maintenance intervals can be scheduled precisely when needed (Ton et al., 2020). Therefore, PdM is defined as the: "*regular monitoring of the actual component condition of the system's operating condition, with data required to ensure the maximum interval between repairs and minimize the cost of unscheduled downtime created by system failure.*" (Mobley, 2002, p. 4)

A multi-component system with complex components does need identification and selection of components that need more attention than other components regarding performance criteria such as system reliability, availability, productivity, security (Nguyen et al., 2014). The importance measure ranks these selected components in a system based on these criteria, where the components are arranged to increase or decrease importance. According to Rausand and Hoyland (2004), there are two dependent factors when using a measure to determine the component importance:

- "The location of the component in the system;"
- "The reliability of the component in question."

The outcome of the results of importance measure depends on the phase of the system's life cycle. System reliability can be improved whenever the importance measure is used in the system's design phase to identify strong and weak components. This identification of components helps design the system; for example, components can be placed in a different position to perform maintenance more efficiently. The importance measure can also be used in the operational phase by allocating inspection and maintenance resources to the most critical components.

1.2 Company background

Lely was founded in 1948 by Cornelis and Arij van der Lely in Maassluis, the Netherlands, where the head office with the executive board still is established. The foundation of Lely introduced was the finger wheel rake that helped farmers with collecting mowed grass. The international breakthrough for Lely came in 1968 with the development of a power harrow, the Lelyterra. Nowadays, Lely is mainly known for its dairy automation, with the first automated milking machine in 1992. Dairy farmers acknowledge this as the most important invention of the 20^{th} century. The fifth generation of this automated milking machine is currently on the market, called the Lely Astronaut A5. After the automated milking machine invention, Lely did develop more machines that released dairy farmers from long working days with the Lely MQC, Lely Discovery mobile barn cleaner, Lely Juno, and Lely T4C InHerd. In 2017 Lely decided to focus on dairy farms worldwide; therefore, Lely did sell the forage harvesting machines to AGCO Corporation.

Currently, Lely has two different production facilities, three research & development departments, where around 1600 employees are working. With customers over 45 countries, divided over 11 clusters, Lely did achieve a sales revenue of approximately €600 million in 2019 and 2020, with 6%, respectfully invested in R&D. Each cluster of Lely does have, mostly privately owned, Lely Centers that provide the sales and service for the customer. These Lely Centers do have their inventory of systems and spare parts and service engineers to maintain customers. Further, it can be said that Lely is very innovative due to its 1600 active patents.

1.3 Project context

This research is accomplished for the Technical Service Support (TSS) department of Lely. The TSS department focuses on all Lely's machines' operational maintenance and technical defects at the farms. Therefore, TSS operates with the mission: "We continuously capture and develop Service knowledge and solution to provide the best customer experience for Customer, Cow and Lely Service Staff, loyal to our service lowest cost of ownership strategy."

Lely is traditionally an original equipment manufacturer of a good functioning product, where technical service was taken care of by warranty, and products were repaired only if necessary. However, Lely has changed its strategy with the so-called "Route25", with goals that need to be reached in 2025. To reach these goals, Lely has created a road map that describes the relationship between company and customer with steps starting from a whole goods supplier towards a service provider, trusted advisor, to end as a strategic business partner. This thesis's focus is on the maintenance services of Lely, which is part of the service department. The maintenance strategy of Lely changes from corrective maintenance, preventive maintenance, predictive maintenance to end as a pro-active maintenance supplier. The service department's primary goal is to aim for 100% uptime of all Lely machines, with limited scheduled service visits and no unscheduled breakdowns. Previous research by Hoedemakers (2020) has focused on developing preventive maintenance concepts for new systems, which is the first step of this roadmap. Therefore, the next focus is on predictive maintenance. This project covers identifying the most interesting predictive maintenance components and will, with that, cover the first steps towards predictive maintenance.

1.4 Problem description

A new maintenance method will be used when altering being an advisor within the maintenance, namely predictive maintenance (PdM). PdM uses information that specifies components' deterioration, resulting in more energy consumption, vibrations, and eventually a machine's failure. Therefore, PdM focuses on failure prevention and efficient operation, hence improved downtime, maintenance staff satisfaction, product quality, and reliability. However, PdM can deliver such improvements when fully implemented, but first, it needs to be known which components can be used for PdM.

PdM's optimal setup is when a combination of sensors, like, vibration sensors, infrared sensors, and ultrasonic sensors, can predict all system components. However, as Olde Keizer et al. (2017) explains, implementation within the industry of CBM is lagging due to inter-component dependencies that affect the availability of the complete system. Besides the inter-component dependencies, other uncertainties for component selection like cost, downtime, measurability, and necessity depend on whether a component can be maintained according to PdM. The next sections describe each of the uncertainties.

Costs
When applying PdM for maintenance of components, it needs to be confident that it is worth replacing based on the cost. Whenever a component is less expensive, it is uninteresting to replace this component according to the PdM setup. The associate cost to replace this component is more expensive than the component itself. However, a less expensive component can have an impact on other components. Therefore, the dependency of components needs to be known for the evaluation of the cost per component. When a component has little to no dependency, replacing it in an age-based or preventive maintenance manner is better. However, when a component has many dependencies is more critical to predict the degradation so that on-time maintenance can be performed.

Downtime
The second uncertainty is the downtime of the machine. Downtime is measured when the machine cannot run due to a system's failure, split into planned downtime (scheduled maintenance) and unplanned downtime (unplanned breakdowns). Downtime can also be measured with the time that the machine is available, which is called availability. Lely has different customers whom all have a different preference for repairing the machine when having a machine failure due to the machines' capacity at every farm. However, unplanned breakdowns are in all circumstances for the product image, as the company image is vexatious. Therefore, unplanned breakdowns need to be reduced as much as possible for all farmers to create the lowest possible downtime. The unplanned downtime can be minimized when PdM defines the components that cause these down-times.

Measurability & Necessity
The third uncertainty is the measurability and necessity of measuring each component. A system consists out of a set of heterogeneous components that have all their dependencies and measurements. With a lot of intelligent sensors currently, a wide variety of measurements can be done. Sensors can measure certain variables, for example, energy usage, vibration, or heat of a component. However, the measurements of all different sensors are not applicable for all components. Besides, it also needs to be considered that there is no necessity to measure components. For example, there is no necessity to measure a car's windshield's vibration because a little stone can hit the windshield at any random moment. Therefore, the model needs to consider why components fail and if it is possible to detect a component's failure. This information is needed to create the best selection of components that can be used for PdM.

Lely has defined three criteria in which the components need to meet for PdM: costs, downtime, and output performance. Eventually, the model needs to consider the multi-criteria and uncertainties to develop a ranking of components for the systems of Lely. To obtain a correct way of choosing PdM's suitable components, a model that assesses the criticality of predictive maintenance components needs to be proposed. Therefore, the first step that needs to be taken towards PdM is choosing which components have the most significant impact on PdM strategy based on the criteria of Lely.

A possible option to find useful components for PdM maintenance is to assess and rank the components. Importance measure is a useful tool for ranking and assessing components. The importance measure ranks the components that need more attention than other components to performance criteria. An example of the importance measure is Birnbaum's measure, which is used in various researches (Nguyen et al., 2014; Vu et al., 2016). Another useful model could be the Failure Mode Effect Cause Analysis (FMECA). The FMECA is a qualitative way of receiving information about components during sessions with experts within the company. According to Tiddens et al. (2018), the best option for finding components that can be used for PdM is combining the FMECA with the four-quadrant. The four-quadrant is based on the work of Labib (2004), Lee et al. (2009), and Tinga et al. (2017) which helps find the most promising components, namely the components that with a low frequency of failure and a high associated failure consequence.

The useful components according to the methods need to be checked with reality for the suitability of PdM. Suitability is seen in this research as if components fit the criteria that are set by Lely. The reality check can be done with decision rules set together by employees and professionals and could differ per system. The decision rule prevents that components are chosen while immeasurable or have no necessity to be measured.

Eventually, the model will be validated on Lely's machines to consider if the theory also works in practice. The machine used is the Lely Discovery Collector 120, which will be explained in more detail in the next paragraph.

1.5 Lely Discovery Collector 120

The Lely Discovery Collector 120 (now called Collector), as visualized in Figure 1.2, is an autonomous driving manure collector. It is used to collect the cows' manure and is useful for barns with a closed floor. The Collector has been introduced to the market in 2016 and is still a relatively new product. There are currently around 2000 active in the field, making the Collector a suitable machine for the model's validation process.

Figure 1.2: The Lely Discovery Collector 120

Before the Collector, the farmers had to manually clean the manure in the barns, which is very time-consuming, or with a scraper system used periodically and is pulled along the barn with a rope or chain connected to a motor. The scraper system's first disadvantage is that the scraper's chain and corner pulley are obstacles in the barn. Second, the waiting areas are not cleaned with such a system. Last, each time the scraper passes, cows can be in front of the crossbar, and the cows are up to their hooves in manure.

The Collector works as follows; it starts every route from the charging station with a programmed route and schedule. The Collector first drives towards the water station to fill the two water bladders in the manure tank whenever the water-spray system is enabled. Once filled, the Collector follows the programmed route. The Collector uses two ultrasonic sensors, a gyroscope, and advanced software that ensure reliable navigation through the barn at all times. During cleaning, the cows can move easily around the Collector, where the Collector also drives underneath separation gates. When collecting, the front is spraying water that dissolves the slippery layer, which helps clean the floor more thoroughly. The vacuum pump within the Collector sucks the manure from the floor. At the back, a nozzle sprays to keep the floor wet and less slippery, preventing manure's rapid adhesion. When the manure tank is full, the Collector drives to a dump station, where an aeration valve opens that releases the vacuum in the manure tank. After dumping the manure, the aeration valve closes, and the vacuum and water pump are turned on again to continue the route. The Collector drives back to the charging station when the route ends, waiting for the next scheduled route.

1.6 Current practice

Lely is currently not using any predictive maintenance methods. Since Lely only started using preventive maintenance for the Collector in the last years, the opportunity of prioritizing has not been introduced yet. Therefore, Lely is not using any theoretical models or principles and bases its importance on service engineers' and TSS employees' experience and gut feeling.

Before a system is running in the field, it should be determined which components have priority. Depending on the system's output, elements such as the point of breakdown of the system need to be known to determine the optimal maintenance policy. With data from the suppliers of the components, calculations can be made on each component's lifespan. In the best case, this is known for every component, and the optimal cycle for maintenance could be made. However, when developing new components, the life span prediction could differ from the reality when the system is working in the field.

Currently, the Collector is maintained by preventive/corrective maintenance. The components that are maintained by preventive maintenance get calculated by the degradation level of each component. A version of the Weibull distribution calculates the degradation level. According to the wear-out failure, the Weibull distribution determines a component-specific optimum replacement/repair interval. The received information from the supplier generates the parameters for the analysis. This technique is used in the paper of Mazhar et al. (2007). However, Lely does not have these calculations for all the components; therefore, engineers adjust the intervals of replacing/repairing components after implementing the service data. With the engineers' and suppliers' data, it is still unknown which maintenance interval needs to be scheduled for some of the components.

Lely is using three different intervals for the preventive maintenance of the Collector at this moment. This sequence (A-B-A-B-C) repeats during the lifetime of the product. The time is set on half-year visits (A), yearly visits (B), and two-and-half-year visits (C). The sequence is based on the products with a high degradation (e.g., scraper and tires), which need to be visited more often. It can occur that between these preventive visits, a corrective maintenance action needs to be performed.

2 Research Design

2.1 Project scope

The scope is set to deal with the complexity of the problem within the amount of available time. This research is part of Lely's steps towards pro-active maintenance in 2025; this research focuses on determining and ranking the suitability of components for predictive maintenance.

This research will not create a prediction methodology to predict a failure of Lely's components because this will be researched in the following projects within Lely. Also, choosing the measurement instruments and models needed to measure the degradation of components is left out of scope because this will be selected by Product Development.

The model should be applicable to all of Lely's systems, where a case study is performed on all versions of the Collector. The Collector received some updates after the first moment it had been implemented in 2016. The model should focus on all versions of the Collector, and therefore be applicable for all Collectors currently active in the field. Besides, the Collector is used in various countries, each with its requirements per farmer. Therefore, the model should make no geographical distinction and be flexible in dealing with the farmers' requirements.

This research will not focus on the sub-components because they are seen as part of an overall component. Automated guided vehicles (AGV) are typically complex systems containing a large number of components. A part of these components is a sub-component for an overall component, like resistors and transistors of a printed circuit board (PCB). However, for this example, the PCB is seen as a component that will be evaluated as interesting for PdM.

This research will focus on creating a model that assesses and ranks the suitability of the components for predictive maintenance. Besides, the bounds for the prediction accuracy will be analyzed to create an overview of when predictive maintenance is more suitable than the currently used maintenance strategy per component.

2.2 Research question & approach

This project's main research question is based on the problem description, current practice, and scope.

How to assess and rank the suitability of components for predictive maintenance within a multi-component heterogeneous system?

To answer the main research question, a set of research questions need to be defined. For each sub-question, the used methodology will be described to clarify the possibility of answering each question.

1. **How to select the components suitable for predictive maintenance?**

The first thing that needs to be considered is which components of a system are suitable for PdM. Applying PdM requires additional costs for investments of machines like sensors, gateways, or servers. Besides, PdM can only be implemented when the data is in an acceptable form. Therefore, a literature review needs to be performed to find a model selecting suitable candidates for PdM.

2. **How to develop a method that assesses the criticality of components for predictive maintenance based on Lely's criteria?**

When research question one has been answered and the most appropriate method to select suitable components for predictive maintenance has been found, the next step to be considered is assessing components' criticality. Criticality is the extent to which a component affects a system and will be assessed on the three criteria Lely uses, namely, cost, downtime, and output performance. The model for criticality is needed to consider the rank of components that have more influence in the total system, which helps find the most important components for predictive maintenance. The costs are identified as maintenance costs incurred during repair, and the downtime is identified as the time that the machine is not working. The output performance can be identified in two ways; (1) quantitatively (e.g., lower milking capacity), or (2) qualitatively (e.g., milking a poor milk quality). A literature review will be performed to find methods that assess the criticality of components for these criteria and find a method that defines dependencies between components. This literature review aims to find methods that assess the criticality of the criteria of Lely.

3. **What approach can be used or developed to combine the assessment of criticalities to get a trade-off between the criteria?**

When research question two has been answered, the model for the criticality of components based on the criteria is formulated, which brings it to the next step of creating a method that combines the three criteria. Components can have a different influence on costs than downtime or output performance; therefore, a trade-off method needs to be considered, combining the criteria and creating one overview for Lely of the essential components for predictive maintenance. The literature will help to find a method that can create a trade-off. However, when no method can be found, an own heuristic needs to be developed, allowing for a trade-off between the criteria.

4. **How to determine the prediction accuracy's bounds per suitable component such that predictive maintenance gains more advantages than the current maintenance strategy based on Lely's criteria?**

    - How to evaluate the implication of accuracy based on predictive maintenance?

When research question three has been answered, a method has been selected to determine the trade-off of Lely's criteria. This research question will determine if PdM is a better maintenance approach than the current maintenance approach. Lely wants to understand the bounds necessary for the prediction accuracy of PdM to compare them on costs with the currently used maintenance approach. These bounds help Product Development by showing the accuracy needed to define a prediction lifetime model for components. To understand how accuracy relates to predictive maintenance, a literature review needs to be performed. Subsequently, the current maintenance strategies of the suitable components for predictive maintenance need to be evaluated based on the criteria of Lely, which is done by calculations of models that need to be found in the literature and performed by previous studies of Hoedemakers (2020). Eventually, a comparison will be made, and the choice is made if predictive maintenance is the best choice for each suitable component.

5. **What components of the Collector are suitable for predictive maintenance?**

Eventually, when all four questions have been answered, the methodology to find the most suitable predictive maintenance components is created. The next step is a case study on the Collector to evaluate the methodologies. The model will be used to identify the components that are suitable for predictive maintenance. Further, a ranking of the most suitable components based on Lely's criteria will be made for the Collector. Eventually, each component's determination will be made on the accuracy bounds when predictive maintenance is more suitable than the current maintenance strategy.

2.3 Project aim and deliverables

This project aims to deliver a model that assesses and ranks the suitability of components on predictive maintenance and find the prediction accuracy bounds for predictive maintenance. Different deliverables are generated for Lely in order to reach the aim.

1. Methodology to select suitable components for predictive maintenance;
2. Methodologies to assesses the importance of components with respect to the criteria downtime, costs, and output performance;
3. Methodology to determine the prediction accuracy bounds per component of predictive maintenance compared on costs to the currently used maintenance approach.
4. Validation of the methodologies on identifying and ranking components for predictive maintenance on the Collector.

2.4 Methodology

This section describes the methodology that is considered for this research. Figure 2.1 provides a general overview of the layout of the thesis, where the Research Question (RQ) and methodologies are considered.

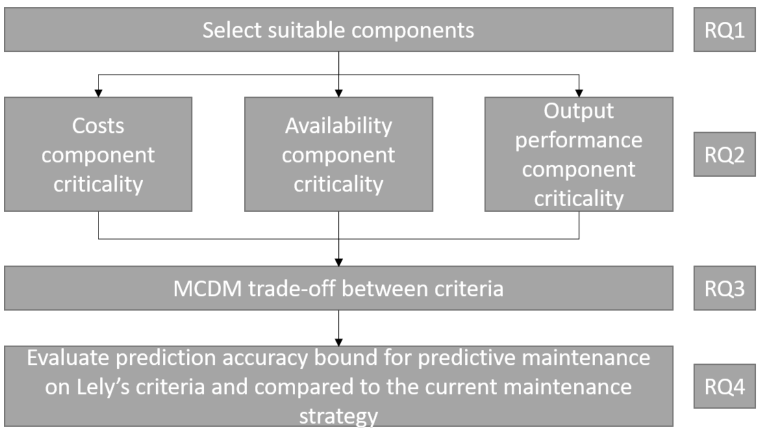


Figure 2.1: Thesis Layout Research Lely

Selecting suitable components for predictive maintenance
The first step in this research is to define suitable components for predictive maintenance (PdM). Approaches of Pham et al. (2012), Lee et al. (2014b), and Tiddens et al. (2018) can be used to define the components suitable for PdM. These approaches define the candidates

for PdM based on a set of indicators. However, these approaches do not include the criticality for components, which is required from Lely. Therefore, this approach is a good step in selecting components interesting for PdM, but other approaches are necessary to define the criticality per criteria for the components.

Component criticallity per criteria
This research will develop an approach to assess the criticality of the components. The criteria set by Lely are downtime, costs, and output performance. Therefore, for each criterion, an approach will be evaluated. In multi-component heterogeneous systems, it is necessary to identify the components that have a higher influence on performance criteria, such as availability, costs, and output performance. The importance of these highly influential components can be identified by importance measures (Nguyen et al., 2014). The availability importance can be determined by the approaches of Barabady and Kumar (2007) and Gravette and Barker (2015). The approaches of Si et al. (2012a), Dui et al. (2017b), or Do and Bérenguer (2020) can be used to determine the cost importance. Besides, the approaches of Si et al. (2012b) and Chen and Zhu (2019) can be used to determine the output performance importance. This output results in three different importances for the criteria of Lely. However, this research aims to provide one overall importance of components. Therefore, an approach for the trade-off between criteria needs to be provided.

Multi-criteria trade-off
The multi-criteria trade-off needs to be provided for the importance of the criteria downtime, costs, and output performance. A multi-criteria decision-maker (MCDM) can be used, which is described in the book of Triantaphyllou (2000). Depending on the data set that will be used, the most suitable MCDM will be chosen. Examples of trade-off MCDM methods are the permutation method, Elimination by aspects, TOPSIS, or ELECTRE.

Prediction accuracy bounds for predictive maintenance
When predicting the maintenance of components, there is a need to avoid too many false negatives because they could lead to high maintenance costs. Therefore, the costs for predictive maintenance need to be calculated to consider whether PdM is better than the currently used maintenance approach. However, to calculate the cost for the PdM approach, prediction accuracy has to be considered. The approach of Mckone and Weiss (2002) is one of the approaches that can be used to evaluate the prediction accuracy with PdM approaches. When evaluating the cost of PdM and comparing them with other maintenance approaches, an overview of components that are more interesting for PdM should be conducted to review the currently used maintenance approach per component.

2.5 Thesis outline

This thesis is structured as follows. Chapter 3 selects and defines the approach used to determine the suitable components for PdM, followed by the explanation of the models that ranks the components based on the criteria of Lely, which is described in Chapter 4. After ranking the importance of the criteria, the multi-criteria decision model has been explained in Chapter 5. A model is determined to assess the accuracy and prediction of the components, which is explained in Chapter 6. Eventually, the model is applied in a case study on the Collector in Chapter 7. The thesis ends with a conclusion and recommendations in Chapter 8.

3 Feasible component selection

Lely is currently in a strategy change, where they are moving towards being a strategic business partner for dairy farmers in 2025. This change concerns all the departments of Lely, where the change for the maintenance department is focusing on changing towards a proactive maintenance partner. However, the current next strategic step for the maintenance department is to look at whether PdM can be implemented for the systems of Lely. As Lely's systems are all multi-component systems, knowing which components have the highest potential for PdM is preferred. Therefore, Lely first wants to understand how components are selected for PdM. Therefore, this chapter selects and explains the methodology used to answer the first Research Question.

1. How to select the components feasible for predictive maintenance?

This chapter is structured as follows. Section 3.1 examines the literature regarding the methodologies and approaches for the selection of components for PdM. In this section, it is discussed why the funnel approach by Tiddens et al. (2018) has been selected for further analysis. Section 3.2 describes how the model of Tiddens et al. (2018) could be applied in the Lely's case.

3.1 Related Literature

The identifications of components for PdM should be assessed using a set of indicators that identify which components are most suitable for PdM. (i.e., candidates). Component suitability is related to whether or not a component can be implemented for PdM. Electronic component failure, for example, occurs mainly at random, making it very difficult to anticipate, which means that such components can not be predicted, so not suitable for PdM. Table 3.1 shows the indicator used to identify candidates that are suitable for PdM.

Pham et al. (2012) & Lybeck et al. (2011) concentrate on a wide range of indicators that determine PdM candidates. First, the timeline requirements are examined, after which the contenders are evaluated to see if they satisfy actual monitoring capabilities. Second, the operation compatibility is verified, in which the authors determine whether or not the sensors will provide an unacceptable risk to other components. Third, the model requires adequate data to provide a visualization of component transformation for PdM. Finally, the authors investigate whether the component data may be used for deterioration mechanisms and mathematical models. The side effect of this paper is that the evaluation of this model depends on maintenance personnel's expertise. Besides, the paper does not employ any scales, which aids in selecting suitable candidates for PdM. Therefore, this paper is useful for understanding why a candidate should be chosen but does not provide insight into the selection of these candidates.

Lee et al. (2014b) use two distinct models to identify PdM candidates. These two models are referred to as model "1" and model "2" for clarity. Model "1" employs a critical component identification, in which components are shown in a graph based on their most significant influence on the system's performance and/or the cost of downtime. Figure 3.1 depicts an example of this graph. The components with a high cost of downtime and low failure frequency are determined as candidates for PdM because their failures are infrequent and cause the most cost of downtime per occurrence. Model "2" chooses candidates for

Table 3.1: Predictive Maintenance Selection Indicators

Selection Indicators	**Tiddens et al. (2018)**	**Pham et al. (2012)**	**Lybeck et al. (2011)**	**Lee et al. (2014b)**	**Scarf (2007)**	**Labib (1998)**
Timeline requirements	*	*	*			
Operational compatibility with other components		*	*			
Operational data/ downtime	*	*	*	*	*	*
Reliable failure data	*	*	*	*	*	*
Physics-based failure models		*	*			
System complexity				*		
System uncertainty				*		
Technical Feasibility	*					
Economical data	*			*	*	*
Organizational feasibility	*					

PdM using a so-called transformation map, which considers various maintenance strategies with corresponding system complexity and uncertainty. When there is static uncertainty and intrusive complexity, the candidates fulfill the PdM criteria. This model, on the other hand, focuses on the selection of systems rather than components. Therefore, model "2" is more challenging to apply at the component level.

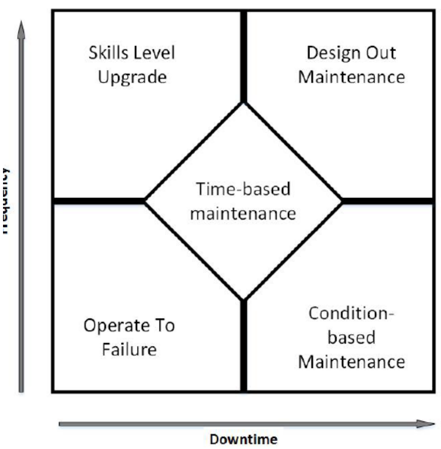


Figure 3.1: Classification diagram by Scarf (2007)

In Scarf (2007), the authors utilize the classification diagram depicted in Figure 3.1. The author defines the suitable components based on their failure modes, where suitable component failure modes for PdM can be found in the bottom right part of this figure because PdM is part of condition-based maintenance. The approaches of Lee et al. (2009) and Labib

(1998) uses the same classification diagram. However, it considers the selection based on components themselves instead of failure modes of components. To implement the model of Scarf (2007), data about the failure modes of components need to be available. Otherwise, the model of Labib (1998) & Lee et al. (2014b) need to be evaluated, together with the corresponding failure frequency and cost parameter of the components.

Tiddens et al. (2018) uses a three-stage funnel approach to identify PdM candidates. This model, shown in Figure 3.2, uses a criticality classification, showstopper identification, and focuses feasibility. The goal of this technique is to minimize the number of prospective candidates at each step. First, the paper uses the model of Scarf (2007) to identify candidates who may be of interest for PdM. Second, the identification of the showstoppers evaluates the probable candidates from the previous stage and determines if they are a showstopper in terms of time consumption, technical feasibility, economic feasibility, and organizational feasibility. The outcome of these showstoppers is "Yes" (it is a showstopper), "No", or "Maybe". Candidates that are considered as a showstopper will be eliminated. Finally, the candidates labeled "Maybe" are subjected to a technical and economic feasibility analysis to confirm that they are candidates focusing on PdM. Although the article is highly detailed in selecting candidates for PdM, the overall model utilization may not be feasible for every organization. Therefore, it is conceivable that modifications need to be made while implementing this model.

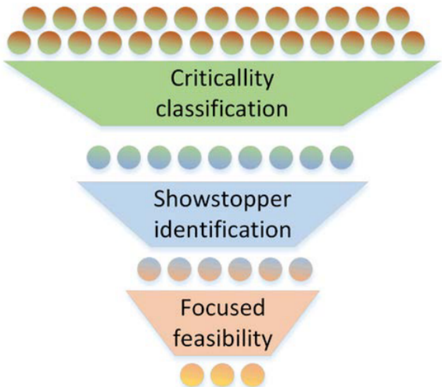


Figure 3.2: Three-stage funnel approach by Tiddens et al. (2018)

To summarize, the methodologies of Pham et al. (2012) & Lybeck et al. (2011) are unsuitable for PdM candidate selection since they do not employ a scale that indicates when components are feasible for PdM. Moreover, model "2" of Lee et al. (2014b) is not an appropriate approach for selecting feasible candidates for PdM because it is too system-level oriented. However, the methodology of Tiddens et al. (2018) could be used since it accurately constrains candidates through different stages, where in the first stage of the funnel approach, the methodology of Labib (1998), Scarf (2007), or model "1" of Lee et al. (2014b) can be used for component selection based on the case study. However, modifications might be made in the second and third stages of the funnel method, depending on the case study.

3.2 Adjusted Funnel Approach

The funnel approach by Tiddens et al. (2018) is used to select the most interesting candidates for PdM. However, certain adjustments are suggested to be made to fit the case of Lely. Table 3.2 shows the differences and similarities between the approach of Tiddens et al. (2018) and the approach used in this research. First, the criticality classification used is based on the approach of Labib (1998) & Lee et al. (2014b), instead of Scarf (2007), because the selection of components is based on failure frequency and cost of downtime. Second, the showstopper analysis will be evaluated on the technical feasibility and failure occurrence. Last, the cost feasibility of the focused feasibility stage will be based on the influence of the total cost of maintenance of all components and technical feasibility.

Table 3.2: Difference and similarities between Tiddens et al. (2018) and the approach used for Lely's case

	Tiddens et al. (2018)	**Approach for Lely's case**
Stage 1: Criticality Classification	- Based on component failure modes variables (Scarf, 2007) - Classification diagram based on failure frequency and downtime per failure mode	- Based on component variables (Labib, 1998; Lee et al., 2014b) - Classification diagram based on failure frequency and cost of downtime per component
Stage 2: Showstopper Identification	- Technical Feasibility - Organizational Feasibility - Economical Feasibility - Clustering	- Technical Feasibility - Failure Occurrence
Stage 3: Focused Feasibility	- Economical feasibility study - Technical feasibility study by Gouriveau et al. (2016)	- Cost based feasibility study - Technical feasibility study by Gouriveau et al. (2016)

Criticality classification

The first stage of the funnel approach of Tiddens et al. (2018) uses the classification diagram by Scarf (2007) that uses the downtime and failure frequency of failure modes to determine components suited for PdM. The authors define the most important components based on the failure modes from the Failure Mode Effect Criticality Analysis (FMECA) with corresponding Risk Priority Number (RPN). The RPN consists of a multiplication of failure occurrence, failure severity, and failure detection possibility. Tinga et al. (2017) state that per failure, this RPN needs to be calculated, where a range of RPN needs to be selected that will be used for further research. However, within Lely, the FMECA is outdated, and no data is available on the failure frequency of a specific failure mode. Therefore, it is assumed that all components have one failure mode to consider. The first difference, as Table 3.2 indicates, focuses on the difference for the input of the classification diagram with the focus on component variables, where Tiddens et al. (2018) uses the failure modes of the different components.

The second adjustment in the criticality classification also focuses on the classification diagram. As Table 3.2 indicates, is Tiddens et al. (2018) focusing on the failure frequency and downtime per candidate. However, the approach for Lely's case will focus on the failure frequency and cost of downtime. Therefore, the x-axis of Figure 3.1 is changed to cost of downtime. These costs in this research are considered as the total cost of maintenance, calculated as:

$$c_i^{PM} = c_i^{part} + t_i^{replacement} \times c^{technician} \tag{3.1}$$

$$c_i^{CM} = c^{S-USD} + c_i^{PM} \tag{3.2}$$

These calculations are the same as in the MSc thesis of Hoedemakers (2020), where the assumption is made that the cost of PM is the cost of a Scheduled Down (S-SD), and the cost of CM c^{S-USD} are the cost of an Unscheduled Down (S-USD). The cost of an unscheduled down consists out of the driving time of the mechanic and a farmers' intake. In addition, the c_i^{part} is the cost of component i, $t_i^{replacement}$ is the time needed, in hours, to repair a component, and $c^{technician}$ is the commercial rate for a technician per hour. The commercial rate is used because the research aims to create an advantage of PdM for the farmers.

The above information has been used to complete the classification diagram. The pre-selection of components that are suitable for PdM must apply with high maintenance cost/-downtime and low failure frequency, as shown in Figure 3.1. For component selection, the choice is made to select the components according to the Pareto analysis because the 80-20 characteristics of the Pareto match the high maintenance costs and low failure frequency. Besides, the Pareto-analysis have also been used in the papers of Labib (1998), Labib (2004), and Scarf (2007). Therefore, the rule is that the components with at least 80% of the total maintenance cost per year are used as pre-selection of components, starting from those with the highest cost. Secondly, the rule is made for the failure frequency that the components responsible for 20% of the total failures per year are considered interesting for this research, starting with the component with the lowest failures. Eventually, a component that meets both requirements is further used for the second stage.

Showstopper analysis
The adjusted approach uses a small part of all the showstopper outlined in the paper of Tiddens et al. (2018), as indicated by Table 3.2. Some showstoppers were not chosen because they did not yet fit into this part of the study for Lely. First, the clustering showstopper of the authors, where they consider if maintenance can be performed between missions of a navy vessel. However, this showstopper did not fit Lely's case because the systems of Lely are always available for maintenance. Besides, economic clustering is not considered within this research. Second, the economic feasibility showstopper, where the authors consider sufficient financial resources for implementing PdM per component. Lely is considering this step in their strategic plan to move towards PdM. Therefore, it is assumed that enough financial resources are available when PdM is implemented for a component. Besides, this research is trying to identify the components that create the highest benefit on costs, which should help pay back the investment costs. Last, the organizational feasibility showstoppers. This showstopper has been excluded because it has been assumed that Lely has enough experienced and trained personnel who can deal with PdM changes. The authors' technical feasibility showstoppers will be used for the selection of feasible components. These results are examined so that when the failure of components can not be detected by existing or additional research, the component is identified as a showstopper, denoted by the letter "Y" (Yes). When a component's failures can be detected using existing or additional research, the component is labeled as a no-showstopper, denoted by the letter "N" (No). When it is uncertain if a components' failure can be detected, the letter "M" (Maybe) indicates this. The components indicated by "M" require additional technical feasibility research performed in the focused feasibility phase.

One showstopper has been added, which has not been used by Tiddens et al. (2018), to determine whether a component is feasible for PdM, called the failure occurrence showstopper. This showstopper has been introduced for the newer systems of Lely that have not reached their expected lifetime because they could have components that have not failed yet. Some of these components may be associated with high maintenance costs and downtime, which would make this component interesting for PdM. Therefore, the expected lifetime of the components has been checked with the expected lifetime of the system. When the expected lifetime of a component exceeds the system's lifetime, we assume that it is not necessary to select such a component for PdM because the likelihood of failing during the system's lifetime is too small. Therefore, this showstopper selects components based on their expected lifetime, also known as the Mean Time to Failure (MTTF), which will be assessed as 'Yes' the MTTF $>$ system lifetime, 'No' the MTTF $<$ system lifetime, and 'Maybe' the MTTF $\approx$ system lifetime. When the likelihood of a failure is identified as Maybe, the additional cost analysis must be performed in the last phase.

Focused Feasibility

The final stage of this adjusted approach is the focused feasibility as indicated by Table 3.2. The candidates for PdM identified with 'Maybe' will be examined in more detail for technical and cost feasibility requirements. First, when components for technical feasibility are determined as 'Maybe', the components are the same examined as the model by Tiddens et al. (2018). This approach focuses on studying the requirements defined by Gouriveau et al. (2016), which are based on the seven functional levels used in the Open System Architecture for CBM of Lebold et al. (2003). Last, the cost analysis, which should determine in more detail if the components identified 'Maybe' for failure occurrence, does a high enough influence on the total maintenance cost of the system. This analysis is required because components with a slightly higher expected lifetime than the system could still be interesting for PdM due to their influence on the system maintenance cost. Therefore, the cost of one component will be compared to the total maintenance cost of the system and checked whether the influence reaches at least 1% of the total maintenance cost of all components in the system.

3.3 Conclusion

The approach for Question 1 has been established in this chapter. The approach of Tiddens et al. (2018) is used to determine the feasible components. However, certain adjustments have been made to make this approach specific for Lely, which are indicated by Table 3.2. First, the criticality classification will be based on components and evaluated on failure frequency and cost of downtime characteristics, rather than the failure modes of components. Second, the showstoppers will be analyzed based on their technical feasibility and failure occurrence. Finally, a focused technical and cost feasibility analysis is performed, with the components identified as 'Maybe' for technical feasibility needing to be further analyzed on the requirements of Gouriveau et al. (2016). Besides, the cost feasibility should determine whether the 'Maybe' components, in terms of failure occurrence, significantly influence the total system maintenance cost.

4 Importance Measures

The implementation of the PdM approach might be considered with the suitable components selected with the methodology described in Chapter 3. However, the methodology of Tiddens et al. (2018) does not provide a criticality of the suitable components. Lely wants to consider this criticality because they want to understand which components have a higher influence on the system based on specific criteria. It is predetermined that Lely wants to consider the criticality of components on the criteria downtime, costs, and output performance. Therefore, it needs to be determined what influence a specific component has with respect to the system, which will be indicated with importance measures. The influence of one component is determined with respect to the system function, which can be modeled by a binary of multi-state structure-function. Therefore, this chapter first explains the methodology for the system structure function before answering the approaches used to answer Research Question 2:

2. How to develop a method that assesses the criticality components for predictive maintenance based on Lely's criteria?

This chapter is structured as follows. Section 4.1 defines the approach used to model the system function for the different criteria set by Lely. Section 4.2 first explains the related literature of availability importance measure and explains why Barabady and Kumar (2007) is used. Besides, this section determines how to evaluate the approach of Barabady and Kumar (2007). Section 4.3 explains why the approach of Si et al. (2012a) is used as a cost importance measure compared to other related literature and defines how the approach should be used. Section 4.4 explains why the approach of Si et al. (2012b) is used as output performance importance measure and defines how this approach should be used. Section 4.5 concludes this chapter.

4.1 System Function

A system can have two different mathematical representations. A binary state system structure function where components only considering two states (functioning or failed), or a multi-state system structure-function that allows multiple states to describe the system's behavior and its components (Kvassay et al., 2018). In this study, both representations are considered because each criterion may use a different system representation. Eventually, these system representations are used to evaluate the influence of the components with respect to the system. Besides, the system structure-function could help give insights into the components' reliability, availability, and probabilities.

The system representation will be conducted based on minimal paths and cuts for the components selected with the funnel approach discussed in Chapter 3. Figure 4.1 shows the representation of the minimal cut and paths, where for the components based on a minimal cut, all components need to fail in order to let the system fail, and for the components based on minimal paths, all components need to function in order to let the system function (Ebeling, 2004). Eventually, the Reliability Block Diagram will be used to create an overview of the representation of the system with minimal paths and cuts. The RBD uses a graphical representation of a system, such that it can be used for analyzing the probability of system failure. Components for the RBD are considered as blocks that are linked to the effect of the system (Čepin, 2011). Eventually, this RBD helps to evaluate the binary and multi-state system structure-function. To understand how these two system functions are models will be evaluated, this section explains each function used.

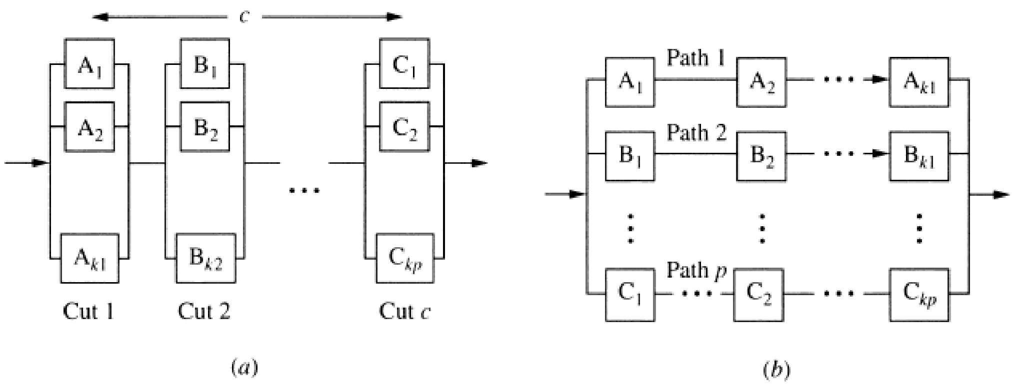


Figure 4.1: Example of system representations by minimal cuts in series (a) and minimal paths in parallel (b) by Ebeling (2004)

4.1.1 Binary System Structure

The structure of the binary system is determined on basis of two states (Ebeling, 2004). The system structure function is indicated as $\Psi(x_1, x_2, ..., x_n) = \Psi(X)$. Let n denote the set of chosen components that are interesting for PdM. The two states of the system function are defined as:

$$\Psi(X) = \begin{cases} 1, & \text{if system operates} \\ 0, & \text{if system has failed} \end{cases}$$

Besides, it is assumed that when the system is evaluated as binary, each component is also indicated binary, and operates by the same two states (operating or failing). The system's evaluation depends on the RBD composed of the minimal cuts and paths. However, Lely's systems consist of multiple components with various failure modes, where it is assumed that the RBD of these systems will consist of a combination of series and parallel components. Therefore, an evaluation of these structures system will be based on the combination of series and parallel structure. An example for such a calculation is given by Ebeling (2004), with minimal paths {A,B} and {C,D}:

$$\Psi(x_A, x_B, x_C, x_D) = [1 - (1 - x_A x_B)(1 - x_C x_D)] \tag{4.1}$$

The system has been modeled such that at least one of the two paths has to function.

4.1.2 Multi-state System Structure

The structure of a multi-state system is determined by more than two states within the system. The system consists out of $M > 2$ states, which are evaluated by components states. The evaluation of a multi-state system is defined as:

$$\Psi(X) \begin{cases} M, & \text{if system operates in perfect state} \\ M-1, & \text{if system operates in a working state} \\ ... & ... \\ 0, & \text{if system has failed} \end{cases}$$

This multi-state system structure function describes the correlation of the system performance level and its components state (Zaitseva and Levashenko, 2017). Hence, $\Psi(X)$ defines the system performance level, which variate between complete failure ($\Psi(X) = 0$) to a perfect state ($\Psi(X) = M$), where $X = (x_1, ..., x_n)$ is the state-vector of the n-th component that also changes from failure ($x_n = 0$) to perfect condition ($x_n = M$) (Kvassay et al., 2018). The evaluation of a multi-state system is an extension of Boolean algebra and uses the categorization of components and minimal paths and cuts of the system to determine parameters. The model used for this evaluation is the Multi-Valued Decision Diagram (MDD) composed by Zaitseva and Levashenko (2017) and is shown in Figure 4.2. This model analysis the properties of the structure-function, such as probabilities of being in a state, availability, and unavailability (Kvassay et al., 2018). Therefore, this model helps understand the properties of the multi-state system and generates outcomes that have to be used in the multi-state importance measures.

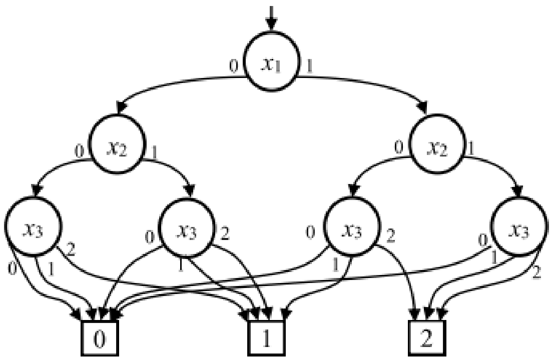


Figure 4.2: Multi-valued Decision Diagram by Kvassay et al. (2018)

4.2 Availability Importance

The first considered criterion is the downtime of the components. The availability has been used to indicate the downtime of components because these two variables are in a relationship. According to Barabady and Kumar (2007), the availability decreases with the components' age increase due to interactions between components, operating environments, and the maintenance policy implemented. When implementing PdM for systems, the components with the highest influence should be considered because these components could increase the system's availability most. Therefore, this section is structured that the related literature with the approaches for the importance of the availability is first determined in subsection 4.2.1, where it is explained why Barabady and Kumar (2007) is used. Subsection 4.2.2 describes the approach of Barabady and Kumar (2007) used for Lely.

4.2.1 Related Literature

According to Barabady and Kumar (2007), the most important performance metric for recoverable systems is component reliability and availability. Component reliability and availability decrease with the components' age increase, influenced by interactions between components, the operating environment, and the maintenance policies implemented. When the aim is to improve system availability, the question that should be answered is which components can best be deployed to increase the availability of a system. This improvement may be accomplished when implementing PdM for a component. Therefore, the components that have the most significant impact on system availability should be evaluated for PdM. These components are selected by implementing an availability importance measure at a system level.

Modeling a system and its components as multiple states is not the most significant factor for determining the availability importance. The availability only concerns whether or not a component is operational. Therefore, while assessing the importance of availability, the components and system will be evaluated as a binary system. This means that the emphasis in the availability measure literature is on binary methodologies rather than multi-state methodologies.

Barabady and Kumar (2007) developed an availability importance measure based on the same principle as the Birnbaum importance measure. The availability importance reveals a system's weak areas and can suggest changes to improve the system's availability. The availability importance measure of Barabady and Kumar (2007) assigns each component a value between 0 and 1, with 1 being the highest degree of relevance. The model implies that all components are repairable and that maintenance provides a good as a new component. Therefore, the system availability is modeled as a function of the failure ratio and the repair ratio, characterized by the Mean Time Between Failure (MTBF) and the Mean Time To Repair (MTTR).

The paper by Gravette and Barker (2015) uses the same availability-importance measure as Barabady and Kumar (2007). However, the paper uses a different method to describe the availability. This method is seen as a more "realistic" availability is called achieved availability, and is measured by the uptime, which is the mean time between maintenance (MTBM) and the mean maintenance time (M), called the achieved availability A_a.

This achieved availability A_a considers both CM and PM activities, with PM activities consisting only of system downtime. This methodology would be beneficial when all components in the system are considered. However, when components are pre-selected for PdM, as in Lely's case, this methodology is ineffective because components have already been identified as interesting for PdM by funnel approach of Tiddens et al. (2018). When considering PdM, the components should be maintained before actual failure. Therefore, the achieved availability of Gravette and Barker (2015) does suit the case of Lely less because the components with CM and PM activities are not considered. Therefore, in Lely's case, the systems' availability as measured by Barabady and Kumar (2007) is preferred to be used for computations. This means that the approach of Barabady and Kumar (2007) will be used for evaluation of the availability importance.

4.2.2 The Methodology

The model of Barabady and Kumar (2007) assumes the following:

1. A system is composed of n stochastically independent components.

2. Failure rate and repair rate of components need to be known.
3. All components are repairable, which makes them as goods as new.
4. The components and systems operate in two states: working or failed.

This availability importance for components is a function of time, the failure and repair rate characteristics, and system structure. Therefore, this importance measure considers the effect of component i on the availability of the whole system. Components with the highest value of this importance are considered as the components that have the most significant effect on the system's availability. As discussed in Section 4.1.1, the system structure function will be based on an RBD, which consists of a combination of components in series and parallel. This RBD will be used to calculate the system's availability, which is calculated as:

$$A_s = \prod_{k=1}^{n} \left(1 - \prod_{l=1}^{m} (1 - \frac{MTBF_{kl}}{MTBF_{kl} + MTTR_{kl}}) \right) \tag{4.2}$$

where n are the independent components in series, m are the components in parallel, and the fraction of $MTBF$ and $MTTR$ is the components-specific availability A_{kl}. This approach assumes that components are replaced by the renewal process where components are replaced randomly in time, which is indicated by a certain probability distribution with expected lifetime (MTBF), and repair times (MTTR). This means that the time between failures is independent and identically distributed. This input is used in the calculations of the availability importance measure, which is given as:

$$I_A^i = \frac{\partial A_s}{\partial A_i} = \prod_{\substack{k=1 \\ k \neq i}}^{n} \left(1 - \prod_{l=1}^{m} (1 - A_{kl}) \right) \times \left(1 - \prod_{\substack{l=1 \\ l \neq j}}^{m} A_{il} \right) \tag{4.3}$$

The importance of a component is calculated by the partial differentiation of component i, meaning that all other components determine the importance. Therefore, the importance of component i is indicated by ij, where i indicates the components in series and j in parallel. To improve the system's availability, effort needs to be focused on the components that will create a maximum improvement in system availability.

4.3 Cost Importance

The second considered criterion is the cost of the components. Maintenance expenses occur when components and systems fail. Therefore, it is necessary to understand how components in a system relate to the system maintenance costs. By addressing the components with the highest influence on these costs, a criticality can be made for components, which helps select the most interesting component for PdM. To determine the cost criticality, Section 4.3.1 describes the related literature and why Si et al. (2012a) is used. Section 4.3.2 explains the approach of Si et al. (2012a) used for Lely.

4.3.1 Related Literature

Importance measurements are used in reliability engineering to enhance reliability and maintenance planning by prioritizing components in a system for a cost-based purpose. Reliability engineering is concerned with the intervals when a component or system does or does not function. However, maintenance expenses arise when components and systems fail. Therefore, this section aims to examine how cost-based importance measures are addressed in the literature. This model identification will be utilized to address the case posed at Lely.

The first paper to describe a cost-importance measure is from Si et al. (2012a). The paper focuses on an importance measure that is determining the most important component considering maintenance processes. This importance measure is distinguished between the importance measure that determines the cost for the components that deteriorate the most, which is indicated by $I_{l,q}^{IIM}(i)$, and the cost importance of the state l of for component i based on the system performance cost, which is indicated by $I_l^C(i)$.

Another study by Dui et al. (2017b) identified a measure of the importance of cost, which considers the focus of maintenance time and cost. This paper identifies components or groups of components that could be selected for preventive maintenance (PM). The calculation used by this paper considers the change in system reliability during a repair, which is indicated by $I_i^{IIM,C}$.

According to this equation, the component with the lowest value for $I_i^{IIM,C}$ should be prioritized for preventive maintenance. Besides, this paper states that components interesting for PM must satisfy two conditions: minimizing the costs and maximizing the integrated importance measure. When performing this methodology for PdM components, these two conditions should also be considered. However, the degradation of the components should also be used since it assists in understanding when a component fails. The failure information can be used as a threshold to evaluate when it is advisable to replace the component with the associated costs. However, the methodology of Dui et al. (2017b) is not supporting this addition for PdM.

Another study by Do and Bérenguer (2020) proposes a new time-varying importance measure for a system with multiple non-repairable components, which exploits the possibility of improving system availability during a mission given the current conditions (states or degradation levels) of the system components. The study makes many assumptions to compute the importance measure, one of which is that all components are stochastically independent. In practice, components with no stochastic dependency are uncommon since components may degrade faster when another component fails. After all, the reliability of one component might be affected by the reliability of another.

This paper uses different cases to evaluate the reliability of the system and its components. These cases are based on the available data on the deterioration of the components. These evaluations of the components are used to calculate a reliability importance measure (RIM) within a time horizon $(t, t+u)$ of the system reliability with the consideration that at time t component i is replaced, given the current conditions of all other components in the system. The drawback of this paper is the assumptions made in modeling the system. This paper assumes that the system can only be defined as a binary system, where only two states are defined (failed or working). Moreover, the paper also assumes that all components are stochastically independent, meaning that the depreciation of other components is not affected when one component fails. However, practice shows that components can be interdependent.

In conclusion, the paper by Si et al. (2012b) is most suited to the situation at Lely. This paper can model the system and its components as binary and multi-state, whereas the model of Do and Bérenguer (2020) cannot. In addition, the methodology of Dui et al. (2017b) will not be used because the paper focuses too much on the importance measure for PM. Therefore, the descending list of most appropriate components of the methodology of Si et al. (2012b) is used for the case of Lely.

4.3.2 Methodology

The paper of Si et al. (2012a) assumes the following:

1. The system is a multi-state monotone coherent system.
2. The components and system have a state space of $\{0, 1, .., M\}$ with 0 the failure of the system, and M the perfect state, which is ordered from 0 to M.
3. The components and systems are stochastically independent.

PdM is a maintenance concept in which components are inspected, the results analyzed, and then a decision is taken for maintenance. Such a concept analyzes the component's states and is maintained when necessary. Replacing components to get to a better stage depends on the state of the system. When the system is in the failed state (state 0), it requires a setup for USD, with cost c^{S-USD}. It is assumed that all components that have failed at that moment can be replaced together in order to get the system to a better state, called positive economic dependency (Olde Keizer et al., 2017). This cost c_0 is defined as:

$$c_0 = \sum_{i \in K} \left(c_i^{part} * f_i + c^{S-USD} \right) \tag{4.4}$$

where c_i^{part} are the cost of component i, and f_i is the number of times the component is likely to fail in the lifetime of the system. The subset K is indicated for the components that need maintenance to get from state 0 to state 1. This subset needs to be based on the RBD because components in series have different influences on the system than components in parallel.

When improving a system from a state m towards the next state $m+1$ or perfect state M the cost of scheduled down (c^{S-SD}) are used for evaluation. Again, the assumption is made that components will be replaced simultaneously. Therefore, the cost for c_m is defined as:

$$c_m = \sum_{i \in J} (c_i^{part} * f_i) \tag{4.5}$$

where the subset J is used for the components that need maintenance when improving from state m to $m+1$, no cost for a scheduled down is considered because these components do not cause any system failure, and therefore, it is assumed that they could be replaced during regular maintenance schedules. However, these components need to be replaced because they decrease the performance of the system.

The cost corresponding to the perfect state M will be considered to be zero because, at that moment, no maintenance of components is necessary to improve the system.

The probability of a component being in a state is indicated by P_{im}, which depends on the distribution that is considered for the components. The probability that component i is in state m is

$$P_{im} = Pr\{X_i = m\}, m - 0, 1, 2, ..., M \tag{4.6}$$

The probability for the system being in state j when a component is in state m is indicated as $Pr(\Psi(l_i, X) = j)$, which will be calculated with the MDD explained in Section 4.1.2. This probability also depends on the distribution that will be considered for the components.

These component and system input parameters will be used to evaluate the cost importance of the components. An evaluation of a multi-state system will be considered, where the component can be modeled as binary or multi-state. The $I_l^C(i)$ model from Si et al. (2012a) is used, which represents the influence of state l of component i to the system's maintenance cost. This model is analyzed such that components with the highest value are considered most influential on the systems maintenance cost. This model is calculated by:

$$I_l^C(i) = \sum_{j=0}^{M-1} c_j P_{il} Pr(\Psi(l_i, X) = j) \tag{4.7}$$

4.4 Performance Importance

The third considered criterion is the output performance of the components. The output performance will be indicated by the quantitative performance loss, which describes the loss of system performance due to the failure of one or more components. This importance measure aims to determine the criticality of components that causing the most performance loss for the system. Therefore, Section 4.4.1 describes the related literature for output performance importance measures and describes why Si et al. (2012b) is used. Section 4.4.2 explains the approach of Si et al. (2012b) used for Lely.

4.4.1 Related Literature

A multi-component heterogeneous system may function on multiple performance levels, with the system's performance defined either qualitatively or quantitatively. Because a system has several performance levels, modeling becomes multi-state rather than binary, with each state corresponding to a performance level. Quantitative performance is determined by the loss of system performance due to the failure of one component or a combination of components. The Collector at Lely, for example, is a robot manure collector that cleans barns for farmers. When the Collector's water system components fail, the system continues to function but collects less manure, resulting in a reduced performance level. Therefore, the failure of one (or more) component(s) or their degradation will determine performance loss rather than actual failure. This indicates that the system will still perform its function but at a lower performance level. Qualitative performance is related to the quality the system needs to perform. The Astronaut, for example, is Lely's cow milking robot. When the milk quality is below a predefined threshold, the system is shut down and regarded as a failed state. Thus, the qualitative performance is related to the system's downtime, which is related to the system's availability. Therefore, this literature review will only consider quantitative performance.

The paper by Si et al. (2012b) creates an integrated importance measure (IIM) based on the loss of system performance. This IIM is based on the importance measures from the papers of Griffith (1980) and Wu and Chan (2003). This IIM assists in determining the most important component i based on the performance loss in the state m. Components with a high-performance loss are interesting candidates for PdM implementation because they have a higher probability of causing a failure of the system. Besides, the paper of Si et al. (2012b) defines the comparison of components based on models with binary and multi-state systems and components, which applies to Lely's case. Therefore, this methodology could be used to determine the components for Lely that are generating the most loss of performance, which are interesting when considering the most interesting components for PdM.

The effect of working conditions is another approach to evaluate a system's performance. Such an importance measure is given in the work by Chen and Zhu (2019). According to the researchers, changing working circumstances could affect reliability, with working conditions contributing to extra degradation for specific components.

The disadvantage of this importance measure is that it ranks the most critical operating conditions, whereas PdM indicates the most interesting component. Moreover, this paper focuses on the additional degradation of a component caused by external factors. However, this additional degradation does not calculate the performance of a component. Therefore, this methodology is less suitable to assess the performance of a component.

In conclusion, the paper of Si et al. (2012b) will be used for Lely's case study because the paper focuses on system performance loss and can be modeled with both binary and multi-state systems and components. Besides, the paper of Chen and Zhu (2019) will not be used because it does not focus entirely on system performance.

4.4.2 The Methodology

The paper of Si et al. (2012b) assumes the following:

1. The system is a multi-state monotone coherent system.
2. The system has a state space of $\{0, 1, 2, ..., M\}$, where state 0 is the failed state and state M is the perfect state, and consist out of n components with state $\{0, 1, 2, ..., M\}$.
3. The system and components are stochastically independent of each other.

The loss of system performance indicates the components' performance importance. Besides, by specifying how a transition of a components states affects the system performance, the most important component for output performance can be chosen.

The components are evaluated based on the system performance a_j, representing the system's performance level in the corresponding state j. Because the system has failed at this point, the system's performance level a_0 will be deemed to be zero. Furthermore, the system performance level for state j is defined by expert knowledge about the system's functioning at the specific state, which is likewise reliant on the system structure-function. Expert knowledge may also be used to define the state M. However, the assumption can be made that the system is operating flawlessly, implying that the condition will be 100%.

Components are degrading during the lifetime; therefore, the probability of a component being P_{im} needs to be known to understand the influence of a component's state on the system performance loss. This probability can be determined by the Markov Property (Lisnianski, 2007), which assumes that components have exponentially distributed lifetimes $\lambda^i_{m,0}$ and repair times $\mu^i_{m,q}$.

The probability $Pr(\Psi(l_i, X) = j)$ of a component being in state l_i and the system in state j will be determined the same as for the components cost importance. Hence, the MDD model explained in Section 4.1.2 will be used.

This input will be used to determine the output performance importance of components. Again, the evaluation of a multi-state system will be considered, where a component can be modeled as binary or multi-state. The Integrated Importance Measure (IIM) of Si et al. (2012b) is going to be used. The model will be evaluated as the component with the highest value is the component that is held responsible for the most system performance loss. This model is calculated by:

$$I^{IIM}_m(i) = P_{im} \cdot \lambda^i_{m,0} \sum_{j=1}^{M} a_j \times [Pr(\Phi(m_i, X) = j) - Pr(\Phi(0_i, X) = j)] \tag{4.8}$$

4.5 Conclusion

This chapter describes the approaches used to answer Research Question 2. Lely wants to know the criticality of components that could be interesting for PdM based on downtime, cost, and output performance criteria. As the funnel approach of Tiddens et al. (2018) only selects the components, the critically of the components still need to be defined. This criticality is based on different importance measures, which describe the influence of one component with respect to the system. Therefore, the system function is considered, which could be different for each criterion. First, the availability importance measure, where the approach of Barabady and Kumar (2007) is used. The components and system considered for this importance will be based on a binary function because availability only concerns whether or not a component is operational. This importance measure defines the effect of the availability of one component with respect to the system's availability. Second, the cost importance measure, where the approach of Si et al. (2012a) is used. The system structure for this importance measure needs to be formulated as multi-state because the system could function in different states when maintenance is performed. The components for this importance measure can be based on either multi-state or binary functions, which depend on the available data. This cost importance determines the influence of one component on the system maintenance costs, where components with the highest influence on these costs are determined as most important for PdM. Last, the output performance importance measure, where the approach of Si et al. (2012b) is used. Also, with this approach, the system structure needs to be formulated as multi-state, and components can be defined as multi-state or as binary functions. This output performance importance measure ranks the components based on their contribution to the loss of system performance, where the component with the highest system loss is the most important for PdM. Eventually, these approaches for the importance measures are used to determine the overall criticality for interesting components for PdM.

5 Multi-Criteria Decision Making

The components' criticality of the three criteria (downtime, costs, and output performance) can be calculated by the methodologies explained in Chapter 4. However, Lely wants to understand how the results of these three different methodologies need to be combined to receive one overall criticality ranking for the components that could be interesting for PdM. To define this overall criticality for components, Multi-Criteria Decision Making (MCDM) approaches need to be investigated, which to be determined as best for Lely. Therefore, this chapter aims to answer Research Question 3:

3. What approach can be used or developed to combine the assessment of criticalities to get a trade-off between the criteria?

This chapter is structured as follows. Section 5.1 explains what MCDM methodologies have been researched from literature and provides reasoning why the approach of Karimi and Rezaeinia (2011) is used. Section 5.2 explains the approach of Karimi and Rezaeinia (2011), and how this approach will be used for Lely. Section 5.3 concludes this chapter.

5.1 Related Literature

In the previous paragraphs, some of the available methods to evaluate the criticality of components in multi-component heterogeneous systems with respect to availability, costs, and output performance criteria have been reviewed, and their relevance to the case of Lely was discussed. However, these three criteria are usually examined separately and can result in three lists with distinct component ordering, implying that the criteria must be merged to perceive a single overall criticality list. The criticality of components should be ranked, and the decision on which components are best suited for PdM implementation should be based on a trade-off of these three criteria. To this purpose, Multi-Criteria or Multi-Attribute Decision Making (MCDM and MADM) approaches can be used. However, the essential question to address when selecting an MCDM methodology is: "*Which MCDM is the best method for a given problem?*"(Triantaphyllou, 2000, p. 21). The book of Chen et al. (1991) analyzed this question. This book developed a taxonomy using the appropriate MDCM methodologies based on the following criteria; (1) the type of information from the decision-maker and (2) the salient feature of the information. Figure 5.1 depicts this taxonomy.

The criticality of the three criteria will be rated at an ordinal scale since components may have a different impact on the system with respect to the criteria. This implies that the methodology must process ordinal data. Methodologies that process cardinal data have been reviewed to understand whether methodologies could generate a criticality with ordinal input data. However, the basis of some of this MCDM does not correspond to the case of Lely. For example, AHP is based on comparisons of pairs where judgments are based on the knowledge of experts for priority scale (Saaty, 2008). The disadvantage of AHP is that the approach can flip or reverse when alternatives are added, which makes it not ideal for Lely because it can be that alternatives are added (Velasquez and Hester, 2013). Moreover, Elimination and Choice Translating Reality (ELECTRE) is an outranking method based on concordance analysis (Velasquez and Hester, 2013). However, when outranking, making criticality for the other alternatives is more complicated. This indicates that such a model is not ideal for Lely's case because a criticality of components is required. Therefore, the choice is made that only methodologies that can model with ordinal data are reviewed. The

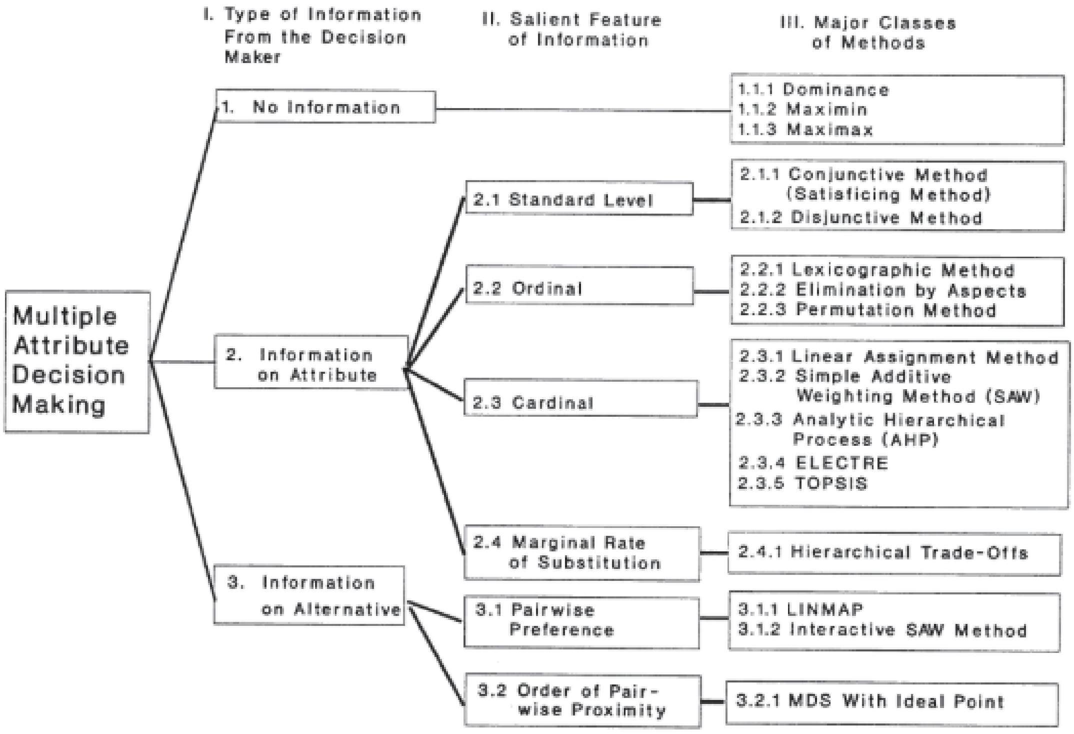


Figure 5.1: A taxonomy of MADM methods according to Chen et al. (1991)

three methodologies that are can deal with this input data are shown in Figure 5.1 and are: (1) The lexicographic method, (2) elimination by aspects, and (3) the permutation method.

First, the lexicographic methodology proposed by Isermann (1982), which optimizes an MCDM using mathematical programming. This methodology uses a finite set of objectives in which low-ordered priority objectives are optimized such that they do not interfere with the optimization of higher-priority objectives, a process known as lexicographic order (Isermann, 1982). This methodology is used when the decision-maker cannot determine the hierarchical order of conflicting objectives in a decision (Khorram et al., 2010). The advantage of the lexicographic method is that it is simple to use and computationally efficient. However, a disadvantage is that this method tends to favor particular objectives (Robles et al., 2018).

Second, the elimination by aspects methodology, developed by Tversky (1972). This methodology selects the best ordinal level by the "process of elimination", in which the evaluation is conducted one at a time, starting with the features considered most crucial (Kahraman, 2008). Alternatives that do not meet the minimal performance requirements for a single attribute of interest are eventually eliminated. However, the model has the disadvantage that while the model can meet the requested criteria, the solution will not be optimal because the model is non-compensatory.

Last, the permutation method proposed by Jacquet-Lagrèze (1969). This methodology assigns a value for each permutation and considers the permutation with the highest value the most important. This methodology is based on the permutation of decision alternatives.

Therefore, m alternatives give $m!$ permutations that can be generated. In the case of Lely, the alternatives are the components. This method, however, can also be tending to favor particular objectives (Karimi and Rezaeinia, 2011). Therefore, Karimi and Rezaeinia (2011) developed a modified permutation method that addresses this favoritism. By addressing the maximum and minimum value of the criteria in the formula, favoritism is excluded. The adjusted permutation method can be computational time consuming with large instances of alternatives. However, meta-heuristics can be used, such as explained in the papers of Karimi and Rezaeinia (2011) and Beyragh and Noor (2016), which decrease the computational time for these larger instances. Another advantage of this methodology is that it does not flip or change the ranking order when alternatives are added.

To conclude, the adjusted permutation methodology by Karimi and Rezaeinia (2011) fits Lely's case study best because this methodology can be modeled with ordinal input data, which cannot be done with approaches based on cardinal data, such as ELECTRE. The adjusted permutation method does not flip or change ranking when alternatives are added, as is the case with AHP. Finally, this approach does not favor any criteria as in the ordinal methods of Tversky (1972) and Isermann (1982)

5.2 MCDM Model

The adjusted permutation approach of Karimi and Rezaeinia (2011) will be used to determine the trade-off in the three criticalities downtime, costs, and output performance. This approach originates from the classic permutation method of Jacquet-Lagrèze (1969), which is based on the permutation of the decision variables. This model assumes a linear utility function for the differences between the alternatives, considering that one alternative will be better than another alternative.

This research focuses on the permutation of the alternatives that can be chosen. For example, m alternatives generates $m!$ different permutations. The permutations in Lely's case will be the sequence of components that are most interesting for the PdM. First, the concordance C_{kl} and the discordance D_{kl} are defined in order to define the best permutation. Both concordance and discordance sets compare the alternatives k and l for each criterion. When criterion j of alternative k is greater than or equal to alternative l, the criteria is added in the concordance set C_{kl}, defined as:

$$C_{kl} = \{j \mid a_{kj} \geq a_{lj}\} \quad \text{for } k, l = 1, 2, ..., m \text{ and } k \neq l \tag{5.1}$$

where m are the alternatives. When the opposite is happening where alternative j is greater than or equal to alternative k, the criteria are added to the discordance set D_{kl}, defined as:

$$D_{kl} = \{j \mid a_{kj} \leq a_{lj}\} \quad \text{for } k, l = 1, 2, ..., m \text{ and } k \neq l \tag{5.2}$$

After determining the concordance and discordance sets, the weights of the criterion need to be determined. It is assumed that the weights per criterion need are given by expert knowledge, where the sum of the weights per criterion w_j needs to add up to one.

This input is used to calculate the adjusted permutation method of Karimi and Rezaeinia (2011), where the first and second terms calculate the sum of weighted standard proportional priority of each permutation with corresponding concordance and discordance sets, and a_j^{max} and a_j^{min} are the corresponding maximum and minimum value of the j-th criterion, which is given as:

$$R_i = \sum_{j \in C_{kl}} w_j \left(\frac{|a_{kj} - a_{lj}|}{a_j^{max} - a_j^{min}} \right) - \sum_{j \in D_{kl}} w_j \left(\frac{|a_{kj} - a_{lj}|}{a_j^{max} - a_j^{min}} \right), \quad i = 1, 2, ..., m! \tag{5.3}$$

The permutation with the highest rate is selected as the sequence of alternatives.

An example is used to illustrate how the adjusted permutation method is used. Suppose there are three different alternatives as components that could be most interesting for PdM. Three different components could lead to 3! = 6 different permutations for choice of criticality. Table 5.1 illustrates the decision matrix for the criteria.

Table 5.1: An example decision matrix

	Criterion		
Alternative	A	B	C
1	4	2	3
2	3.5	1.5	2
3	5	1	1.5

The concordance and discordance set are generated between the alternatives. Therefore, Table 5.2 illustrates the concordance and discordance sets for the example. When looking at the $C_{1,3}$ in this table, it is checked for which criterion component 1 is outperforming component 3. When looking at $D_{2,3}$ in this table, it is checked for which criterion component 3 is outperforming component 2. This comparison for the concordance and discordance has been made for all the different combinations.

Table 5.2: Concordance and discordance sets for example

Concordance sets		**Discordance sets**	
$C_{1,2}$	A, B, C	$D_{1,2}$	-
$C_{1,3}$	B,C	$D_{1,3}$	A
$C_{2,3}$	B,C	$D_{2,3}$	A
$C_{2,1}$	-	$D_{2,1}$	A,B,C
$C_{3,1}$	A	$D_{3,1}$	B,C
$C_{3,2}$	A	$D_{3,2}$	B,C

The results of the permutation method are illustrated in Table 5.3. The weights (w_j) for this example are set as 0.4, 0.2, and 0.4, respectively. This example shows that permutation 1,3,2 is the best because this has the highest value for R_i.

Table 5.3: Example results different permutations

Permutation	R_i	**Permutation**	R_i
1,2,3	1.47	2,3,1	-1.76
1,3,2	**1.76**	3,1,2	0.29
2,1,3	-0.29	3,2,1	-1.47

5.3 Conclusion

This chapter describes the approach used to answer Research Question 3. Lely wants a trade-off between the different criticalities generated for downtime, cost, and output performance criteria. Therefore, a literature review for MCDM has been performed. The approach of Karimi and Rezaeinia (2011) has been selected as the methodology most suitable for Lely because 1) the model can deal with ordinal input and output data, 2) expert knowledge is only necessary for the criterion weights, 3) the model does not flip or reverse when alternatives are added, and 4) the model does not favoritism any criteria. This approach defines the scoring of each permutation by creating concordance and discordance sets and settings weights for criteria, which results in a favorable criticality of components.

6 Accuracy Determination

The previous approaches in this research could select and ranked the components on the criticality of downtime, cost, and output performance. However, to be sure that these components are more beneficial for PdM, an analysis needs to be performed on the expected cost of the components when implementing this policy. Therefore, this chapter aims to answer Research Question 4:

4. How to determine the prediction accuracy's bounds per suitable component such that predictive maintenance gains more advantages than the current maintenance strategy based on Lely's criteria?

This chapter is structured as follows. Section 6.1 describes how to deal with accuracy and precision within a predictive maintenance approach. Section 6.1.1 & 6.1.2 describe the mathematical models to determine the average cycle cost for FBM and PdM, respectively. Section 6.1.3 describes how the two maintenance approaches are compared to each other. Section 6.2 concludes this chapter.

6.1 Accuracy Measure

When Lely is considering implementing PdM, a prediction model needs to be selected. However, such a prediction model will not always be 100% accurate and precise because this prediction model can have different outcomes. To understand the accuracy and precision in this research, the definitions are explained before using. The term accuracy is defined as: *"the likelihood of predicting an equipment problem prior to an actual failure"*(Mckone and Weiss, 2002, p. 112). The term precision is defined as: *"the proximity of the signal to the time of the actual failure"* (Mckone and Weiss, 2002, p. 112). The prediction model could generate four outcomes when looking at accuracy and precision, which are evaluated as confusion matrix in Table 6.1. The columns of this confusion matrix present the predicted value of a model, and the rows present the actual classes of a system. Hence, the matrix is divided into four different measurements;

- **True Positive (TP):** The number of correctly classified positive cases
- **True Negative (TN):** The number of correctly classified negative cases
- **False Positive (FP):** The number of incorrectly classified positive cases
- **False Negative (FN):** The number of incorrectly classified negative cases

Table 6.1: Confusion Matrix by Sun et al. (2009)

	Predicted as Negative	Predicted as Positive
Actually Negative	True Negative (TN)	False Positive (FP)
Actually Positive	False Negative (FN)	True Positive (TP)

The accuracy and precision of a prediction model do have consequences for the downtime and cost of the system. For example, when a prediction model misclassifies an FP, the system is not failing, and a scheduled down is considered for cost and downtime. However, the component is repaired unnecessarily. Same for an FN, because the system will fail without any notice of the prediction model, where extra downtime and an unscheduled down needs to be considered, which are higher than a preventive, which can add up to high costs and downtime. Chawla et al. (2002) therefore considers that these FN have more consequences than FP. To prevent the FN from becoming too high, the accuracy of the prediction model must be accurate.

This research will use accuracy and precision to determine the average cost per cycle per component for PdM. Therefore, the standard metrics of a prediction model, the *accuracy* and *precision*, are necessary to understand. The accuracy is determined by the percentage of the actual number of correct prediction classifications (both TP & TN) of the total predictions. Moreover, the precision is determined by the percentage of the TP classification of all positive classifications, as shown in Table 6.2.

Table 6.2: Threshold Metrics for Classification Evaluations by Hossin and Sulaiman (2015)

Metrics	**Formula**	**Definition**
Accuracy	$\frac{TP+TN}{TP+FP+TN+FN}$	The likelihood of predicting an equipment problem prior to an actual failure (Mckone and Weiss, 2002, p. 112)
Precision	$\frac{TP}{TP+FP}$	The proximity of the signal to the time of the actual failure (Mckone and Weiss, 2002, p. 112)

The research of Mckone and Weiss (2002) is used to evaluate the accuracy and precision factor of a predictive maintenance model. The accuracy and precision factor of the prediction approach are used in this model to provide a joint probability distribution of numerous maintenance tools. The precision is represented by a factor p, which has a value of $p \geq 1$ and is proportional to the prediction precision. The higher the factor, the more accurate the signals are to the time of failure, preventing maintenance from being performed prematurely. The accuracy is determined in the same manner as described in Table 6.2. This paper examines four different maintenance policies that are examined, as shown in Figure 6.1. The goal of this research is to determine the limits of accuracy and precision. Lely is using corrective maintenance for the majority of its components. As a result, it is assumed that only the improvement from reactive maintenance, also known as Failure Based Maintenance (FBM), to Predictive Maintenance (PdM) will be evaluated for this research (PdM). That is, the All Maintenance Model (AMM) and Traditional Maintenance Model (TMM) of Mckone and Weiss (2002) will not be utilized in this research.

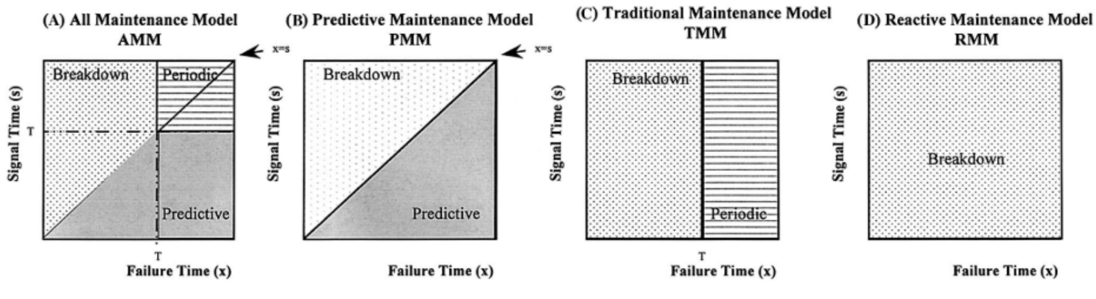


Figure 6.1: Comparison of Different Maintenance Policies by Mckone and Weiss (2002)

The renewal theory calculates the average cost rate per year in the models for determining accuracy and precision. This idea employs a time gap between two maintenance operations as a maintenance cycle, which aids in determining the average cost per year. The application of the renewal theory balances the loss of useful lifetime when maintaining components frequently with the additional risk of late performance maintenance.

6.1.1 Failure-based components

We use the FBM model of Hoedemakers (2020) for determining the cycle cost of this maintenance methodology. The lifetime for this component is following a certain probability distribution function, with a denoted probability density function of the lifetime as $f_i(u)$, and expected lifetime (MTTF) as μ_i.

The cost for a corrective replacement requires an unscheduled setup for an unscheduled down (USD), which has the corresponding cost c^{S-USD}, and the replacement cost for one component c_i^{REP}. The expected cost per cycle is

$$K_i = c^{S-USD} + c_i^{REP} \tag{6.1}$$

The expected cycle length is considered to be

$$L_i = \mu_i \tag{6.2}$$

When we use the renewal theory, we consider the expected average long term cost rate as:

$$Z_i = \frac{K_i}{L_i} = \frac{c^{S-USD} + c_i^{REP}}{\mu_i} \tag{6.3}$$

6.1.2 Predictive Maintenance components

This section corresponds to the PdM determination of the paper of Mckone and Weiss (2002). The lifetime of the components is a random variable that is determined by a probability distribution $g_i(x)$, with corresponding probability density function $f_i(u)$. When a component is maintained predicatively with a scheduled down (SD), the cost of c_i^{PdM} occurs. These costs include the material cost c_i^{part} and the corresponding labor cost of the replacement.

If a component fails when the predictive model does not give a signal for replacement, a CM action is incurred, with related costs. We assume that the cost for a CM is higher than the cost for a PdM replacement.

The decision variable for timing the PdM action depends on the accuracy $(1-\alpha)$ and precision (p) of the prediction. An important principle of PdM is a P-F curve, which is visualized in 6.2. This illustration estimates components' Remaining Useful Life (RUL) and illustrates the deterioration of the components to the point at which it can be detected (the potential failure point s). After that, when a failure is not detected by a model and no action is taken, the component continues to deteriorate, which often accelerates until it reaches the functional failure (point x) (Bousdekis et al., 2015). The time between the potential failure can be detected, and the point where a component deteriorates into a functional failure is known as the P-F interval, which can be considered as a "window of opportunity" with actions that reduce the effect of a functional failure or aim to eliminate it (Veldman et al., 2011). The model of Mckone and Weiss (2002) incorporates this signal time s and failure time x of the P-F curve in a joint probability distribution $f(s|x)$. The probability and cumulative distribution of this joint probability distribution are bases as follows:

$$f(s|x) = \begin{cases} p(1-\alpha)s^{p-1}x^{-p}, & 0 \leq s \leq x \\ \alpha, & s > x \end{cases}$$

$$F(s|x) = \begin{cases} (1-\alpha)(\frac{s}{p})^{p}, & 0 \leq s \leq x \\ 1, & s > x \end{cases}$$

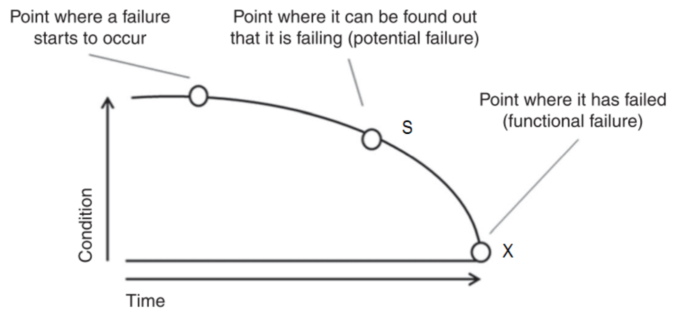


Figure 6.2: P-F curve by Bousdekis et al. (2015)

The expected cycle length is considered to be a combination of the cycle length for CM and PdM. The expected cycle length for failure based components is based on the accuracy and the expected lifetime of a component, which is calculated by the probability:

$$Pr\{u > x\} = \alpha_i \int_o^{\infty} ug(u)du \tag{6.4}$$

This equation calculates the probability that a component fails at time x is larger than the time point of maintenance at time u. The expected cycle length of the PdM components needs to be in between the moment of detecting the failure s and the moment of failure x. Therefore, the joint probability of these components is used for considering the $Pr\{s \leq u \leq x\}$.

$$Pr\{s \leq u \leq x\} = \int_0^{\infty} \int_0^{x} sf(s|x)g(x)dsdx \tag{6.5}$$

Combined the expected cycle length for PdM L_i becomes:

$$L_i = \left[\int_0^{\infty} \int_0^{x} sf(s|x)g(x)dsdx\right] + \left[\alpha \int_o^{\infty} ug(u)du\right] \tag{6.6}$$

The expected cost of a maintenance cycle for with PdM and CM is denoted as K_i, and calculate as

$$K_i = c_i^{PdM}(1-\alpha) + c_i^{CM}\alpha \tag{6.7}$$

When considering the renewal theory, the expected cost per cycle is

$$Z_i = \frac{K_i}{L_i} = \frac{c_i^{PdM}(1-\alpha_i) + c_i^{CM}\alpha_i}{\left[\int_0^{\infty} \int_0^{x} sf(s|x)g(x)dsdx\right] + \left[\alpha_i \int_0^{\infty} xg(x)dx\right]} \tag{6.8}$$

6.1.3 Component Comparison Maintenance Policies

The average cycle cost will be used to compare the various maintenance strategies. These costs decide whether the PdM policy is more appealing than the FBM policy. According to Mckone and Weiss (2002), the PdM policy is particularly appealing for components with a non-increasing failure mode, owing to the critical start-up state of the system, in which components may fail due to early faults. However, Mckone and Weiss (2002) also states that when the component has an increasing failure frequency, the PdM policy may be intriguing when the precision and accuracy prediction is near perfect, the $c_i^{PdM} \ll c_i^{FBM}$, and the components have low deterioration levels. As a result, the choice between the PdM policy and the FBM policy is determined by comparing the estimated costs of the Equations 6.8 and 6.3. When the signal is valid, it is assumed that a failure with a high precision of the prediction signal's timing is less expensive. When this signal is received too soon, money is lost on the remaining usable life of a component, which may surpass the cost of a breakdown.

Sensitivity Analysis
A sensitivity analysis will be performed while considering the accuracy bounds. This analysis demonstrates when PdM is preferable to FBM. The accuracy and precision bounds are proportional to the estimated cycle cost. Mckone and Weiss (2002) has completed an example of a sensitivity analysis on the cumulative distribution of the joint probability, with various levels of precision (p) and accuracy $(1-\alpha)$, shown in Figure 6.3. Finally, this sensitivity analysis must answer the reasonable bounds for the accuracy and precision of a prediction model and examine if, with the accuracy and precision, the average cycle cost of PdM is still a better policy than FBM with increasing accuracy and precision.

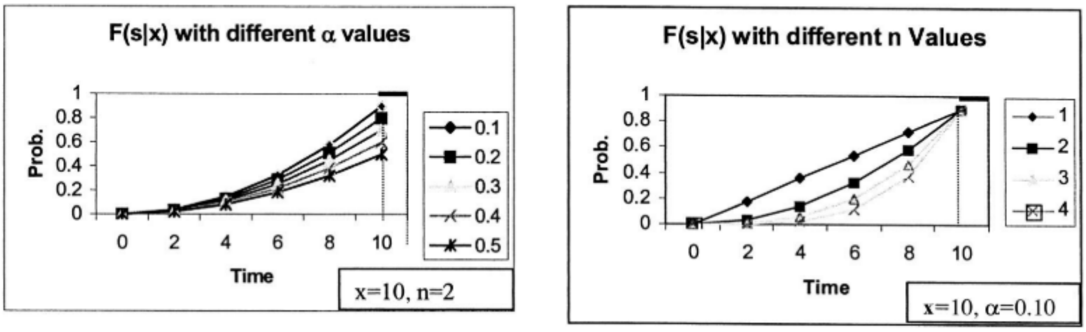


Figure 6.3: Joint Probability Sensitivity Analysis by Mckone and Weiss (2002)

6.2 Conclusion

The model of Mckone and Weiss (2002) has been used to determine the accuracy of the prediction model. These approaches are compared by calculating the average cycle cost per component for FBM and PdM. However, to understand the accuracy needed for Lely's prediction models, a sensitivity analysis per component needs to be considered.

7 Case Study

This chapter will evaluate the selected approaches to determine the components for PdM with a case study. The Collector of Lely is used to perform this evaluation, which is described in Section 1.5. This chapter aims to answer Research Question 5:

> 5. *What components of the Collector are feasible for predictive maintenance?*

This chapter is structured as follows. Section 7.1 starts with selecting the components with the approach of Tiddens et al. (2018). Section 7.2 gives an system description of the selected components, and describes the models used to evaluated the system. Section 7.3 describes the necessary input parameters for the methodologies used to evaluate the criticality of components. Section 7.4 describes the results of the criticality analysis. The methods of Barabady and Kumar (2007), Si et al. (2012a), Si et al. (2012b), and Karimi and Rezaeinia (2011) were used for the criticality determination of components, and the approach of Mckone and Weiss (2002) is used to evaluate the accuracy of the PdM maintenance model. Section 7.5 describes the performed sensitivity analysis for the MCDM and accuracy determination. Section 7.6 concludes this chapter.

7.1 Funnel Approach Collector

The funnel approach by Tiddens et al. (2018) is used to determine which components of the Collector are interesting for the implementation of PdM strategies. As written in Section 3.2, some parts of the funnel approach have been adjusted to fit Lely's and problem-specific standards. However, the stages used by the author are still the same.

7.1.1 Stage 1 - Criticality Classification

This stage reduces the number of potential PdM candidates for the Collector by evaluating the Collector's spare parts' maintenance cost and failure frequency (i.e., components). A selection is made of the most feasible components for PdM. To understand how this diagram is constructed, the composition of failure frequency and cost is first determined.

Failure Frequency
The failure frequency of the spare parts is gathered from the field service data. Together with experts from Lely, it is chosen that the failure data from 2020 and 2021 will be used. These years the service data was the most reliable and had the most registered maintenance cases since the start of the Collector in 2016. This means that only the failure frequency of 2020 and 2021 is considered. The data set used for this research is assumed to be complete and correct. However, further research is needed to understand if the data set of Lely is correct.

Components without failures have been included in the selection of interesting components for PdM. The Collector has been introduced in 2016 and has an expected lifetime of 15 years. This indicates that components that have not failed yet might fail in the future, in which they could be interesting components for PdM. However, the lifetime distributions are unknown of these components due to the lack of service data. Therefore, the lifetime distributions variables have been estimated and are eventually controlled by experts.

Cost

A subset of the costs of the components is listed in Table 7.1. The components cost used for this calculation is retrieved from the LC74 list, which is the recommended retail price for the farmers. These costs are considered because the focus is on maintenance improvements for the farmer. For the components that are currently maintained according to a CM policy, an unscheduled down is used. The c^{S-USD} is same considered as Hoedemakers (2020), indicates as:

$$c^{S-USD} = c^{technician}(2 \times t^{drivingUSD} + t^{intake}) = 75(2 \times 1.5 + 0.17) = 237.50$$

where the $c^{technician}$ is the retail hour price of the technician, $t^{drivingUSD}$ is the average time for one-way driving, and t^{intake} is the intake with the farmer before maintaining. The downtime of the components has been evaluated by the experts of Lely, as retrieving the downtime data from the service field data has appeared to be hard because Lely does not log this kind of data. In addition, these engineers perform several maintenance actions simultaneously, making it hard for each maintenance engineer to register the downtime of each component.

Table 7.1: Subset Maintenance Prices Components

Component ID	Maintenance Price (€)	Component ID	Maintenance Price (€)
1	474.00	6	668.51
2	1895.90	7	708.50
3	247.36	8	325.31
4	325.70	9	1248.60
5	446.25	10	1263.14

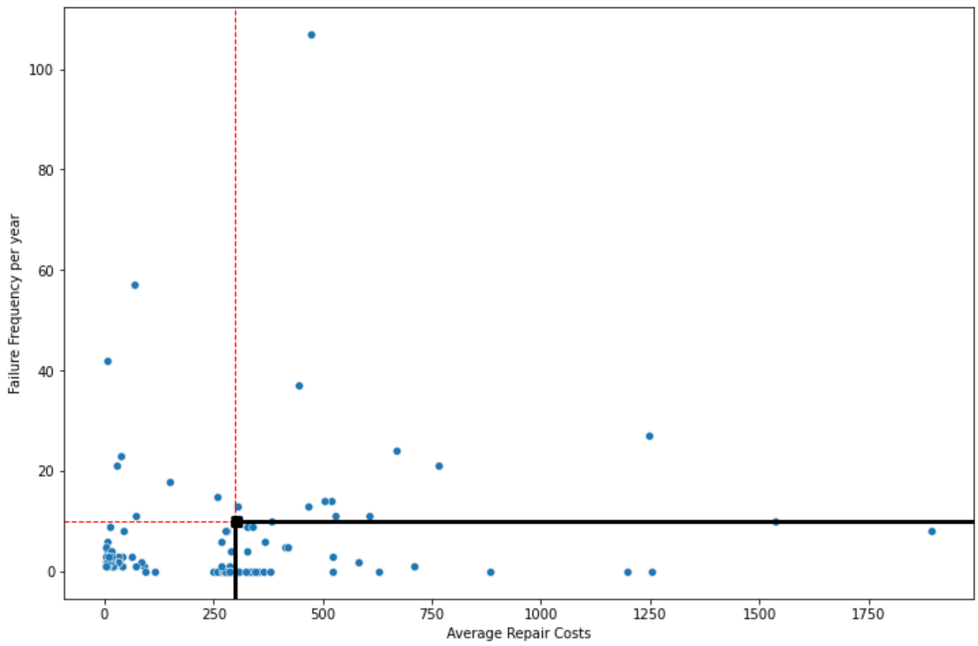


Figure 7.1: Classification of the Collectors components

The obtained cost and failure frequency of the components of the Collector have been used to plot it in the classification diagram, which is visualized in Figure 7.1. In total, 108 components have been tested for their feasibility on PdM. Each component is indicated as a blue dot. The Pareto analysis has been used to select the components that could be feasible for PdM. We chose the components that cover 79.9% of the costs and 30.2% of the total failures of all components. The failure frequency deviates from the 20% suggested by the Pareto Analysis because we consider all components up to 10 failures. As the figure illustrates, are the components in the bottom right chosen to be feasible for PdM. In total, 30 components have been selected for the following two stages.

7.1.2 Stage 2 - Showstopper Analysis

The performed showstopper analysis is listed in Table 7.2. As defined in Section 3.2, the technical feasibility and failure occurrence are the showstoppers that are used to identify the PdM candidates. Whenever a component in Table 7.2 is indicated as 'Y', it is considered a showstopper, and this component is not included for further investigation, and 'M' is considered as maybe, which occurs to need further research. When a component is indicated as 'N', the component is no showstopper and can be used for PdM.

Table 7.2: Showstopper analysis Collector

Component ID	TF1	TF2	FO1	Component ID	TF1	TF2	FO1
1	N	N	M	16	Y	N	N
2	Y	N	N	17	N	N	N
3	Y	N	N	18	Y	N	N
4	Y	N	N	19	Y	N	N
5	N	N	N	20	Y	N	N
6	Y	N	N	21	Y	Y	N
7	N	N	N	22	N	N	N
8	N	N	N	23	Y	N	N
9	N	N	N	24	N	N	N
10	N	N	M	25	N	N	Y
11	Y	Y	N	26	Y	Y	N
12	Y	N	N	27	Y	N	N
13	Y	N	N	28	N	N	N
14	N	N	M	29	N	N	Y
15	Y	N	N	30	N	N	Y

The components are evaluated on technical detection/prediction. This showstopper identifies if adequate failure detection is possible with existing research (*TF1*) or with additional research (*TF2*). Of the chosen components from the first stage, sixteen components could not be used for PdM. These components have been identified as showstopper since they have a constant failure rate ($\beta = 1$), meaning that they can fail randomly (Components 3, 4, 6, 11, 12, 13, 20, 21, 26, 27, 29). In addition, component 2 has been identified as a showstopper because this product is an electronic product. These components have also had a constant failure rate ($\beta = 1$), which is inappropriate for PdM. Moreover, components 15, 16, 18, 19, 23 have been identified as technical showstoppers because these components are not eligible to be measured with any sensor. For example, the lagoon protection frame only breaks when a cow kick against this object.

The showstoppers regarding the failure occurrence (*FO1*) in the lifetime of the component are considered. This showstopper tries to filter the components with an expected lifetime that is longer than the expected lifetime of the system. These components are filtered because the probability that such a component fails is too small. Therefore, the choice is made that these products are not interesting for maintenance with a PdM policy. Table 7.2 shows that components 21 to 30 are validated as a showstopper regarding the failure occurrence. The Weibull distribution estimates the component lifetime and indicates that these components all have a longer lifetime than the 15 years lifetime of the system. In addition, components 1, 10, and 14 have been addressed as Maybe, because these components have a lifetime of 16.88, 15.59, 15.23 years, respectively. Therefore, these components need to be considered further to evaluate whether they are interesting for PdM.

7.1.3 Stage 3 - Focused Feasibility

The final stage of the funnel approach is focused on feasibility. This part focuses on the components that have been identified as Maybe for technical feasibility and failure occurrence. There are no components identified as Maybe for technical feasibility. Therefore, only the components identified as Maybe for failure occurrence are further analyzed with a cost analysis. When the cost of one component has at least a 1% impact on the total maintenance cost for the selected components, they are seen as feasible components. The check is performed for components 1, 11, and 14. The result shows that these components impact 10.84%, 1.06%, and 1.18% on the total maintenance cost, respectively. Therefore, the three components that have been identified as Maybe will be seen as components that are feasible for PdM.

To conclude, eight components in Table 7.2 which are indicated by only 'N' and 'M' are selected as feasible for PdM. The following paragraphs explain the system description of these components and determine the criticality of the used criteria.

7.2 System Description

The system concerns the eight components identified as feasible in the previous section. As described in Section 4.1, the structure of the system can be based either as a binary or as multi-state, where each evaluation of criterion has its preference. However, to give an overall system description, the Reliability Block Diagram (RBD) is used. Table 7.3 helps to explain how the RBD is constructed. The third column of this table indicates each component's location of the system it is installed. These categorizations are ranked together with the experts of Lely, which is shown in the fifth column. This means that the charging components (Component C and D) are ranked most important for the system reliability and will be modeled first in the RBD. Therefore, the rank is used for the visualization of the RBD, as shown in Figure 7.2. The fourth column of the table indicates if the component will be illustrated as a minimal path or a minimal cut, as explained in Section 4.1. For example, the components for the driving gear (Component E and F) of the Collector are modeled as a minimal path because both components need to function in order to let the system operate. In addition, the water system and driving guide components are such modeled that both need to fail before the system fails. All this information is used to model the RBD of the Collector, which is visualized in Figure 7.2.

Table 7.3: Identification of components

Component	ID	Categorization	Minimal Path or Cut	Rank
Drive Pancake	A	Driving gear	Path 1	2
Motor cable	B	Driving gear	Path 1	2
Battery charger box	C	Charging	Path 2	1
Charge strip rubber	D	Charging	Path 2	1
Wall guide (skid)	E	Driving guide	Cut 1	3
BT Antenna	F	Driving guide	Cut 1	3
Water pump	G	Water system	Cut 2	4
Water tank	H	Water system	Cut 2	4

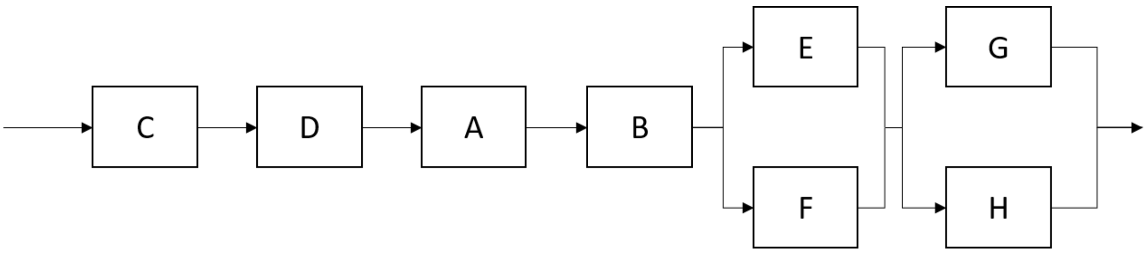


Figure 7.2: Reliability Block Diagram Collector

The system is modeled as follows. Figure 7.2 shows that the charging and driving gear components are placed in series because they all need to function to let the system function. For example, when the drive pancake (component A) fails, the total system fails. The driving guide and water system components are placed in parallel because these components both need to fail to let the system fail. For example, the water pump (component G) and water tank (component H) both need to fail before a mechanic is sent for maintenance.

The battery charger box used in this research consists of two versions, the American version with 115V and the European version with 220V. In this research, these two components are assumed to be the same because the components are almost identical. However, the two components differ in failure frequency and have different lifetime distributions. Therefore, the average maintenance cost of these two components is considered. However, the input variables for the lifetime distribution of the European version will be used due to more available data.

7.2.1 Component modeling

All eight components within the system will be modeled binary because there is no degradation information known of the components within Lely. We assume that the lifetime (MTBF) of the components is Weibull distributed with scale parameter η_i and shape parameter β_i, which is calculated as:

$$MBTF_i = \eta_i \cdot \Gamma(\frac{1}{\beta_i} + 1) \tag{7.1}$$

The mean repair time (MTTR) of the components is retrieved from the experts of Lely. For the evaluation of the components, the failure rate ($\lambda^i_{1,0}$) and repair rate ($\mu^i_{0,1}$) will be used, which are the inverses of the MTBF and MTTR of each component. The steady-state of the component is used to evaluate the availability for these components, which is calculated by:

$$\begin{cases} 0 = & P_{i1}\lambda^i_{1,0} - P_{i0}\mu^i_{0,1} \\ 1 = & P_{i1} + P_{i0} \end{cases}$$

where 0 is the failed state, 1 is the function state, P_{i1} is the availability of component i at steady state calculated by $P_{i1} = \mu^i_{0,1}/(\lambda^i_{1,0} + \mu^i_{0,1})$, and P_{i0} the probability that component i being failed.

7.2.2 System modeling

The system will be modeled based on a binary and multi-state evaluation, depending on the criterion used. The evaluation of the availability importance will be based on a binary modeled system because this importance measure focuses on the two states working or failed. The cost and performance importance evaluation will be based on a multi-state modeled system because 1) the system maintenance cost can differ per state, in which a multi-state depicts the reality better, and 2) the performance of a system is based on multiple stages. The binary and multi-state system models are explained as follows.

Binary
The binary system will be given as a two-state evaluation, namely working of failed. The RBD, depicted in Figure 7.2, is used as a system model. The binary system is evaluated as 1) when a component in series fails, the system fails, and 2) when both components in parallel fail, the system fails. Both failures will result in downtime for the system.

Multi-state
The multi-state system will be given as a three-state evaluation, which is depicted in Figure 7.3. This multi-state system is modeled that state 0 is the failed state, state 1 is a performing state, but the system is not functioning perfectly, state 2 is the perfect state.

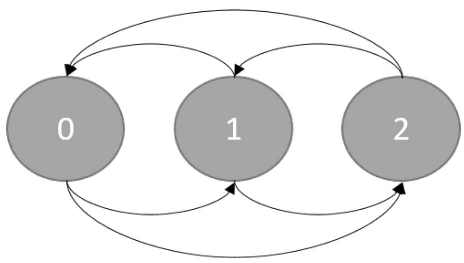


Figure 7.3: Multi-state System Model of Collector

For each state, a set of components that need to function is considered, which is checked by the experts. Therefore, the system function $\Psi(X)$ is given where $X = [x_a, x_b, x_c, x_d, x_e, x_f, x_g, x_h]$. An example per function structure of the multi-state is given as:

$$\Psi\{X\} = \begin{cases} 2, & \text{for } \{X = 1\} \\ 1, & \text{for } \{x_A = 1, x_B = 1, x_C = 1, x_D = 1, x_E = 0, x_F = 1, x_G = 0, x_H = 0\} \\ 0, & \text{for } \{x_A = 0, x_B = 1, x_C = 1, x_D = 1, x_E = 1, x_F = 1, x_G = 0, x_H = 0\} \end{cases}$$

The system structure-function is defined as follows. When all of the components are operational, the system is classified as being in state 2. To be in state 1, components A, B, C, D, and one of the two F & G components must all be operational. Components G and H are not required to function because they result in a performance loss rather than a system failure. The system enters state 0 when one of the components of A, B, C, or D fail, or when both of the driving guide components F and G fail.

The multi-valued decision diagram of Kvassay et al. (2018) have been used to find the probability distribution of component i being in a certain state l and the system X being in a certain state s, which is denoted as $Pr(\Psi(l_i, X) = s)$. The results of this probability distribution are given in Table 7.4. For example, $Pr(\Psi(1_A, X) = 1)$ is described as the probability that component A is in state one and the system is in state one, with a probability of 2.03E-04.

Table 7.4: Input parameters system probabilities

	Pr(X=0)	**Pr(X=1)**	**Pr(X=2)**		**Pr(X=0)**	**Pr(X=1)**	**Pr(X=2)**
Pr(A=0)	2.48E-05	0.00E+00	0.00E+00	**Pr(E=0)**	1.33E-09	6.20E-05	0.00E+00
Pr(A=1)	3.49E-04	2.03E-04	9.99E-01	**Pr(E=1)**	0.00E+00	1.41E-04	9.99E-01
Pr(B=0)	3.49E-04	0.00E+00	0.00E+00	**Pr(F=0)**	1.33E-09	2.14E-05	0.00E+00
Pr(B=1)	1.33E-09	2.03E-04	9.99E-01	**Pr(F=1)**	0.00E+00	1.82E-04	9.99E-01
Pr(C=0)	3.25E-05	0.00E+00	0.00E+00	**Pr(G=0)**	0.00E+00	2.19E-05	0.00E+00
Pr(C=1)	4.03E-04	2.03E-04	9.99E-01	**Pr(G=1)**	0.00E+00	1.81E-04	9.99E-01
Pr(D=0)	2.94E-05	0.00E+00	0.00E+00	**Pr(H=0)**	0.00E+00	9.79E-05	0.00E+00
Pr(D=1)	3.74E-04	2.03E-04	9.99E-01	**Pr(H=1)**	0.00E+00	1.05E-04	9.99E-01

7.3 Input parameters model

In this section, the input parameters for the approaches that are needed are explained. The required input parameters are lifetime distributions and probabilities, cost, and downtime parameters.

7.3.1 Component Lifetime Parameters

One of the most critical issues in maintenance and reliability modeling is the input of the lifetime distribution. By evaluating historical data, these lifetime distributions can be calculated. Lely employs the SuperSMITH Weibull tool[1] to estimate the Weibull distribution using field service data. However, all Collectors' spare parts will be examined in this study, including those that have not yet failed. These components' field service data is not available. As a result, for the components for which there was insufficient field service data, the engineers' and Technical Service Support department's experience/knowledge was used to estimate the distributions for these variables for the lifetime parameters.

The component lifetime parameters are presented in Table 7.5. The second column indicates whether the lifespan distribution is approximated or fitted using data from field service. For the lifetime of these components in years, the Weibull distribution was utilized.

[1] https://fultonfindings.com/supersmith%C2%AE

Table 7.5: Lifetime parameters

Components	Based on	Current Maintenance	Weibull shape	Weibull scale
Component A	Data	FBM	1.48	18.68
Component B	Data	FBM	1.95	12.77
Component C	Data	FBM	4.20	2.70
Component D	Data	FBM	1.60	12.43
Component E	Data	FBM	2.10	6.07
Component F	Data	FBM	1.23	16.28
Component G	Data	FBM	1.07	1.02
Component H	Expert	FBM	1.90	4.16

7.3.2 Availability parameters

Table 7.6 lists the input parameters for the availability importance measure. The lifetime of these components is calculated by Equation 7.1. The current maintenance strategy is used to determine the average downtime per component in hours. As the third column in Table 7.5 is indicating, are all components currently maintained by the FBM maintenance approach. Therefore, a failure of any of these components will result in unscheduled downtime (S-USD). This downtime can be calculated as follows:

$$MTTR_i = d_i^{S-USD} + t_i^{replacement} = t^{react} + t^{drivingUSD} + t^{intake} + t_i^{replacement} \tag{7.2}$$

The setup time for a USD is the same as Hoedemakers (2020), where t^{react} is the time it takes to respond to a service call, which is estimated to take an hour on average, $t^{drivingUSD}$ is the one-way driving time, which is estimated to take 1.5 hours on average, and t^{intake} is the time it takes to take an intake with the farmer before maintaining the Collector, which is estimated to take 10 minutes.

Table 7.6: Input parameters availability

Components	$MBTF_i$ (yrs)	$MTTR_i$ (h)
Component A	16.88	3.67
Component B	11.32	2.92
Component C	2.45	3.17
Component D	11.14	3.17
Component E	5.38	2.92
Component F	15.23	2.92
Component G	15.59	2.92
Component H	3.69	3.17

7.3.3 Cost parameters

Table 7.7 lists the input parameters for the cost importance measure. The table is composed of the component as follows. First, the components price c_i^{part} is given, which are the component's commercial prices, because the optimization for this study is focused on the farmer's advantage. Second, the probability of a component being in state zero P_{i0} is given to determine the possibility of failure of a component. Last, the number of time the component is likely to fail, to indicate the influence of a component's failure on the systems' lifetime.

Table 7.7: Input parameters costs

Component	c_i^{part}	P_{i0}	f_i
Component A	€ 1.583,40	2.48E-05	0.89
Component B	€ 69.45	2.94E-05	1.33
Component C	€ 247.50	1.47E-04	6.11
Component D	€ 143.42	3.25E-05	1.35
Component E	€ 69.06	6.20E-05	2.79
Component F	€ 83.98	2.19E-05	0.99
Component G	€ 125.06	2.14E-05	0.96
Component H	€ 47.51	9.80E-05	4.06

These component-specific costs are used to evaluate the system expenses. As concluded in Chapter 4, the system for cost evaluation is modeled as multi-state because the system could function in different states when performing maintenance. The multi-state system model for the Collector is considered as a $M = 3$, as shown in Figure 7.3. To calculate the cost importance, the different maintenance costs per state need to be defined, given as:

- **Cost state 0:** The system costs for state zero are calculated throughout the system's lifespan, which in the Collector's instance is 15 years. Equation 4.4 determines the cost of this state. f_i is the number of times a component is likely to fail in the system's lifetime, as shown in column 5 of Table 7.7. Because these components cause the system to fail, the subset K is defined as the replacement of the components A, B, D, E, and F & G. Components F and G are treated as if both must fail in order for the system to fail. Hence only one c^{S-USD} is taken into account for these two. The c^{S-USD} is the equivalent to Hoedemakers (2020), which is mentioned in Section 7.11. As a result, the cost of state 0 is as follows:

$$C_0 = 4.668, 29$$

- **Cost state 1:** The system cost for state one is an improvement for the system as it moves closer to its perfect state. Equation 4.5 determines the cost of this state. The subset J comprises the improved components E & F and G & H. The cost of improvements to the perfect state over the system's lifetime is:

$$C_1 = 588, 72$$

- **Cost state 2:** The system cost for state two is zero because state two is the perfect state with no attributable cost for improvement.

$$C_2 = 0$$

7.3.4 Output performance parameters

Table 7.8 shows the input parameters for the output performance importance measure. The lifetime of the components is modeled as binary and considered to be estimated by the

Weibull distribution, as explained in Section 7.2.1. Table 7.8's third column displays the system's availability.

Table 7.8: Input parameter output performance

Components	$\lambda_{1,0}$	P_{i1}
Component A	1.62E-04	0.99998
Component B	2.42E-04	0.99997
Component C	1.12E-03	0.99985
Component D	2.46E-04	0.99997
Component E	5.10E-04	0.99994
Component F	1.80E-04	0.99998
Component G	1.76E-04	0.99998
Component H	7.42E-04	0.99990

The system performance state will be expressed as a percentage of the total system performance. As stated in Section 7.2, the system of the Collector will be evaluated as multi-state with three different states ($M = 3$). The three distinct states have three distinct performance levels a_j, which can be computed as follows:

- **Performance state 0:** Because the system failed at that moment, the performance in state zero is assumed to be 0%.
- **Performance state 1:** When the system is in state 1, the Collector is no longer sucking manure efficiently. As a result, it is assumed that the system is operating at 70% of its peak performance.
- **Performance state 2:** State two is regarded as the system's ideal state. As a result, this performance state is regarded as 100%.

7.3.5 Accuracy parameters

Table 7.9 lists the input parameters for determining accuracy. We use the Weibull distribution to model the joint density function for s and x because it provides good fits for many different types of characteristics (Mckone and Weiss, 2002). Table 7.5 lists the scale and shape parameters. The probability density function is given as follows, with scale parameter η_i and shape parameter β_i:

$$f_i(u) = \frac{\beta_i u^{\beta_i - 1}}{\eta_i^{\beta_i}} exp\left\{ -\left(\frac{u}{\eta_i}\right)^{\beta_i} \right\}, u \geq 0$$

The derivation for the cost of the maintenance activities is considered the same as the research of Hoedemakers (2020), which is:

- The cost of a predictive replacement of component i is denoted by c_i^{PdM}. These costs include the component specific costs c_i^{part}, the replacement time $t_i^{replacement}$, and the technician's labor cost $c^{technician}$. The c_i^{PdM} is calculated as follows:

$$c_i^{PdM} = c_i^{part} + t_i^{replacement} \times c^{technician}$$

- The cost of a component i replacement is denoted by c_i^{CM}. These costs are composed of an unscheduled downtime cost c^{S-USD}, as defined in Section 7.1.1, and a replacement cost c_i^{PdM}, which in total is given as:

$$c_i^{CM} = c_i^{PdM} + c^{S-USD}$$

Zhang et al. (2019) summarized the PdM prediction applications, which lists a table with different accuracy achieved by different machine learning and deep learning methodologies. The perceived accuracy from this paper show that machine and deep learning RUL predictions start from 46.51% (Soualhi et al., 2014). Besides, fault diagnoses/detection predictions start from 50.96% (Seryasat et al., 2010). Therefore, it is assumed that Lely's prediction model should perform a prediction with at least an accuracy of 50%.

Table 7.9: Input parameters accuracy

Component	$1-\alpha_i$	p_i	c_i^{CM}	c_i^{PdM}
Component A	0.5	1.5	€1895.90	€1658.40
Component B	0.5	1.5	€325.70	€88.20
Component C	0.5	1.5	€522.50	€285.00
Component D	0.5	1.5	€418.42	€180.92
Component E	0.5	1.5	€325.31	€87.81
Component F	0.5	1.5	€340.23	€102.73
Component G	0.5	1.5	€381.31	€143.81
Component H	0.5	1.5	€322.51	€85.01

7.4 Results of the Collector

For the Collector, the approaches provided in the Chapter 4, Chapter 5, and Chapter 6 have been used. Since Excel and Python are frequently used within Lely, these applications were utilized to calculate the importance. The itertools package [2] was used to compute the various permutations of the potential answers.

Table 7.10: Results importance model

Component	Availability importance	Ranking	Cost Importance	Ranking	Output Performance Importance	Ranking
Component A	0.99979	4	2.87E-06	5	0.05921	8
Component B	0.99980	3	4.79E-05	1	0.08829	5
Component C	0.99991	1	2.24E-05	2	0.40734	1
Component D	0.99980	2	4.47E-06	4	0.08974	4
Component E	0.00002	7	2.26E-06	6	0.18591	3
Component F	0.00006	6	2.76E-07	7	0.06563	6
Component G	0.00010	5	2.75E-07	8	0.06412	7
Component H	0.00002	8	5.65E-06	3	0.27052	2

The results for the importance measure are shown in Table 7.10. Equation 4.3 has been used to evaluate the availability of the Collector, indicated as I_A^i. The findings of the availability importance of the components are shown in the second column. Based on availability, the components with the highest value are regarded as the most significant. As a result,

[2] https://docs.python.org/3/library/itertools.html

component C is the most critical for availability. It also demonstrates that components constructed in series (A, B, C, D) have a more significant effect on availability than components structured in parallel (E, F, G, H) due to the larger value for this importance measure. This conclusion was predicted since failure is likely higher when components are connected in series than when they are connected in parallel.

The findings of the cost importance measure are shown in the fourth column of this table. As stated in Section 7.2, the components are modeled as binary, and the system is modeled as multi-state with three states. As the components are modeled binary, maintenance only occurs when the system fails in state zero. Therefore, the choice is made to compare the influence of the components when being in their failed state zero. This means that the comparison will be based on Equation 4.7, which is defined as $I_l^C(i)$, where l is stated zero of the components. The component with the highest value is also the most significant component for this importance measure. The component repair duration is significantly shorter than the equivalent failure times, making choosing the component having the most significant effect on the cost more challenging. However, we want to select the importance ranks of the components, which are likewise denoted by smaller numbers. As a result, component B is the most critical component based on costs.

The findings of the output performance important measure are shown in the sixth column of this table. Again, as stated in Section 7.2, the components are modeled as binary and the system as multi-state. In this case, the components only deteriorate from state one to zero. Therefore, the comparison of performance will be based on the components state one. The output performance measure is calculated by Equation 4.8, which is defined as I_m^{IIM}, where m is indicated as component state one. The components with the highest value on this importance measure are thought to have the most impact on output performance. As a result, Component C is the most significant component for output performance.

The results of the three different criteria have been used as input for the adjusted permutation method. The weight distribution (for the three criteria, Availability (w_A), Output Performance (w_{OP}), and Costs (w_C), is 0.4, 0.2, and 0.4, respectively. This distribution was chosen in collaboration with Lely specialists because they believe that knowing which component loses the most availability and is most expensive over its lifespan.

The system consists out of 8 different components, which means that in total $8! = 40320$ different permutations are possible. For each permutation, Equation 5.3 has been used to calculate the rate of the permutation with the corresponding weights. The permutation with the highest value is eventually chosen, which is illustrated in Table 7.11.

Table 7.11: Ranking most important components Collector

Configuration	Rank							
	1	2	3	4	5	6	7	8
$w_A = 0.40$; $w_{OP} = 0.20$; $w_C = 0.40$	B	C	D	A	H	E	F	G

The table shows that component B is the most significant component. However, a sensitivity analysis is used to understand the impact of the weights on the output of the best permutation.

Table 7.12 shows the results of the components using FBM and PdM. The cycle cost for the two maintenance operations was calculated using the mathematical model described in Section 6. The average cost rate per cycle for both maintenance techniques is shown in the third and fifth columns of the table. In addition, columns two and four show the component cycle lengths under each maintenance approach. The final column shows the savings that may be realized by adopting the PdM policy instead of the FBM policy. When this value is negative, the average cycle cost for PdM is higher than that of FBM.

Table 7.12: Results FBM & PdM average cycle cost

	FBM		**PdM**			
Component	L_i (yrs)	Z_i (€/yr)	L_i (yrs)	Z_i (€/yr)	**FBM cost savings**	**% FBM cost savings**
Component A	16.88	€ 112,31	10,80	€ 131,59	-€19.28	-17%
Component B	11.32	€ 28.77	7.25	€ 22.85	€5.92	21%
Component C	2.45	€ 212.97	1.57	€ 205.71	€7.26	3%
Component D	11.14	€ 37.57	7.13	€ 33.63	€3.94	10%
Component E	5.38	€ 60.52	3.44	€ 48.03	€12.48	21%
Component F	15.23	€ 22.34	9.75	€ 18.18	€4.16	19%
Component G	15.59	€ 24.46	9.98	€ 21.06	€3.41	14%
Component H	3.69	€ 87.31	2.36	€ 68.95	€18.36	21%

By comparing the Z_i of FBM and PdM, we can show that the $Z_i^{FBM} < Z_i^{PdM}$ relationship does not hold for all components. These results suggest that PdM is not necessarily a better solution as a maintenance method with the current accuracy and precision because, for the drive pancake, the average cycle cost is higher for PdM. This conclusion is surprising because it was thought that having no unscheduled failures would lower the farmer's costs. Besides it was true for all components that $c_i^{CM} \ll c_i^{PdM}$. According to the present results, PdM is a less expensive maintenance technique for seven of the eight components, with cost savings ranging from 3% to 17%.

Columns six and seven of Table 7.12 demonstrated that PdM is not always a better approach for the average cycle costs. Besides, as these columns indicate, the difference in cycle cost between FBM and PdM is not that substantial. However, considering that 2500[3] Collectors currently are maintained, there is a margin for investments in a PdM approach. For example, for component E, the difference is €12.48 for one system and €12.48 * 2500 = €31200 for all systems. Therefore, considering the current input variables for this component, there could be an investment to consider PdM. An investment of this amount leads to equivalent average cycle costs for FBM and PdM. Therefore, from a cost base perspective, this implementation would make no difference. However, the PdM approach should result in fewer unscheduled failures that improve the availability of the Collector.

However, the aim is to determine the accuracy and precision limits for the prediction model under consideration. Therefore, a sensitivity analysis is used to model the uncertainty of these input parameters.

[3] This is a fictive number due to confidentiality

7.5 Sensitivity Analysis

This section performs different sensitivity analyses to address the uncertainty of the parameters of the model. The variations of the model by adjusting the input variables are showed. We first start with the sensitivity of the weights for the adjusted permutation method. After that, an analysis is performed on the bounds of the accuracy and precision to understand when PdM is more interesting to use than the current maintenance policy.

7.5.1 Sensitivity Analysis Weights

Table 7.13 shows the sensitivity analysis over the weights of the adjusted permutation method. The first row in this table shows the permutation with the chosen weights by Lely. It can be seen that components E, F, and G are the least important components to implement for PdM regarding the three criteria. However, components B and C are the two components to consider for implementing PdM because they score best for all different sensitivities of the weight distribution. Besides, components D, A, and H can be considered second best for implementation of PdM, as they consistently score positions three to five in a different order for the sensitivity on the weight distribution.

Table 7.13: Sensitivity Analysis Weights

Configuration	Rank							
	1	2	3	4	5	6	7	8
$w_A = 0{,}40$; $w_{OP} = 0{,}20$; $w_C = 0{,}40$	B	C	D	A	H	E	F	G
$w_A = 0{,}20$; $w_{OP} = 0{,}40$; $w_C = 0{,}40$	C	B	H	D	A	E	F	G
$w_A = 0{,}40$; $w_{OP} = 0{,}40$; $w_C = 0{,}20$	C	B	D	A	H	E	F	G
$w_A = 0{,}33$; $w_{OP} = 0{,}33$; $w_C = 0{,}33$	C	B	D	A	H	E	F	G
$w_A = 0{,}50$; $w_{OP} = 0{,}20$; $w_C = 0{,}30$	C	B	D	A	H	E	F	G
$w_A = 0{,}30$; $w_{OP} = 0{,}20$; $w_C = 0{,}50$	B	C	D	A	H	E	F	G
$w_A = 0{,}30$; $w_{OP} = 0{,}50$; $w_C = 0{,}20$	C	B	D	H	A	E	F	G

7.5.2 Sensitivity Analysis Cycle Cost PdM

In this section, the sensitivity analysis results for the cycle cost of PdM are investigated more closely. This sensitivity analysis has been divided into two different categories. First, the sensitivity analysis is based on different input parameters for accuracy, and the second part focuses on the precision input parameters. Component D and E have been used to visualize the sensitivity analysis for the accuracy, precision, and investment costs. However, Appendix A and B visualize the other components selected as suitable for PdM for the Collector.

Accuracy Sensitivity Analysis

Figures 7.4 and 7.5 show the effects of increased prediction accuracy. As mentioned in the input variable in Section 7.3, the lower bound for accuracy is set at 50%. The literature is utilized to determine the bounds for prediction accuracy. It is found that the accuracy of the RUL prediction by Soualhi et al. (2014) reaches up to 93.15%. Moreover, RUL predictions can reach up to 100% (Ali et al., 2015). As a result, it is decided that the sensitivity analysis would be performed to an accuracy of 100%. According to the figures, the average cycle cost for these components decreases as the accuracy increases, indicating that the prediction model is predicting failures more accurately.

Furthermore, the figures show that the average cycle cost for these products is always lower for PdM when compared to FBM. However, as illustrated in Figure A.1, the average cycle cost for the drive pancake rises in conjunction with the accuracy. Moreover, the figure shows that the drive pancake does not outperform FBM under any circumstances with different accuracy values.

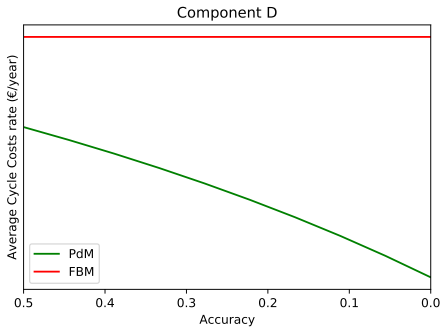


Figure 7.4: Sensitivity Analysis Accuracy Component D

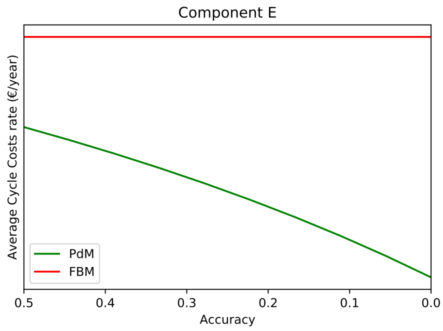


Figure 7.5: Sensitivity Analysis Accuracy Component E

Precision Sensitivity Analysis

Figures 7.6 and 7.7 depict the impact of raising the prediction precision factor. The precision factor for prediction is assumed to be from 1.5 to 4 because a precision factor of 4 suggests that with a component with the desired lifetime of ten years, the chance of receiving the observed values is high. Additionally, a high precision factor is associated with a high prediction precision. The graphs illustrate that the cycle costs become concave as forecast precision increases. This reduction applies to all components, as demonstrated in Appendix B. As a result, as the precision factor grows and the precision improves, the average cycle cost of the components decreases.

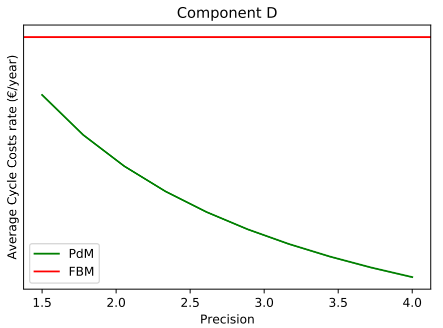


Figure 7.6: Sensitivity Analysis Precision Component D

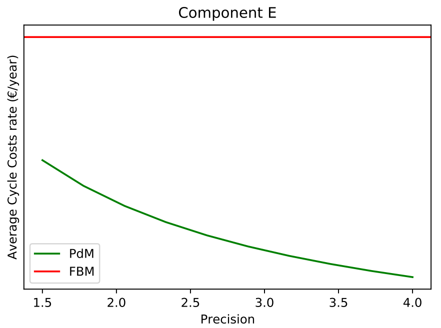


Figure 7.7: Sensitivity Analysis Precision Component E

7.6 Conclusion

In this chapter the mathematical approaches from Chapters 3, 4, 5, and 6 have been applied on the Collector. The results show that eight components of the Collector are interesting for PdM. Component C has the most influence on the availability and output performance of these eight components, while component B has the most influence on costs. Eventually, Table 7.11 shows that component B and component C are the components that first should be considered for PdM implementations.

The sensitivity analysis considers the bounds for accuracy for the prediction model. The results out of the paper of Soualhi et al. (2014) have been used to determine the lower bound for the prediction accuracy that should be possible by Lely to predict. The analysis on accuracy shows that the higher the accuracy is reaching, the lower the average cycle cost, except for the drive pancake. Besides, the precision factor analysis shows that the higher the precision factor is, the lower the average cycle cost reach.

All components could be implemented with an accuracy of 50% and a precision factor of 1.5, except component A. The average maintenance cost presented in Table 7.12 already shows that the cycle cost of component A is not profitable than an FBM approach. Besides, the sensitivity analysis shows that component A does not improve enough to be a better approach for both an increased accuracy and precision factor.

8 Conclusion & Recommendations

When being a company that wants to improve continuously, opportunities need to be addressed and researched. Lely is such a company that wants to improve continuously. Therefore, Lely has set a goal for the strategy of the company and maintenance, called Route25. This maintenance goal is to be a proactive maintenance supplier in 2025. The next step to achieve this maintenance goal is to look at predictive maintenance. Therefore, this research aims to create a model that can select components within the systems of Lely that would be interesting for predictive maintenance and validate this model on one of Lely's systems, namely the Collector. Based on this objective, we have defined the main research question as follows:

How to assess and rank the suitability of components for predictive maintenance within a multi-component heterogeneous system?

This chapter further outlines the main findings of this research. In addition, future research suggestions and recommendations for Lely are made.

8.1 Conclusion

The main research question has been divided into five research questions. Each question's main findings are summarized by answering these research questions one by one.

How to select the components suitable for predictive maintenance?
Based on their current maintenance strategy, the components with the highest potential to increase the cost of downtime are selected. For the selection of these components, the funnel approach with some adjustments has been used. These adjustments mainly focus on the identification of showstoppers where 1) clustering is not required because all Lely systems can always be reached for maintenance, 2) the economic feasibility will be evaluated with the importance measure subsequently in the research, 3) Lely already has enough experienced and trained personnel that can deal with the changes regarding PdM, 4) the showstopper failure occurrence is added which checks if the average lifetime of the components is smaller or equal to the system lifetime. Based on this approach, it can be concluded that eight components of the Collector could be feasible for the PdM approach.

How to develop a method that assesses the criticality components for predictive maintenance based on Lely's criteria?
Lely wants to consider the components' criticality based on downtime, costs, and output performance criteria. This assessment is, therefore, based on the importance measure with respect to these criteria. The approaches of Barabady and Kumar (2007), Si et al. (2012a), and Si et al. (2012b) have been used for downtime, costs, and output performance, respectively. The Weibull distribution has been used to calculate the lifetime of the components. Besides, the repair times have been received from the experts of Lely. The results show that component C is the most important component influencing availability and output performance. For the cost importance, component B is the most important.

What approach can be used or developed to combine the assessment of criticalities to get a trade-off between the criteria?
The trade-off of the three criteria of Lely will be evaluated by the adjusted permutation

approach of Karimi and Rezaeinia (2011). This approach defines the scoring of each permutation by creating concordance and discordance sets and setting weights for criteria, which result in a favorable criticality of components. The results show that the motor cable is the component that should be considered first when implementing PdM for the Collector.

How to determine the prediction accuracy's bounds per suitable component such that predictive maintenance gains more advantages than the current maintenance strategy based on Lely's criteria?

The accuracy will be determined by the PdM approach of Mckone and Weiss (2002), where PdM will be compared to FBM. The lower bound of accuracy is set at 50%, which is determined by the paper of Zhang et al. (2019). The precision factor is set as 1.5. This approach shows saving per cost cycle that could reach up to 21% for components E and H. However, PdM is not a more beneficial approach for component A because the average cycle cost is 17% more expensive with these corresponding input parameters than FBM. The sensitivity analysis shows that if the accuracy increases from 50% to 100%, the average cycle cost of the components is lower for PdM than FBM, except for the component A. The sensitivity analysis for the precision factor shows that an increasing precision factor decreases the average cycle cost for all components. However, for component A, the average cycle cost remains higher than the FBM approach. Therefore, we recommend to not implement component A for PdM.

What components of the Collector are suitable for predictive maintenance?
The case study results for the approaches show that component B and C are the components first to consider when implementing PdM for the Collector. These components score best on the three criteria and appear best in the sensitivity analysis on the different weights for the multi-criteria decision-maker. Besides, when considering implementing all selected components of the Collector for PdM, in total €90,000[4] could be saved compared to the current maintenance approach when not considering the investment costs necessary. However, these costs can be used to invest in PdM for these components.

8.2 Limitations & future research

In this section, the limitations of this research are discussed, and directions for future research will be indicated.

Multi-state modeling components
The focus of this case study on the Collector has been to model the system as a multi-state. However, as described in Section 7.2.1 the components were modeled as binary because no degradation information is available at Lely. Therefore, it is suggested that Lely starts with measuring the components' conditions to generate a more realistic model for selecting feasible components. When modeling the components as multi-state, the selection of components for PdM implementation could be more realistic. We refer to Dui et al. (2017a), who gives an overview of how multi-state transition rates with the Weibull distribution can be modeled.

[4]This is a fictive number due to confidentiality

Include structural and stochastic dependency
The models used to calculate the importance measures of Lely's criteria assume that components are statistically independent of each other. This means that the stochastic relationship between components has not been taken into account. However, a failed component can influence interconnected components. Therefore, it would be an improvement of this research when the stochastic dependency is researched within Lely. We refer to Nguyen et al. (2014), who gives an overview of reliability prediction modeling with structural and stochastic dependencies.

Include heuristic for adjusted permutation method
In chapter 5 the adjusted permutation have been used to generate a ranking of the components feasible for PdM. The model is constructed such that for all different permutations, a value has been calculated. Therefore, with the current case study $8! = 40320$, different permutations have been considered, in which Python could generate a result within one minute. However, when more components are selected as feasible for PdM, the computational time for the permutation method is growing exponentially. Therefore, it is suggested that a heuristic for this method should be used. We refer to Beyragh and Noor (2016), and Karimi and Rezaeinia (2011), who both give different heuristic models to reduce the computational time for the adjusted permutation method.

Include comparison preventive maintenance for comparison accuracy
In Section 6 the model only compares the FBM with the PdM methodology because the majority of components are currently maintained by FBM. However, it could be the case for other systems within Lely that a component currently maintained by a preventive maintenance approach could be improved to a predictive maintenance approach. Therefore, it would be interesting to investigate how preventive maintenance is performing in comparison with predictive maintenance.

8.3 Recommendations

Update FMEA and include the failure mode with failure data
In Section 3 the components could have been selected based on the failure modes of the components. However, within Lely, the Collectors' latest FMEA version dated from 2012, which was in the design phase of the Collector. When this information was known, a more accurate selection of components could have been made that could be interesting for PdM. Therefore, we recommend that Lely update their FMEA periodically to understand the valuable knowledge of the systems failure behavior. We refer to Chapters 2 and 3 of the PhD thesis of Braaksma (2012) for creating an FMEA in asset maintenance.

Investigate the effect of finite time horizon for PdM methodology
The model used for determining the average cycle cost for PdM is based on an infinite time horizon. However, the systems of Lely have an expected lifetime of 15 years. Modeling with a finite time horizon could be more realistic for determining the average cycle cost for PdM. Therefore, it is recommended to find a methodology that models the average cycle cost for PdM as finite and compared it to the current maintenance approach. It is expected that the average cycle cost will be lower than when modeling it with an infinite horizon because the results of the MSc thesis of Hoedemakers (2020) show a higher average cycle cost for infinite horizon than the MSc thesis of Langen de (2021) with a finite horizon.

Deep learning methodology

When one of the components will be implemented for PdM, it is recommended that the model used to predict the Remaining Useful Life (RUL) of the component will be based on a deep learning methodology. The paper of Zhang et al. (2019) has done a survey comparing the results of different papers of machine learning with deep learning prediction methodologies. This paper shows that for RUL estimations, the deep learning methodologies have higher accuracy than machine learning.

Determine effect of qualitative output performance on system

In Section 4.4.2 the output performance has been divided into qualitative and quantitative output performance. We assumed that qualitative output performance only considered downtime because a failure due to a quality issue was hard to define. Besides, this downtime was already included by the availability. However, these quality issues can significantly impact systems in terms of the breakdown of some components. Therefore, we recommend that more profound research is needed to define how qualitative output performance affects the system's behaviors.

References

Ali, J. B., Chebel-Morello, B., Saidi, L., Malinowski, S., and Fnaiech, F. (2015). Accurate bearing remaining useful life prediction based on weibull distribution and artificial neural network. *Mechanical Systems and Signal Processing*, 56:150–172.

Arts, J. (2017). *Maintenance, Modeling and Optimization*, volume 526. Eindhoven.

Barabady, J. and Kumar, U. (2007). Availability allocation through importance measures. *Journal of Quality & Reliability Management*, 24(6):643–657.

Beyragh, A. A. and Noor, J. R. (2016). Adjusted permutation method for multiple attribute decision making with pruning solution approach. *Journal of Global Pharma Technology*, 8(5):22–29.

Bousdekis, A., Magoutas, B., Apostolou, D., and Mentzas, G. (2015). A proactive decision making framework for condition-based maintenance. *Industrial Management and Data Systems*, 115(7):1225–1250.

Braaksma, J. (2012). *Asset information for FMEA-based maintenance*. PhD thesis, Rijksuniversiteit Groningen.

Čepin, M. (2011). Reliability block diagram. In *Assessment of Power System Reliability*, pages 119–123. Springer.

Chawla, N. V., Bowyer, K. W., Hall, L. O., and Kegelmeyer, W. P. (2002). Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357.

Chen, S.-J., Hwang, C.-L., and Hwang, F. P. (1991). *Fuzzy Multiple Attribute Decision Making*.

Chen, Z. and Zhu, X. (2019). Working-Condition Importance Measures for Multi-Component Systems. *IEEE Transactions on Reliability*, pages 1124–1128.

Do, P. and Bérenguer, C. (2020). Conditional reliability-based importance measures. *Reliability Engineering and System Safety*, 193(June 2019):106633.

Dui, H., Chen, L., and Wu, S. (2017a). Generalized integrated importance measure for system performance evaluation: application to a propeller plane system. *Eksploatacja i Niezawodnosc - Maintenance and Reliability*, 19(2):279–286.

Dui, H., Si, S., and Yam, R. C. M. (2017b). A cost-based integrated importance measure of system components for preventive maintenance. *Reliability Engineering and System Safety*, 168:98–104.

Ebeling, C. E. (2004). *An introduction to reliability and maintainability engineering*. Tata McGraw-Hill Education.

Gouriveau, R., Medjaher, K., and Zerhouni, N. (2016). From prognostics and health systems management to predictive maintenance 1: Monitoring and prognostics, volume 4.

Gravette, M. A. and Barker, K. (2015). Achieved availability importance measure for enhancing reliability- centered maintenance decisions. *Journal of Risk and Reliability*, pages 1–11.

Griffith, W. (1980). Multistate Reliability Models. *Journal of Applied Probability*, 17(3):735–744.

Hoedemakers, J. (2020). Creating a preventive maintenance concept for new systems using multi-objective optimization. Technical report, Einhoven University of Technology, Eindhoven.

Hossin, M. and Sulaiman, M. N. (2015). A review on evaluation metrics for data classification evaluations. *International journal of data mining & knowledge management process*, 5(2):1.

Isermann, H. (1982). Linear Lexicographic Optimization. *OR Spektrum*, pages 223–228.

Jacquet-Lagrèze, E. (1969). L'agrégation des opinions individuelles. *Informatique et Sciences humaines*, 4:1–21.

Kahraman, C. (2008). Multi-criteria decision making methods and fuzzy sets. In *Fuzzy Multi-Criteria Decision Making*, pages 1–18. Springer.

Karimi, H. and Rezaeinia, A. (2011). Adjusted permutation method for multiple attribute decision making with meta-heuristic solution approaches. *International Journal of Industrial Engineering Computations*, 2:369–384.

Khorram, E., Zarepisheh, M., and Ghaznavi-Ghosoni, B. (2010). Sensitivity analysis on the priority of the objective functions in lexicographic multiple objective linear programs. *European journal of operational research*, 207(3):1162–1168.

Kvassay, M., Levashenko, V., Rabcan, J., Rusnak, P., and Zaitseva, E. (2018). Structure function in analysis of multi-state system availability. *Safety and Reliability - Safe Societies in a Changing World - Proceedings of the 28th International European Safety and Reliability Conference, ESREL 2018*, (June):897–906.

Labib, A. W. (1998). World-class maintenance using a computerised maintenance management system. 4(1):66–75.

Labib, A. W. (2004). A decision analysis model for maintenance policy selection using a CMMS. *Journal of Quality in Maintenance Engineering*, 10(3):191–202.

Langen de, B. (2021). Preventive maintenance optimization with updating capabilities for multi-component heterogeneous systems using multi-objective optimization. Technical report, Einhoven University of Technology, Eindhoven.

Lebold, M., Reichard, K., and Boylan, D. (2003). Utilizing dcom in an open system architecture framework for machinery monitoring and diagnostics. In *2003 IEEE aerospace conference*, pages 1227–1236.

Lee, J., Kao, H. A., and Yang, S. (2014a). Service innovation and smart analytics for Industry 4.0 and big data environment. *Procedia CIRP*, 16:3–8.

Lee, J., Liao, L., Lapira, E., Ni, J., and Li, L. (2009). Informatics platform for designing and deploying e-manufacturing systems. In *Collaborative Design and Planning for Digital Manufacturing*, pages 1–35. Springer London.

Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., and Siegel, D. (2014b). Prognostics and health management design for rotary machinery systems - Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 42(1-2):314–334.

Lisnianski, A. (2007). Extended block diagram method for a multi-state system reliability assessment. *Reliability Engineering & System Safety*, 92(12):1601–1607.

Lybeck, N., Pham, M., Tawfik, M., Coble, J., Meyer, R., Ramuhalli, P., and Bond, L. (2011). Lifecycle Prognostics Architecture for Selected High-Cost Active Components. *Idaho National Laboratory and Pacific Northwest National Laboratory, INL/EXT-11-22915*, (August).

Mazhar, M. I., Kara, S., and Kaebernick, H. (2007). Remaining life estimation of used components in consumer products: Life cycle data analysis by Weibull and artificial neural networks. *Journal of Operations Management*, 25(6):1184–1193.

Mckone, K. E. and Weiss, E. N. (2002). Guidelines for implementing predictive maintenance. *Production and Operations Management*, 11(2):109–124.

Mobley, R. K. (2002). *An introduction to predictive maintenance*. Butterworth-Heinemann.

Nguyen, K. A., Do, P., and Grall, A. (2014). Condition-based maintenance for multi-component systems using importance measure and predictive information. *International Journal of Systems Science: Operations and Logistics*, 1(4):228–245.

Olde Keizer, M. C., Flapper, S. D. P., and Teunter, R. H. (2017). Condition-based maintenance policies for systems with multiple dependent components: A review. *European Journal of Operational Research*, 261(2):405–420.

Pham, B. T., Agarwal, V., Lybeck, N. J., and Tawfik, M. S. (2012). Prognostic Health Monitoring System : Component Selection Based on Risk Criteria and Economic Benefit Assessment. *Idaho National Laboratory (INL)*, pages 1–8.

Pintelon, L. and Parodi-herz, A. (2008). Maintenance : An Evolutionary Perspective Maintenance : An Evolutionary Perspective. *Springer*, (January 2008):21–48.

Rausand, M. and Hoyland, A. (2004). *System Reliability Theory*. Wiley-Interscience.

Robles, J. O., Almaraz, S. D. L., and Azzaro-Pantel, C. (2018). *Methods and tools for hydrogen supply chain design*.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International journal of services sciences*, 1(1):83–98.

Scarf, P. A. (2007). A Framework for Condition Monitoring and Condition Based Maintenance. *Quality Technology & Quantitative Management*, 4(2):301–312.

Seryasat, O. R., Honarvar, F., Rahmani, A., et al. (2010). Multi-fault diagnosis of ball bearing based on features extracted from time-domain and multi-class support vector machine (msvm). In *2010 IEEE International Conference on Systems, Man and Cybernetics*, pages 4300–4303. IEEE.

Si, S., Dui, H., Cai, Z., and Sun, S. (2012a). The integrated importance measure of multi-state coherent systems for maintenance processes. *IEEE Transactions on Reliability*, 61(2):266–273.

Si, S., Dui, H., Zhao, X., Zhang, S., and Sun, S. (2012b). Integrated importance measure of component states based on loss of system performance. *IEEE Transactions on Reliability*, 61(1):192–202.

Soualhi, A., Medjaher, K., and Zerhouni, N. (2014). Bearing health monitoring based on hilbert–huang transform, support vector machine, and regression. *IEEE Transactions on instrumentation and measurement*, 64(1):52–62.

Sun, Y., Wong, A. K., and Kamel, M. S. (2009). Classification of imbalanced data: A review. *International journal of pattern recognition and artificial intelligence*, 23(04):687–719.

Tiddens, W. W., Braaksma, A. J. J., and Tinga, T. (2018). Selecting Suitable Candidates for Predictive Maintenance. *International Journal of Prognostics and Health Management*, page 20.

Tinga, T., Tiddens, W., Amoiralis, F., and Politis, M. (2017). Predictive maintenance of maritime systems: Models and challenges. *researchgate.net*.

Ton, B., Basten, R., Bolte, J., Braaksma, J., Di Bucchianico, A., van de Calseyde, P., Grooteman, F., Heskes, T., Jansen, N., Teeuw, W., Tinga, T., and Stoelinga, M. (2020). Primavera: Synergising predictive maintenance. *Applied Sciences*, 10(23):1–19.

Triantaphyllou, E. (2000). *Multi-Criteria Decision Making Methods: A Comparative Study*, volume 1. Kluwer academic publishers, applied op edition.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, 79(4):281–299.

Velasquez, M. and Hester, P. T. (2013). An Analysis of Multi-Criteria Decision Making Methods. *International Journal of Operations Research*, 10(2):56–66.

Veldman, J., Wortmann, H., and Klingenberg, W. (2011). Typology of condition based maintenance. *Journal of Quality in Maintenance Engineering*.

Vu, H. C., Do, P., and Barros, A. (2016). A Stationary Grouping Maintenance Strategy Using

Mean Residual Life and the Birnbaum Importance Measure for Complex Structures. *IEEE Transactions on Reliability*, 65(1):217–234.

Wu, S. and Chan, L.-Y. (2003). Performance Utility-Analysis of Multi-State Systems. *IEEE Transactions on Reliability*, 52(1):14–21.

Zaitseva, E. and Levashenko, V. (2017). Reliability analysis of multi-state system with application of multiple-valued logic. *International Journal of Quality & Reliability Management*.

Zhang, W., Yang, D., and Wang, H. (2019). Data-Driven Methods for Predictive Maintenance of Industrial Equipment : A Survey. *IEEE Systems Journal*, 13(3):2213–2227.

A Appendix A

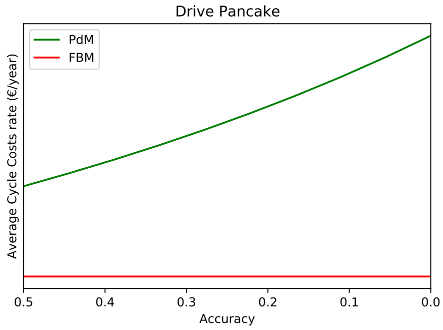


Figure A.1: Sensitivity Analysis Accuracy Component A

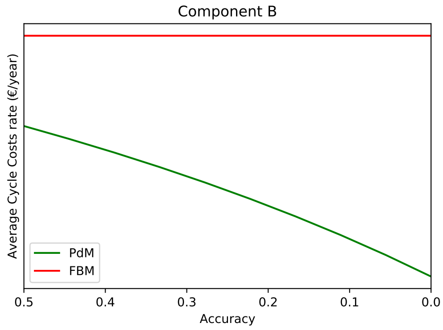


Figure A.2: Sensitivity Analysis Accuracy Component B

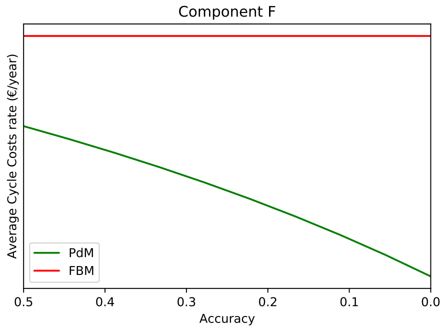


Figure A.3: Sensitivity Analysis Accuracy Component E

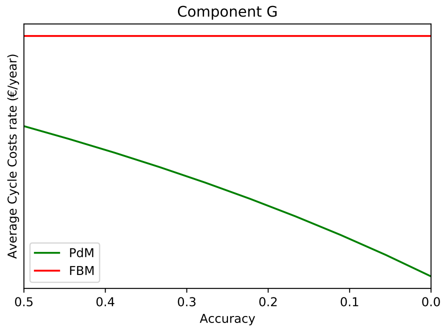


Figure A.4: Sensitivity Analysis Accuracy Component F

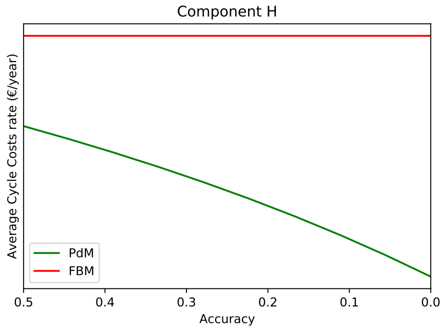


Figure A.5: Sensitivity Analysis Accuracy Component G

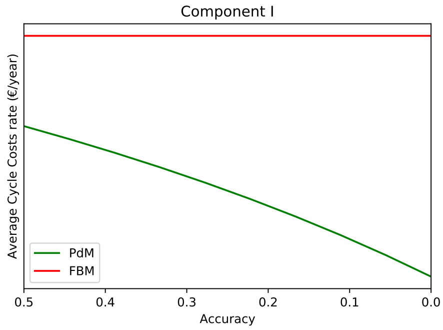


Figure A.6: Sensitivity Analysis Accuracy Component H

B Appendix B

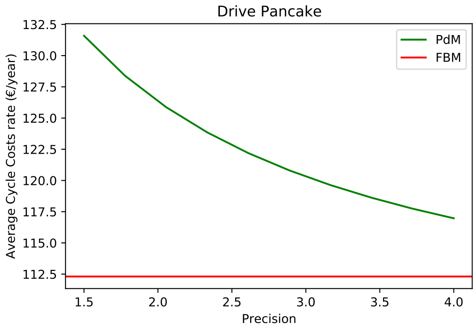
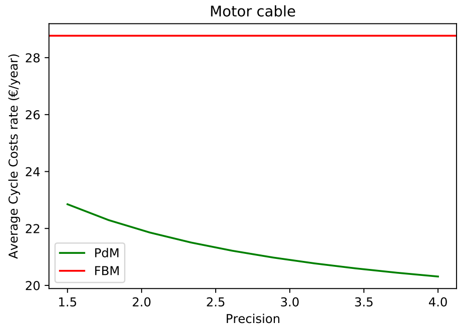


Figure B.1: Sensitivity Analysis Precision Component A



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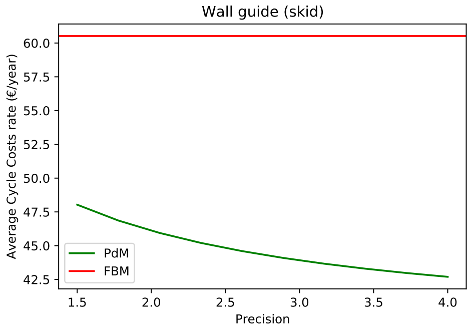

Figure B.3: Sensitivity Analysis Precision Component E

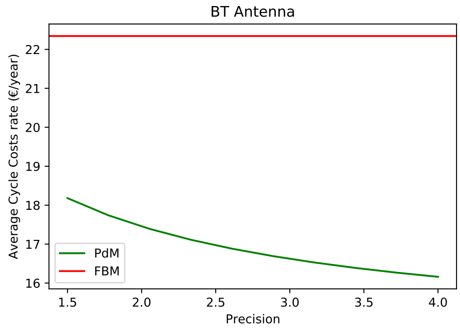

Figure B.4: Sensitivity Analysis Precision Component F

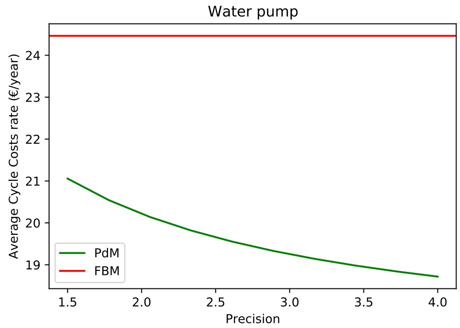

Figure B.5: Sensitivity Analysis Precision Component G

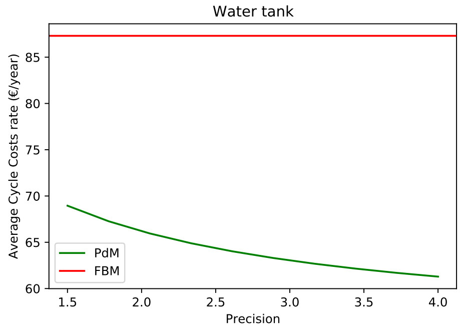

Figure B.6: Sensitivity Analysis Precision Component H