MASTER

Gaining faster maintenance knowledge by introducing and using data within Marel

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Gaining Faster Maintenance Knowledge by Introducing and Using Data within Marel

Master Thesis

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Abstract

This master thesis describes a research project carried out within the Structural Group of Service within Marel Stork Poultry Processing. The topic is the creation of knowledge from data to maintain and modify new developed machinery. A model is developed, based on six criteria, for selecting the ten most interesting components for predictive maintenance. Furthermore, a model is introduced by combining two methods, Statistical Process Control and Multiple Linear Regression. The model is used to explain degradation in performance of a newly developed machine by examining its external production factors. Both models are applied within case studies for Marel, to test for applicability and correctness.

Executive summary

Main subject of the research

This report contains the result of my master thesis study performed at Marel Poultry. Marel Poultry is a company which main aim is to deliver advanced in line poultry processing solutions. The company is based in Boxmeer, the Netherlands. It is the market leader and therefore needs to be innovative to be able to stay ahead of the competition. For Marel Servitization is important. Servitization can be defined as "the role of services in sustaining the competitiveness of manufacturers" (Lightfoot, Baines, & Smart, 2013). Servitization on a new piece of machinery at a customer is time consuming. The wear and failure behaviour is not yet known, and this may cost the company and the customer money due to too high or too low frequency of maintenance.

Problem statement

Marel is interested in Proactive maintenance. Proactive maintenance can be defined as a combination of predictive and preventive maintenance. Predictive maintenance is of major importance for Marel to introduce. Predictive maintenance is intended to contribute to solving Marel Poultry's problem: "Understanding degradation and failure behaviour of new equipment and making the right modification and maintenance decisions" (Marel, 2017). The implementation of predictive maintenance within Marel has been discussed in several previous master thesis projects. It is known how to implement predictive maintenance when knowledge about a machine's working is available. However, for new machines this is often not the case, so the implementation of predictive maintenance is troublesome. Therefor the focus of this research will be on the period during innovation and when the prototype is introduced in the working field.

Research approach

The research is approached by dividing prototyping in three periods: development, prototype introduction, and running at a test customer. These three periods are also linked to scopes. The first period can be defined on component level, the second phase on machine level, and the third phase on how the machine behaves within a production environment. Within this research the first and third period are discussed. For the first period the choice for beneficial components for predictive maintenance is discussed. Within the third period a method is introduced for using data from within the process to determine the influence of external production factors on the performance of the machine. The main research question is:

How can Marel use its data to get faster acquainted with factors affecting performance of its newly introduced machines?

The main research question is divided into two questions, hereafter denoted as research question 1 and research question 2. The focus is on acquiring more knowledge for applying predictive maintenance.

Research Question 1 with main findings

Research Question 1: How can it be determined for which components it is beneficial to implement predictive maintenance?

Within the first question it is determined that B- and E-components within the Marel Global Maintenance Concept (MGMC) are most interesting. These components possess the traits defined for predictive maintenance components:

- Random failure pattern
- Critical for the performance of the machine
- Subject to wear

The main criteria which are used for assessment of the components are defined and introduced in such a way that these could be used for quantification. The six criteria which are selected are:

- Criticality
- Skill level needed for repair
- Mean Time To Failure
- Mean Time To Support
- Mean Time To Repair
- Component costs

Based on these criteria, a quantitative model is developed to determine which components are most beneficial for applying predictive maintenance before the introduction of the new machine.

Therefore the answer to the first research question lies is using the introduced model to score parts on the suggested criteria, which results in a selection of components that will benefit most from predictive maintenance.

Research Question 2 with main findings

Research Question 2: How can it be determined which external production factors are of importance in affecting the degradation of a newly introduced machine?

For answering this research question three steps were taken. First the interesting data was found and prepared, by retrieving it from two IT-systems, Innova and ChainLive. Several process variables were taken into account. Next, two data analysis methods were introduced, Statistical Process Control, and Multiple Linear Regression. Statistical Process Control (SPC) is used to find out of control production moments by using a 3-sigma limit. Multiple Linear Regression (MLR) is used to explain a dependent variable (in this case the performance) by using several independent variables (process variables). This approach of using the two models was tested on a case study. This test revealed that the approach was applicable and led to valid results.

So, to answer the second research question, the external production factors can be determined by first finding the periods of time the process was out of control. This is done by using Statistical Process Control. Subsequently, Multiple Linear Regression is used to find the variables that caused the performance degradation for that specific period.

Main research findings

To conclude the main research question, the machines' components are introduced within the first research question by adding predictive maintenance. Interesting components can be determined and these can subsequently be monitored. Furthermore, there is data available about the process within a production plant. Using this data and find out how other machines, broilers, or plant characteristics can be used for finding factors outside the machine influencing the performance. Specifying the degradation, may result into a modification in the design.

The discussed methods can be used for setting up maintenance especially for original equipment manufacturers who also deliver services. Furthermore, the machines of these manufacturers are not stand alone machines. This would especially entail the second part of the project. Hence there are less outside factors which influence the performance of the machine when it is a stand alone machine. For introduction of the first part it is important that there is a similar way of setting up maintenance and some variables are already taken into account. For example, a method for classifying components into maintenance categories.

Recommendations

- Predictive maintenance is not yet a service product which can be offered to the customers. A separate service product needs to be created along with a matching support organization. For example by hiring more data scientists or create a monitoring system which automatically can find explaining variables. Furthermore, by introducing predictive maintenance the period of predicting needs to be established and discussed with the supply chain to be able to detect an error and be on time for delivery of new parts. This will both decrease the inventory and increase the delivery performance.

- For execution of predictive maintenance more knowledge has to be gathered. Especially the knowledge about how certain components behave or measurements can be registered reliably. This is of importance to be able to apply predictive maintenance. After determination if a component is interesting for predictive maintenance the real measurement and setup needs to be created.

- Design a standard monitoring method for the standard components used within the rotating equipment. These components are used very commonly and within many systems therefore this would benefit cost wise. Furthermore, by introducing such a system it may increase the knowledge about these components.

- To be able to implement the mid-term stage, depicted in Chapter 2, put more emphasis on creating a Failure Mode Effect & Criticality Analysis (FMECA). This may lead to faster detection of problems. Furthermore, it could increase the knowledge in adding data creating elements to the machine.

Preface

This report represents my final hurdle I have to take before receiving my master degree. Hurdles were a long time a big part of my life, but I could not have overcome them without the help of a number of people.

First of all, Ivo Adan, I have always appreciated your feedback during the thesis but also as mentor during my master. We had some good discussion about both the Manufacturing Systems Engineering track but also while performing this research. You were always able to give me new directions for further elevating my research.

Secondly, I want to speak out my appreciation for Rob Basten. As second supervisor we agreed that we had little contact, but the moments we had contact were important for the final result. Great criticism and advise is what I experienced. Furthermore, I want to thank you for giving me the opportunity for performing my research at Marel as part of the ProSeLoNext project.

Thirdly, I want to thank Alp Akçay for the time to read this report as my third supervisor.

Marel as company, I want to thank for giving the support fpr performing my research. I experienced the company as a family who is always open to help each other. Some people within Marel need to be addressed with special notice. First and most important Robert Lemmens. As company supervisor you were a great support in guidance through the total research. You had some very interesting ideas and was continuously evaluating the steps. Furthermore, Steef Laurijs who I want to thank for our fruitful sessions in which much information was shared about the maintenance concept. In general I want to thank the Structural Group Service who gave me an inspiring environment in which I could perform my thesis. The jokes but also serious conversations made my time within Marel special.

Moreover, I want to thank my family. To start, my father who helped me a lot in my total study career with his expertise and ongoing moral support. My mother for the encouragement and the occasional kick under my bottom. Lastly, my brother Thomas, your moral support and grammatical guidance has been greatly appreciated.

Unfortunately, this also marks the end of my student career which could have never been so great without all the friends I have made during this time. Especially, the laughs and cries, moral support, and a lot of "coffee" with the boys of Duçibus made it a beautiful time.

Now I am doing one person still no justice: my girlfriend. You were a great support last year during, for me, the most difficult part of my study. I am grateful for our evening walks discussing my project and weekends motivating me to getting this thesis to a higher level. From now on books and laptops will stay closed during weekends.

Enjoy reading!

Wouter Schuwer
Eindhoven, January 2019

Contents

List of Figures

List of Tables

List of Acronyms

BOM Bill of Materials. 11, 16, 21, 22, 29

CBM Condition Based Maintenance. 9, 10, 15, 20, 22, 24, 28–31

FMECA Failure Mode Effect & Criticality Analysis. 45

IoT Internet of Things. 22, 33

MGMC Marel Global Maintenance Concept. 5, 6, 9, 11, 13

MLR Multiple Linear Regression. 38, 39, 41, 44

MSPP Marel Stork Poultry Processing. 1, 2, 9

MTTF Mean Time To Failure. 22, 24

MTTR Mean Time To Repair. 22, 24

MTTS Mean Time To Support. 22, 24

OEE Overall Equipment Effectiveness. 9

OEM Original Equipment Manufacturer. 1, 6

PMS Preventive Maintenance Schedule. 18, 22, 29, 30

SPC Statistical Process Control. 35–39, 41, 44

TREC Transfer Evisceration & Cooling. 10, 12, 14, 15, 29, 32, 33, 38, 43

Chapter 1

Introduction

This report discusses a master thesis project which is executed at Marel Stork Poultry Processing (MSPP). MSPP is an Original Equipment Manufacturer (OEM) for whom servitization of their machines at customers is becoming more important. Servitization is introduced by Vandermerwe and Rada (1988). Servitization can be defined as "the role of services in sustaining the competitiveness of manufacturers" (Lightfoot et al., 2013).

It is important for MSPP to be able to stay competitive and therefore the development of new machinery is important. After development and installation at a customer, servitization begins. A downside to this is that setting up a maintenance program for a new piece of machinery at a customer is time consuming. It is time consuming because the wear and failure behaviour of the machine is not yet known. Although it is time consuming, it is very important for MSPP to implement a correct maintenance strategy. It costs the customer money when maintenance is executed too often (cost of maintenance) but also too little (downtime costs). Because of the benefits in terms of money and time, the implementation of a correct maintenance strategy is important to customers. In addition to that, it is beneficial for MSPP since it can reduce defects, improve product quality, and optimized machine performance. This increases customer satisfaction and enlarges competitive advantage (Mobley, 2002).

Service on machinery at customers of MSPP is executed with the help of schedules. An important part of after-sales service is the correct timing of service activities. By making use of condition monitoring techniques, wear patterns of components within machinery can be detected earlier. As a result, breakdown of random parts can be better predicted or recognized. Predicting failure patterns may become easier, since new technology is introduced. With these new technologies condition monitoring can be implemented more easily.

The previously discussed development is also the subject of this master thesis. In other words, how condition based maintenance based on condition monitoring can be used to speed up the process of identifying wear and failure patterns within new machinery at MSPP. This speeding up will be done by improving the service related process during development.

This project is part of a bigger inter-company and university project called ProSeLoNext (short for: pro-active service logistics for capital goods - the next steps). This is a consortium consisting of four universities and nine companies including Eindhoven University of Technology and Marel. The consortium aims to orchestrate all aspects of the after sales service for OEMs (Basten, 2015).

This chapter is organized as follows. Section 1.1 describes the company background and in Section 1.2 a poultry processing process is explained. Subsequently, the Marel maintenance concept in Section 1.3 and in Section 1.4 the structure of this thesis is explained.

1.1 Company Background

Marel is an Icelandic company founded in 1978. It currently has 5,400 employees based in 30 countries over six continents. Marel is an original equipment manufacturer in advanced food processing systems and services. Marel aims to be the leading global provider of advanced food processing systems and services. Marel has three main divisions: poultry, meat, and fish. Besides delivering machines to customers, a big part of the business is also delivering services to the customers in order to operate the machines at their best.

In 2017, Marel had a revenue of 1,038 million Euros of which 57.8 million Euros (5.57%) was spent on R&D. The specific part of the company at which this research is being conducted is at MSPP. MSPP is based in Boxmeer and is specialized in the poultry sector. MSPP was acquired by Marel from Stork in 2008. MSPP accounted for 54.0% of the total earnings of Marel over 2017 (Marel, 2018).

1.2 Poultry Processing Process Description

MSPP delivers every part of the slaughter and processing process of life broilers into customer ready labelled packages which can be delivered straight to the supermarkets. The process is divided into two parts as can be seen in Figure 1.1. Within primary processing, all processes are taken into account in whole broilers, afterwards in secondary processing the broilers are processed into end products, which in most cases means that the broilers are cut up.

In Figure 1.2 the different possible process steps are depicted together with the sequence in which the steps will occur. Furthermore, the side processes are depicted which are: internal logistics, rendering and waste water treatment, and data acquisition and logistic control.

Between the different processing steps, the broilers are transported using chains/conveyor belts. After the live bird supply, the broilers are hung onto a transportation system. This transportation system will not transport the broiler until the end of the line. Between different steps in the production process the broilers are rehung onto another transportation line, because of hygienic reasons and needed flexibility of shackles per line. These systems, which rehang the broilers, are called Transfer Systems. Within Figure 1.3 three different transportation lines are depicted (blue, black, and green). The transfer systems are depicted within the yellow boxes.

As can be noticed, there are a lot of different machines and operations within a broiler processing plant. These machines are operated under harsh conditions. Large amounts of detergents and water is used to make sure the machines stay hygienic and to secure food safety. This degrades the lifetime of a machine significantly because of the negative influence on lubricants. The machines are also of significant sizes and consist out of many components. To keep the different machines running, maintenance needs to be executed on the machines. Maintenance will increase the customers' up time. Increasing the up time will reduce the standstill costs, increase the ability to meet the contracts with end customers (all final products can be supplied at the agreed moment), and there will be less congestion within the live broiler supply. How maintenance can be defined and how MSPP handles this, is explained in the next section.

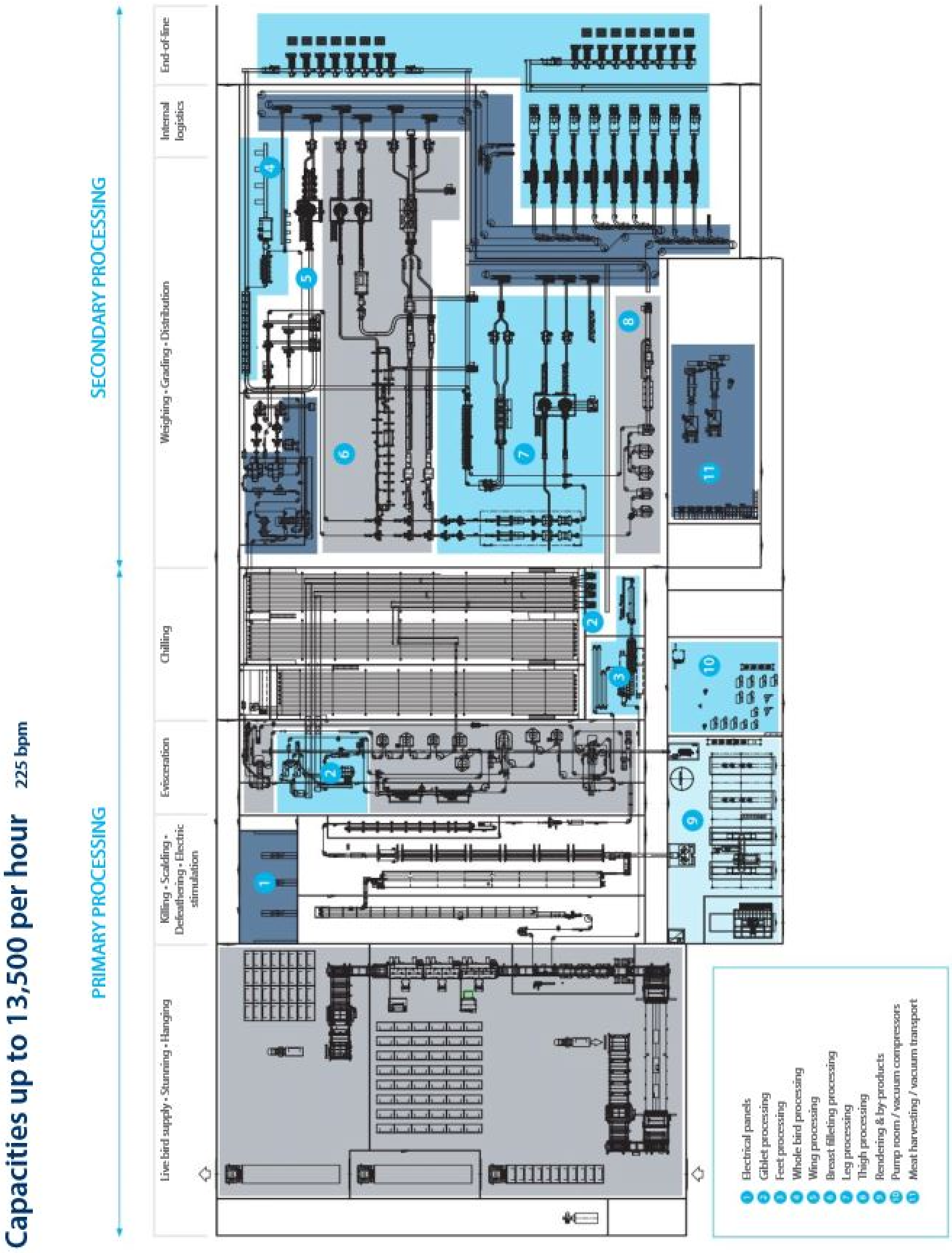

Figure 1.1: Poultry processing overview (Marel Stork Poultry Processing B.V., 2016)

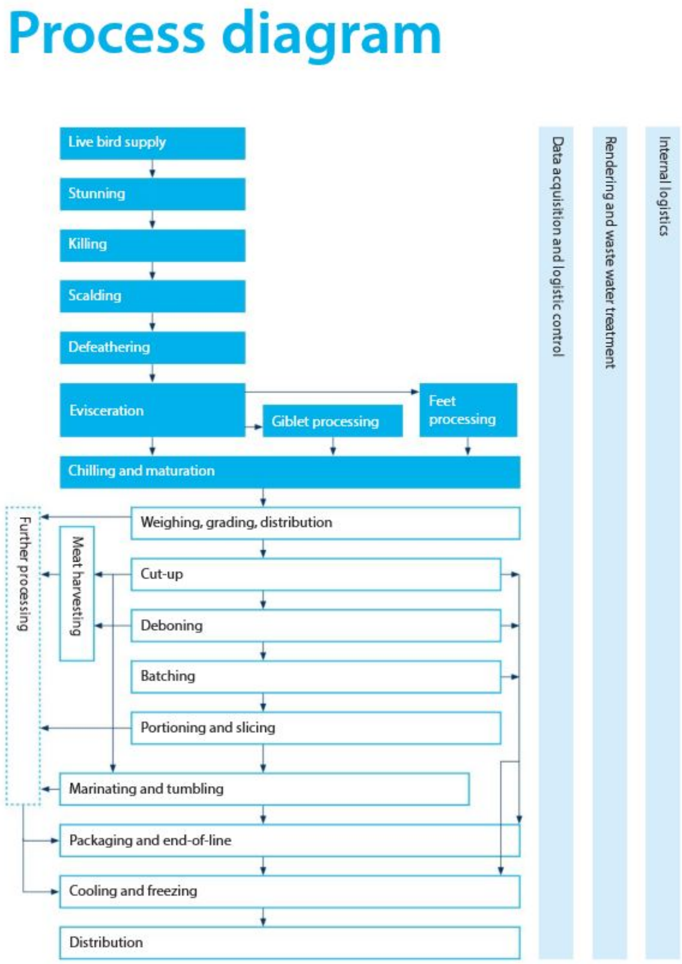

Figure 1.2: Process Diagram (Marel Stork Poultry Processing B.V., 2016)

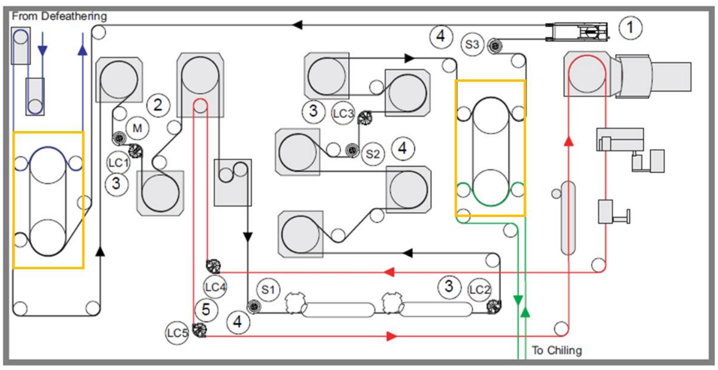

Figure 1.3: Different transportation lines (Marel Stork Poultry Processing B.V., 2015)

1.3 Marel Global Maintenance Concept

In this section maintenance will be described and how maintenance is applied within Marel by using the MGMC.

1.3.1 Maintenance

When describing maintenance operations it is important to identify a machine as a collection of interrelated components. Most of the time maintenance entails replacing or repairing parts of a system and not a total system (Arts, 2016). Within maintenance of equipment and components there are several strategies. The different strategies are depicted in Figure 1.4.

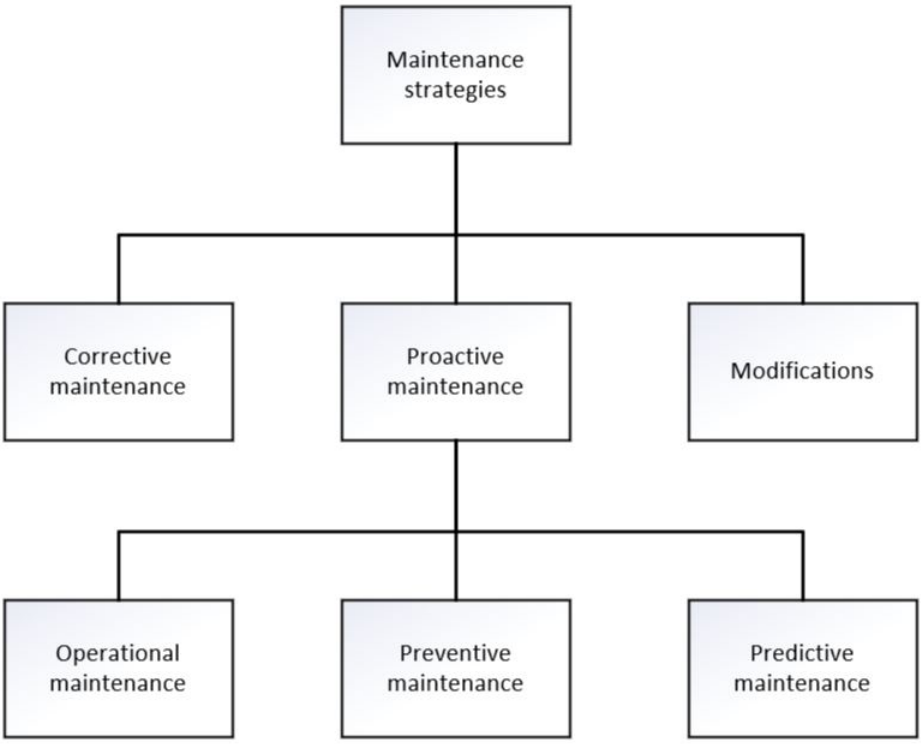

Figure 1.4: Maintenance strategies for components

Explanation of the different strategies, based on Kothamasu et al. (2006):

- Modificative maintenance (Modifications): Concerns interchanging a part with a technically more advanced part in order to make the equipment better. This is mostly non-recurring.
- Corrective maintenance: Concerns carrying out an activity after a failure has occurred and is intended to restore an item to a state in which it can perform its required function.
- Proactive maintenance: Concerns replacing a part before failure. Different types of proactive maintenance can be distinguished:

  - Operational maintenance: Concerns every day care and minor maintenance of equipment for which detailed technical knowledge is not required.
  - Preventive maintenance: Concerns a strategy organized to perform maintenance at predetermined intervals to reduce the probability of failure or performance degradation (both time- and count-based).
  - Predictive maintenance (Condition based maintenance): Concerns a decision making strategy where the decision to perform maintenance is reached by observing the condition of the system and/or its components.
    * Condition monitoring: Continuously measuring of the condition of a component through sensors.
    * Periodic inspections: Periodically measuring a part during inspections.

It is chosen to use the following terminology, since these terms are used within Marel.

- Corrective maintenance is all maintenance executed after breakdown
- Proactive maintenance is all maintenance planned before breakdown
  - Operational maintenance is every day maintenance which results in correct way of working for the machines (e.g. lubrication)
  - Preventive maintenance is executed before breakdown on a time- and/or count based interval
  - Predictive maintenance is executed by making a maintenance decision based on the condition of a component or piece of machine.

1.3.2 Concept

As OEM, Marel also delivers services, for example installing the machines at a food processing factory and/or provide support to customers to execute the maintenance of their machines. This also incorporates the sales of spare parts. Furthermore, to keep the machines on a steady performance Marel designed a maintenance program. This program is called the Marel Global Maintenance Concept (MGMC). The MGMC has been set up in 2013 with the motivation to deliver added value to the customer. Service is always needed even when there is economic fluctuation. An internal maintenance concept also secures spare part business (no competing companies may be involved). Overall service is an extra step to deviate from competitors since service is less visible so more difficult to imitate. With the concept, especially proactive maintenance is encouraged and because of that the corrective maintenance and production loss will decline which in the end will lead to a lower total cost. This way of thinking is depicted in Figure 1.5.

All machines will be maintained by using the maintenance concept. Within this concept several types of maintenance are taken into account, which may be executed during the lifetime of a machine. In other words, maintenance can be performed in different ways and are all beneficial for a specific type of part. When concerned with these types it is most important to take into account the frequency of replacement and how well the wear of the specific parts can be predicted. Since there are several maintenance strategies (see previous section), these strategies can also be used to give the parts their specific coding. To start, there are the consumables, A-parts, (for example knives). These need to be changed for the day-to-day

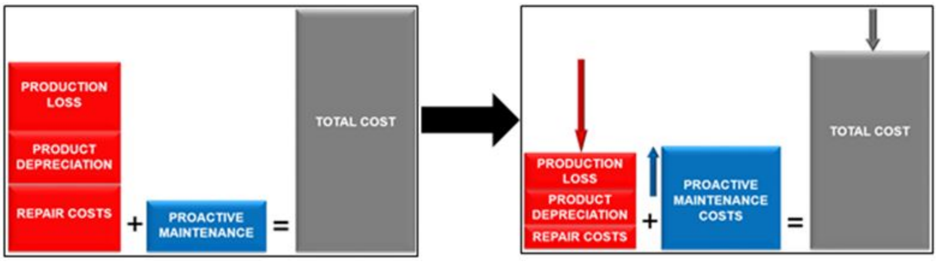

Figure 1.5: Cost changes due to proactive maintenance (Marel, 2013)

operation. There are the B-parts, which have uniform and constant failure distributions. These parts are unpredictable and may break down at any moment in time when in use. C-, D-, and E-parts are defined based on lifetime: C-parts have on average a shorter expected lifetime than the D-parts and subsequently the D-parts have a shorter expected lifetime than the E-parts. Within the maintenance concept also the kind of maintenance is taken into account. The different part coding is given by an employee with experience in service at customers and considerable knowledge about the different coding aspects. For the C-, D-, and E-parts a maintenance schedule can be set up. This schedule is a preventive maintenance schedule (time-based). The C-parts will be changed in small (S) overhauls; the D-parts will be changed together with the C-parts in medium (M) overhauls and E parts in total (T) overhauls together with the C- and D-parts. A representation of the maintenance concept and the position of the A-, B-, C-, D-, and E-parts is depicted in Figure 1.6.

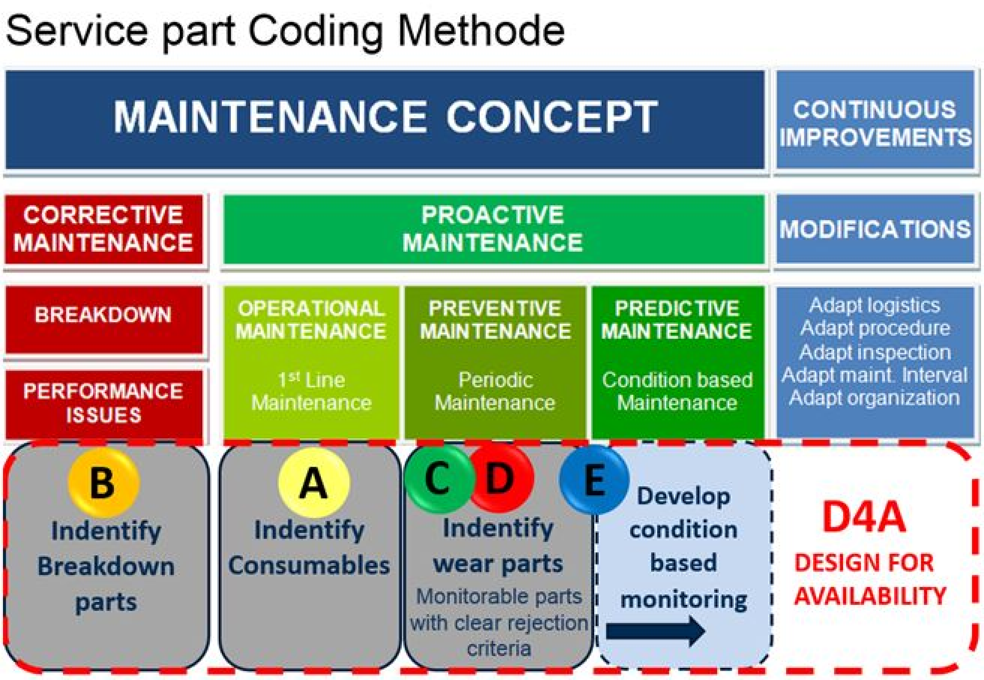

Figure 1.6: Marel Global Maintenance Concept (Marel Stork Poultry Processing B.V., 2013)

1.4 Project outline

After this introduction first of all the research setup will be discussed in the next chapter. Chapters three and four will each describe the results of the research questions. In chapter five the conclusions and recommendations of the research will be described.

Chapter 2

Research Outline

Within this chapter the context of this research is set and subsequently the research questions are designed and elaborated. It will start with the discussion of the problem Marel is facing. Next the problem will be defined and the goal of this research is given. This will afterwards be translated into research questions accompanied with the used method to answer these research questions.

2.1 Company Problem

For MSPP it is time consuming to predict when a machine will fail and to identify the correct maintenance schedule. Especially for newly introduced systems there is limited knowledge about the degradation of parts. When components are performing badly, they may be replaced by other components with different specifications, which in turn leads to a system which behaves different. So in short, MSPP's problem is "understanding degradation and failure behaviour of new equipment and making the right modification and maintenance decisions" (Marel, 2017). The research objective of this master thesis is to provide a better understanding of degradation and failure behaviour of new equipment, so that the optimal modification and maintenance decisions can be made.

2.2 Problem Definition

Marel is interested in predictive maintenance, which is also seen within the MGMC. To be able to introduce CBM, condition monitoring would be the next step. That is, what should be monitored and at what point is a machine and/or component fully degraded? These questions are hard to answer when a company is introducing new machines or improves their current machines. This therefore is a challenge which Marel is facing when their machines need updates or when completely new equipment is developed. The applicability of CBM within Marel is already proven by several master thesis projects in the past (Hussein, 2012; van Dorst, 2014; Houben, 2014; Gutierrez, 2017). The project of Gutierrez (2017) had as takeaway that CBM could be improved by having more data sources. Within the study of Gutierrez, only failure data was taken into account. Since her project, the business has developed additional tooling with a focus on the condition of Marel's machines. The two most important projects are Innova OEE (Overall Equipment Effectiveness (OEE)) and ChainLive. These projects generate additional data which were not available within previous researches and are built to provide more information to the customers about the state and performance of their machines and/or total production system. Because of the usability of CBM in maintaining their equipment it is also important that from the first moment all functionalities can be monitored such that from the start a correct maintenance schedule can be used.

2.3 Goal

The goal of this project is to give a better insight into the setup of maintenance without knowing a lot about the wear patterns of the systems, so early failure detection will be of importance. Currently, it takes a lot of time to evaluate components wear and decide on maintenance by using field validation. Increasing the generation of data to assess the performance of a machine is therefore important. This data may be additional data which has to be generated or already available data within the systems. These types of data need to be combined to be able to evaluate the performance. Also component specific data could be of interest for specific components which are believed to be essential for the performance of the machine. Besides this, it would also be interesting to give insight into how current data can be used for investigating how a specific newly introduced machine will perform within the production environment. In other words, investigating the effects of external production factors on the performance of the machine.

The case studies within this project will be on a specific machine. It is chosen to take one machine as starting point. The chosen machine is a transfer system called the Transfer Evisceration & Cooling (TREC). This transfer system is placed between the evisceration line and the cooling line. The choice for this machine is made since this machine is in production for 1.5 years but there are still parts for which it is unknown how they perform and how they account for failures. Furthermore, Innova and ChainLive are available for this machine. Especially within the ChainLive project, there is already additional data available which is not available for other parts of the production system at a leading customer. This data is generated by additional sensors which are added to the cooling section of a poultry processing plant. This project made it also beneficial to chose the TREC since more factors can be taken into account within the data crunching part.

2.4 Research Questions

Based on the problem defined and the goal of Marel, the main research question of this master thesis project reads as follows:

How can Marel use its data to get faster acquainted with factors affecting performance of its newly introduced machines?

To be able to answer the main research question, additional research questions have been developed. The additional research questions are defined by using a subdivision in terms of the size of the focus area. When one is getting acquainted with a newly developed machine, one needs to start with a small focus by getting to know the components of the machine. One will finish with a larger focus by taking into account the external production factors influencing the performance of the machine as well. So first of all, it is of importance to identify on component level which components are appropriate for predictive maintenance and how this can be implemented within the MGMC. Secondly, when the machine is tested without broilers within the Marel testing environment, new knowledge can be acquired about factors affecting the machines' performance. Lastly, when a prototype machine is placed at the customer, the influence of the external production factors affecting the performance of the machine can be identified. This setup is depicted in Figure 2.1. It is of importance to note that the mid term focus will be left out of scope within this project, since for Marel the component level and machine within the process level are more of interest. Within Figure 2.2 the scope of each phase is depicted.

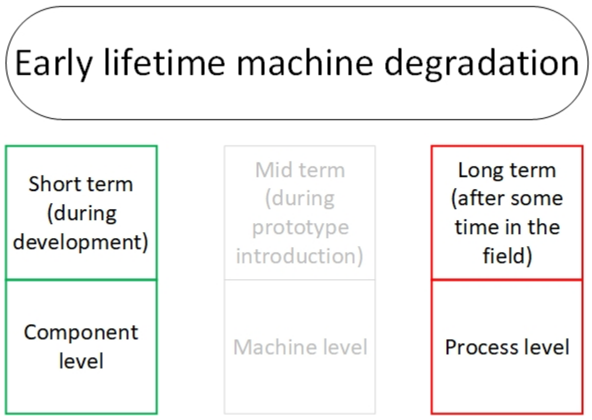

Figure 2.1: Project outline

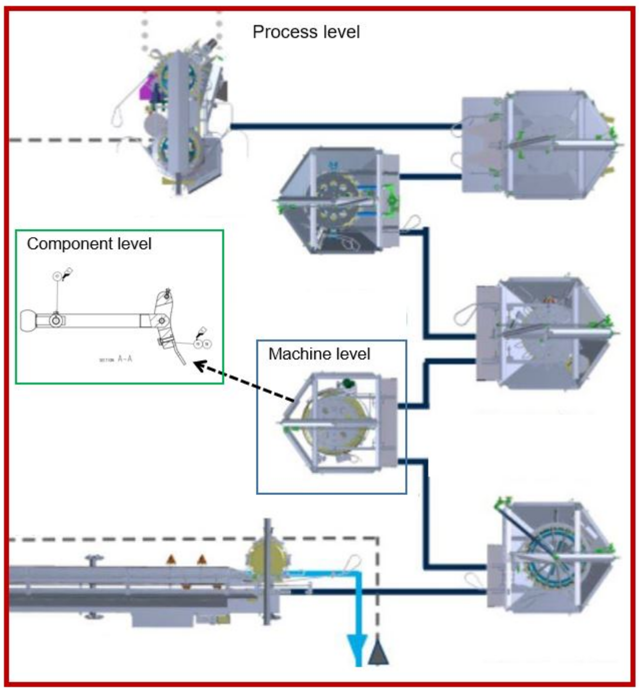

Figure 2.2: Project outline graphical

In conclusion, the first phase will be focusing on the component level of the machine. This can already be taken into account during the final stages of development when the Bill of Materials (BOM) is known. This parts' focus will be on increasing knowledge about the components' failure behavior. The long term part is about how the prototype machine will act within the total production process at one of the customers. This can be done from the moment the machine is introduced at the first customers. This is of importance since the machines cannot be tested in a representative process at Marels' production location/R&D locations since there is no total production line available. Also due to regulations it is not possible to create a mock up factory since these regulations have to be met before being able to process broilers. Therefore, the process of getting acquainted with the machine is important to be able to modify the machine when problems arise and let the machine perform better. Next, the research questions will be presented and the method of answering will be discussed.

2.4.1 Component Level

Different components within a machine need different ways of maintenance. As stated before, there are different types of maintenance strategies. The first part of this master thesis will be about gaining knowledge about the possible maintenance strategies. Currently, this is known for the corrective, preventive, and operational maintenance strategies. However, predictive (condition based) maintained components is something Marel wants to additionally implement. Which components are beneficial for predictive maintenance will be the interest of the first research question. This research question will be answered by using sub-questions.

1. *How can it be determined for which components it is beneficial to implement predictive maintenance?*
   (a) *How does Marel currently determine the maintenance strategy for a newly developed machine?*
   (b) *For which component types is it beneficial to implement predictive maintenance?*
   (c) *What criteria are relevant for determining components suited for predictive maintenance?*
   (d) *What does this mean for the TREC?*

To reach an answer for this research question the main focus will in the beginning be on the current maintenance strategy and the way of determining these maintenance strategies per component in a new developed machine. Subsequently, it is of interest how predictive maintenance can be implemented within the previous described maintenance strategy determination. This will start with determining the traits the components need to possess to be a candidate for predictive maintenance. Finally, after developing a method to determine the predictive maintenance components, this method needs to be tested if it is suitable for implementation. This will be done by using the TREC as a case study.

Method

As final part of this section the method for answering the first research question will be discussed. The questions will be discussed in the order of appearance. Combining the sub-questions will give an answer to the first research question. So, to start; "How does Marel currently determine the maintenance strategy for a newly developed machine?". Within this question the current process of determining for each component the maintenance strategy will be explained.

Next, question 1b; "For which component types is it beneficial to implement predictive maintenance?". This question will be answered by combining the different component types within Marels' MGMC and by reviewing literature on which component characteristics indicate which maintenance strategy is best to apply. Comparing the literature and Marels' MGMC will result in an advice on what maintenance strategy suits best to the different components. This will also be the answer to the question, namely an overview of which component types are suited for which maintenance strategy and more specifically for predictive maintenance.

Continuing with question 1c, "What criteria are relevant for determining components suited for predictive maintenance?", it has to be determined which criteria can be used to score for predictive maintenance. What is meant is that components get extra characteristics which can be documented by maintenance service engineers to determine if a specific component may be suitable for predictive maintenance. These characteristics are translated to criteria which will deal with the specifics used for predictive maintenance. For this part additional information will be gathered within Marel and the employees experienced with service/executing service/focusing on condition monitoring. Afterwards, on the basis of the determined criteria a formula will be composed that can be used to point out which components are the best candidates for predictive maintenance.

As the last step within research question 1, question 1d will be discussed. To recall question 1d, "What does this mean for the TREC?", is focused on the TREC being the case study. Questions 1b and 1c will result in a way to determine which components are most beneficial for implementing predictive maintenance. The case study is used for testing the applicability and to verify the decisions made in questions 1b and 1c are correct. This will result in a list of components that are best suited for predictive maintenance. This list of components will be verified with a number of employees within Marel to check whether they agree with the resulting components. As final part of the first research question, a conclusion will be given in which the results of the different questions will be discussed.

2.4.2 Process Level

For the second part of this project, i.e. investigating how the machine will perform within a production environment, the focus will be on modeling data and converting the data into information. The process may impact performance and/or wear of components in the machine (e.g. weight of the broilers, line speed, other machines). With this additional information different conclusions/maintenance decisions could be made. Which methods can be suitable for this and how these methods can be used is the focus of research question 2. This research question will again be answered by using sub-questions.

2. *How can it be determined which external production factors are of importance in affecting the degradation of a newly introduced machine?*

    (a) *Which data is available, and what steps need to be taken to prepare the data in order to be able to use it for determining the external production factors affecting the degradation in performance?*

(b) *Which methods are suited for evaluating which external production factors cause performance degradation?*

(c) *How can these methods be implemented and evaluated by using the available data supplied from the TREC?*

To reach an answer for this research question the main focus will in the beginning be on the available data and the steps which have to be taken. When the data are explored suitable methods can be found to reach the goal of the question, finding production factors which affect the degradation of a newly introduced machine. Finally, the chosen methods will be tested with the available data to reach conclusions and show the capability of implementing the methods within Marel. This will be in the form of a case study on, again, the TREC.

Method

As final part of this section the method of answering this second research question will be discussed. The questions will be discussed in the order of appearance. Combining the sub-questions will answer the second research question. So, to start with question 2a, "Which data is available, and what steps need to be taken to prepare the data in order to be able to use it for determining the external production factors affecting the degradation in performance?", concerns the process to create correct and sufficient data as input for the methods selected in the next sub-question. The steps to prepare the data and the final format in which the data needs to be before using it within the model will be important within this question and also needs to be the outcome.

Next, question 2b; "Which methods are suited for evaluating which external production factors cause performance degradation?". This question will be answered by using literature to assess which data methods can be used to reach the goal of machine understanding. The methods will especially focus on influences between variables, since the goal of the methods is to find the external production factors which are affecting the degradation of a machine. When the performance of the machine is decreasing this could mean that a variable has changed and therefore these two trends need to be evaluated. This question will result in the best methods conform this type of problem such that the research can continue with answering the next question.

Afterwards, question 2c, "How can these methods be implemented and evaluated by using the available data supplied from the TREC?" is the final step for answering research question 2. Like in research question 1, this final step is a case study. This case study will show the applicability and correctness of the model. The case study will also show how the chosen methods can be used in practice. From the sub-questions, conclusions will be drawn to answer research question 2.

When both research questions 1 and 2 are answered, a final conclusion can be drawn that answers the main research question which was defined as: "How can Marel use its data to get faster acquainted with factors affecting performance of its newly introduced machines?". Now that the company problem, the research goal and its accompanied questions and methodology to answer these research questions are described, the research will continue with the execution of the first research objective.

Chapter 3

Predictive maintenance components

This chapter discusses the first research question:

How can it be determined for which components it is beneficial to implement predictive maintenance?

This question will be answered by using the following sub-questions:

- *How does Marel currently determine the maintenance strategy for a newly developed machine?*
- *For which component types is it beneficial to implement predictive maintenance?*
- *What criteria are relevant for determining components suited for predictive maintenance?*
- *What does this mean for the TREC?*

To answer these questions, first of all the current maintenance strategy determination process used by Marel is explained. Furthermore, by taking the second sub-question into account, the maintenance strategies in combination with the component types will be reviewed. Afterwards, the third sub-question will be answered, which criteria are important to take into account to determine which components are beneficial for CBM. Finally, the developed method will be tested on the TREC and a conclusion will be drawn.

3.1 Process description

To make a correct maintenance strategy decision for each component, within a newly developed machine, Marel follows a certain process. This process is aimed at getting acquainted with the components within a new machine and is depicted in Figure 3.1. This process will be explained within the rest of this section. The reason why Marel follows a predefined process is because classification of the components within a new machine is not easy. This is caused by the fact that besides the techniques that are used during development, there are also the external conditions in which the machines operate. These conditions are different per customer and are difficult to determine in advance. For example, the temperature, humidity, and detergents play a huge role in the wear and failure patterns of the components within a machine. The process starts during the development of the prototype and further continues due to changes in process parameters (e.g. production speed).

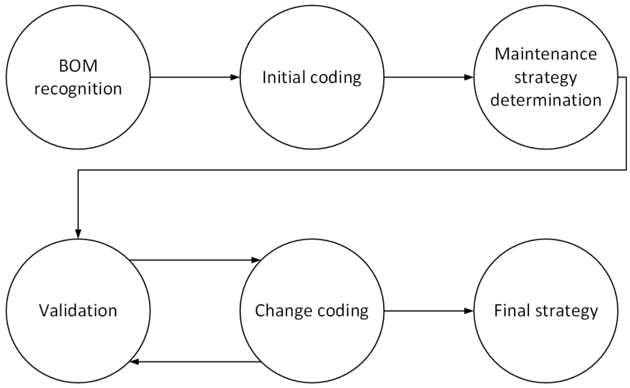

Figure 3.1: Process steps to determine maintenance strategy

3.1.1 BOM recognition

With BOM recognition it is meant that both the R&D-employees and maintenance service specialists get acquainted with the machine and its components can be compared to prior experience within previous versions of the machine or other types of machines. It is common that assemblies are reused with new machines. All components on a BOM are assigned a standardized name and checked for correctness.

3.1.2 Initial coding

When a new machine is developed the second step of the process is initially coding all the components within the machine. This coding is called the AE-coding and categorizes components based on their expected lifetime. However, before coding components on their lifetime, previously used components are coded, which can in most cases be copied, since experience learns that these components experience similar degradation in different machines. As stated in section 1.3.2, Marel uses A-, B-, C-, D- and E-components in its coding scheme. The different codes stand for:

- A-components: Consumables with direct contact to the broilers and low in cost.
- B-components: Essential components for the execution of the process intended by the machine. Upon failure downtime may be created. For B-components it is also possible to add an additional sub-code (C, D, or E) to the component when there is an uniform failure distribution with an additional increasing failure distribution over the lifetime of the component. Furthermore, B-components which are not critical for the performance of the machine and upon failure will be changed, or need to be changed when other components have failed.
- C-components: Contribute to the process and upon failure will affect the performance of the system but will not immediately result in stoppage of the system. C-components are also characterized by periodic failure and have a known lifetime.
- D-components: Maintenance components with a longer lifetime as C-components but with similar wear characteristics. D-components are also characterized by periodic failure and have a known lifetime.

- E-components: Maintenance components with the longest lifetime. Which have in general a periodic replacement. In general a known lifetime, but this can be affected by other components/production variables.

Moreover there are components of the machine which will receive no coding, since these are not subject to wear. These components will not be taken into account during overhauls, and failure of these components are caused by incidents which do not occur in normal conditions (e.g. a forklift bumping into the machine). Therefore, these components can be left out of further consideration.

Some examples of components which give an indication for the different component types are given in Table 3.1.

Component Type	Components
A	Knives, Drills, Plucking Fingers
B	Sensors, Valves, Belts, Motor Reducer
C	Bearing, O-Rings, Chain
D	Spray Nozzles, Grease Nipples, Grooved Pins
E	Cams, Gearbox, Plastic Guides
No coding	Frame, Support Beams

Table 3.1: Example components per type

3.1.3 Maintenance strategy determination

Overall a code resembles a specific maintenance strategy used by Marel. These codes also resemble in some cases a maintenance interval. With these initial codes a first Preventive Maintenance Schedule will be created. The goal of this subsection is to discuss the current maintenance strategies per component type. In addition to that, an evaluation will be given whether predictive maintenance could be a possible maintenance strategy per component type. Before this discussion and evaluation will be executed, it is of importance to describe each maintenance strategy that Marel uses in more detail.

Elaboration on maintenance strategies

It is important to get more acquainted with each possible maintenance strategy before being able to evaluate the usage at Marel. In other words, it is needed to create an overview of the pros and cons and the correct usage of the maintenance strategies by consulting the available literature.

Corrective maintenance

Corrective maintenance is mostly used for components and equipment which are non-critical and have no safety, operational, or economic consequence as a result of a failure. More specifically, it is useful for components and equipment that are of non-critical nature, are unlikely to fail or for which the failure rate is not increasing with time. The benefits of corrective maintenance are that it is low in costs and research and less staff is involved.

The disadvantages, however, are firstly that when the equipment fails, the machine has unplanned downtime. This causes production loss and increased labor cost, especially if overtime is needed. Secondly, there is possible consequential or process damage from the failure (Chandrahas & Mahapatra, 2015).

Preventive maintenance
Preventive maintenance is used for components or equipment that have a known failure pattern and that are subject to wear. Preventive maintenance can be time-based or count based. Repairing or replacing damaged equipment before the real problem occurs is a cost effective strategy in capital intensive processes. It causes an increased machine life cycle, energy savings and reduced equipment or process failures. On the other hand, catastrophic failure is still possible to occur, it is labor intensive and it can lead to unneeded maintenance and potential damage to other components during conducting unneeded maintenance (Chandrahas & Mahapatra, 2015).

Operational maintenance
Operational maintenance is a special form of preventive maintenance. It is used to extend the life of equipment or components by applying minor adjustments, cleaning and inspections. Such maintenance may also include minor components replacement that does not require the person performing the work to have highly technical skills. Operational maintenance can be performed during the normal course of operations by the equipment operator himself, causing lower labor costs, reduced downtime and lower costs associated with repairs and replacement components due to insufficient maintenance. However, it does not include more complex repairs and diagnostics and it is also not used for replacement of large or dangerous components (TPub, 2018).

Predictive maintenance
Predictive maintenance can be used for components or equipment that have a random failure pattern for which the current or future condition or performance can be monitored. By monitoring the condition of the component or equipment an action can be taken prior to the component having serious effect on the performance of the machine. It maximizes the lifetime of each component, decreases machine downtime and costs for components and labors and improves product quality and worker and environmental safety. Contrary, it will cause an increase in investment to be able to monitor the equipment or components and the company should train their staff. In addition to that, the savings might not be readily seen by the management which make them reluctant to invest in predictive maintenance (Chandrahas & Mahapatra, 2015; Ellis & Byron, 2008).

Now that the different maintenance strategies are known in more detail, it is possible to evaluate the maintenance at Marel. This is discussed in section 3.2.

3.1.4 Validation

Periodic inspection is the basis for validating the initial component coding and chosen maintenance strategy. Maintenance visits are planned to inspect broken components and to evaluate the component coding of parts preventively replaced according to the Preventive Maintenance Schedule (PMS). Currently, technical service employees are going to the customer to evaluate the replaced components.

3.1.5 Change coding

Since the proposed maintenance strategies are validated within the Validation step and this can lead to proposed changes, these changes have to be followed up within the maintenance strategies schedule. In other words, changes can be made to the moment of maintenance since faster or slower wear of a component is recognized.

3.1.6 Final strategy

Within the final strategy step, the created maintenance structure can be taken as guidance when creating other maintenance schedules under other slightly different circumstances. In addition to that, important information is retrieved about, for example, how components behave in different settings. This provides Marel with valuable information on the behaviour of its components and possible future improvements.

3.2 Component types interesting for predictive maintenance

In section 3.1.3 the different maintenance types were introduced. Based on this knowledge Table 3.2 is created. In this table a summary of the characteristics, that components need to possess per maintenance strategy, are given.

Maintenance strategy	Suitable for
Corrective	Non-critical components and equipment Random failure patterns
Operational	Small components and equipment Non-complex components and equipment Critical component and equipment Known failure patterns
Preventive	Components and equipment subject to wear Critical components and equipment Known failure patterns
Predictive	Components and equipment subject to wear Critical components and equipment Random failure patterns

Table 3.2: Component characteristics per maintenance strategy

Taking these characteristics into account, it is possible to evaluate the different maintenance strategies at Marel.

3.2.1 Evaluation of maintenance strategies at Marel

Currently, Marel uses different maintenance strategies for each of its five component types:

- A-components: These components are replaced preventively on short intervals since these components have a very high impact on the quality of the end product. This is because these components are in direct contact with the broilers. In most cases these components are low in cost. Marel identifies the maintenance of these components as operational maintenance. According to the literature, this is the right maintenance strategy since A-components are small, but essential, components that can be replaced or maintained by less skilled personnel.

- B-components: Currently, B-components are maintained on a corrective basis. Since most B-components are critical for the functioning of the machine, corrective maintenance might not always be the correct strategy according to literature. These components have a uniform failure distribution, which means that a failure can happen at a random moment in time. Therefore a time- or count-based maintenance strategy (preventive maintenance) is not appropriate to implement. Nevertheless, during discussions with Marel maintenance engineers it was mentioned that failures of these components are a consequence of wear of the component. Currently, Marel is unable to predict a failure. There might be an opportunity to predict a failure within a B-component and with that decrease downtime. So for these components condition monitoring (predictive maintenance) could be beneficial. There are also B-components which are not critical but are given a B for other reasons. For these components it is suggested to replace them using a corrective maintenance strategy.

- C-components: C-components have a preventive maintenance strategy. These components have an increasing failure rate and these components degrade relatively quickly and therefore, the time-/count-based (preventive) strategy is most beneficial. Whether it is time- or count-based depends on the function of the component within the machine. A running motor for example, is less influenced by count and more influenced by the time it has been running. Since C-components are critical for the process and have a known failure pattern, the preventive maintenance strategy is indeed the correct strategy.

- D-components: Marel uses the preventive maintenance strategy for D-components as well. Since these components have the same characteristics as the C-components for determining the correct maintenance strategy, this is the right strategy to use.

- E-components: For these components the same maintenance strategy is used as for the C- & D-components (preventive maintenance). Nevertheless, because the lifetime of this component is larger, there is a higher chance that these components need to be replaced as result of a random failure. Therefore, it may be interesting to consider condition monitoring or periodic inspection (predictive maintenance), since these components are still critical for the performance of the system. Furthermore, some E-components are very expensive and can last longer than initially predicted.

So to have a clear overview of which maintenance strategy is best to use for which component type, Table 3.3 is created in which a summary is given of the different component types and their maintenance strategy. As one can see predictive maintenance can be of interest for the B- and E-components.

For the preventive maintenance strategies, initial overhaul moments are scheduled, which will be tested during validation. Currently, for predictive maintenance or CBM, little work has been done since CBM is not implemented within the maintenance process yet and there is still little knowledge on how to implement CBM. Therefore it is especially interesting to determine which components are suited for CBM. This will be the focus in Section 3.3.

Component Type	Optimal Maintenance Strategy
A	Operational Maintenance
B	Corrective Maintenance or Predictive Maintenance
C	Preventive Maintenance
D	Preventive Maintenance
E	Preventive Maintenance or Predictive Maintenance

Table 3.3: Component Type and Maintenance Strategy

3.2.2 Conclusion

Now that the process of determining the correct maintenance strategy is discussed and the decision was made to focus on the B- and E-components for implementing predictive maintenance, it is important to discuss on which criteria Marel should determine which components in these two categories are suited for predictive maintenance. The reason for this is that there are simply too many components and not all components contribute in an equal manner to the performance of the complete system. Another comment which has to be made is that the interesting components are only the components which have a B, E, or B & E code to them. This means that B & C and B & D combinations will not be taken into account. These components are exchanged already a lot during their lifetime and the B coding is only added to be able to recommend it to the customer because there is always a chance that this component will fail in between preventive maintenance actions. Otherwise, this will result in an excessive maintenance costs, since preventive and corrective actions are already executed.

So, to answer research question 1b, the interesting component types are the B, E, and B & E components, since these components have the characteristics for predictive maintenance.

3.3 Criteria for components relevant for CBM

Within the previous section it was addressed that condition based maintenance could be introduced for several component types, namely the B- and E-components. It was also addressed that currently, predictive maintenance is left out of the maintenance schedules. So after a new machine is introduced, preventive, corrective and operational maintenance can be determined per component. Predictive maintenance, both on inspection and condition monitoring is not defined since there is little experience. Stating which characteristics a component needs to have to be interesting for predictive maintenance, will be the aim of this question to be able to recommend which components are interesting for predictive maintenance.

To take into account which components are beneficial for predictive maintenance, as is stated within this first research question, a classification has to be given to the components within the BOM. Concerning the process after introduction of a new piece of machinery, it is most interesting to identify the way of working of the machine and recognize specific wear patterns for specific components. To judge which components are most beneficial to monitor, a model is created to be able to give values to the different components. First of all, it needs to be defined what criteria are important for condition based maintenance. To define the criteria which are relevant for condition based maintenance, the industries'/companies' specific interests are taken into account. This is chosen because, as stated by Pintelon and

Waeyenbergh (2004), the maintenance concept needs to account for the factors of interest for the situation and the company. So in this case what Marel thinks about which components are interesting to monitor and what is interesting to monitor concerning the system itself. When knowing which components are beneficial for predictive maintenance, these can be indicated by adding additional coding to their previously determined AE-code.

The first step is to use the initial coding to be able to decide on which components are beneficial for additional coding. The most interesting criteria will be considered first, to make sure not all the components on the BOM have to be graded. To accomplish that, a process has been developed to eliminate most components of the BOM and afterwards a decision process can be set up to identify the correct component. This process is accomplished with the help of maintenance engineers and is depicted in Figure 3.2 and subsequently the steps are explained.

The process is an addition to the already existing process which is depicted in Figure 3.1. It will start after the maintenance strategy is initially determined (Section 3.1.3) and will be finished as start of the validation step (Section 3.1.4).

The additional process will begin by deleting all components which have an AE-code other than B or E. Afterwards, sales prices are added and multiplied by the quantity the specific component occurs within the BOM. Subsequently, every component with a total cost smaller than 100 Euro are removed. Next, the criticality of the component is determined. Afterwards, only the Essential and Vital components should be selected. The scores of the remaining criteria are determined which are skill level needed for repair, Mean Time To Failure (MTTF), Mean Time To Support (MTTS), Mean Time To Repair (MTTR), component costs and lead time. Each of these criteria are explained in more detail below. This finally results in a score per component on how relevant the component is for CBM (by using Formula (3.1)). These scores are sorted in descending order and then it is determined whether CBM is possible for the highest 10 scores. For the chosen components it is determined what data has to be gathered and which measurement techniques can be used to achieve that and what the maximum tolerance is before the components have to be exchanged. This will result in additional coding in the PMS which is ready for validation.

Criteria

For the execution of this process two additional things need to be explained i.e., the different criteria for which the components are ranked and the formula to determine the best components for CBM.

Previous research at Marel was mainly focused on machines which already were introduced at a customer. Within these studies, emphasis was on the cost and downtime caused by failure of a component or machines in general. Since these are not known when the machine is in the development phase it is not possible to make use of knowledge about the machines' actual performance. The criteria which will be used are all criteria that need to be estimated. Also the classification of the criteria will be in ranges since real times, costs, performance details are not available yet.

For defining the interesting criteria, meetings were held with the maintenance concept engineer. Furthermore, meetings were held with field service engineers who actually do the maintenance and inspection on the machines and with project managers of a new Internet of Things (IoT) project based on CBM. With the help of experience from the field the interesting criteria are defined. With each employee, two meetings were held. The first meeting was used

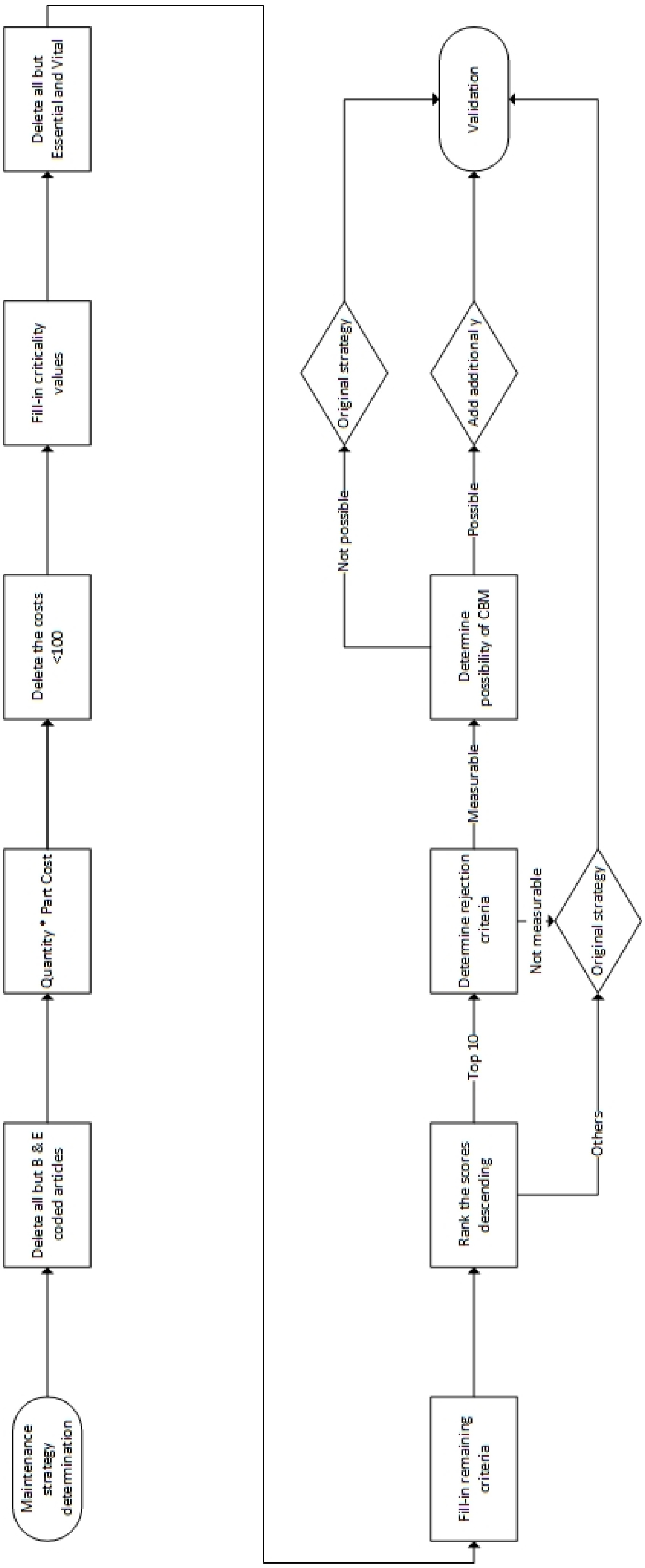

Figure 3.2: Process steps to determine CBM components

to gather the possibly interesting criteria. The resulting criteria from the different meetings were evaluated and combined into a list of the most important criteria. These criteria were evaluated in a second meeting to check for completeness. The different criteria that resulted from these meetings are in the list below. Afterwards they will be shortly discussed.

- Criticality
- Skill level needed for repair
- MTTF
- MTTS
- MTTR
- Component costs
- Lead Time

For each of these criteria, a score will be given based on specified classifications. The higher the score for a specific criterion, the more this criterion contributes to the suitability of predictive maintenance. These classifications will be introduced below. Within the rest of this section a component will be taken as example to illustrate and justify the choices made for the scores given to the different criteria. The component taken into account will be a CAM-insert. This components is chosen in consultation with a maintenance engineer since it is one of the components which is initially believed to be interesting for predictive maintenance.

Criticality

A component within a machine is critical when in case it breaks or loses its full functionality, the machine will have a lower performance or breakdown, leading to a production stop. Critical components are vital for the execution of the process of a machine. Criticality is taken as criterion for predictive maintenance since components which are critical for the process is important to know its condition for and when these will break.

Within Marel four criticality levels are defined:

- Auxiliary: Does not break down itself but is needed when other components break down
- Desirable: Does break down itself, but is not critical for performance
- Essential: Is critical for uptime and can be easily repaired by the customer/locally sourced OR is critical for the performance but cannot be easily sourced locally by the customer
- Vital: Is critical for the uptime and cannot be easily repaired by the customer/locally sourced

Since Auxiliary and Desirable components have no direct influence on the machines' performance, these components are not of interest for CBM. Therefore, the only classifications needed for this criteria are:

Score	Classification
1	Essential
2	Vital

The CAM-insert is a vital component since it executes a critical part of the process. Furthermore, CAM-inserts are specialized products which are manufactured solely by Marel. Therefore, for the CAM-insert a score of 2 is given for criticality.

Skill level needed for repair

A machine developed by Marel consists of a lot of components. Although accessibility of components is considered during development, this is not always optimal. This implies that not all components are easy to exchange when broken. In general this means that the components on the exterior of the machine are easier to exchange than components inside of the machine. Furthermore, there is the possibility that for changing a component experience is needed to do this successfully, because it could be a difficult job. The skill level needed for the repair is also dependent on whether the machine needs a complete restart to set the timing right again.

For this criteria the classifications are given by using:

Score	Classification
1	Customer with no specific knowledge can exchange the component (It is in most cases an easy accessible component)
2	Trained customer can exchange the component (No restart is needed and the component is relatively easy to exchange when the customer has experience through training)
3	Marel stand-by is needed (After exchanging the component a restart is needed and extended knowledge about Marels machines is needed)
4	Marel service specialist is needed (After exchanging the component a restart of the machine has to be executed and expert/in depth machine knowledge is needed)

The CAM-insert is relatively easy to replace since it is not needed to dismantle the complete machine. Alignment of the components after replacement is needed, therefore some knowledge is needed. The score for the skill level needed for repair will therefore be 2, since it is easy to exchange the part but some basic knowledge of the Marel machine is needed.

MTTF

This is the mean time to failure of the specific component. MTTF is taken into account since, the higher the failure frequency, the more downtime the part causes. The scores are based on the scheduling of maintenance moments within the Preventive Maintenance Schedule used by Marel. The first small overhaul (preventive maintenance on C-components) is initially scheduled on average, around 1 year. To be able to combine the visits, this means the medium overhaul needs to be not before 2 years and the total overhaul at 4 years. Everything longer than 4 years will be the final category. This will result in the following mean time to failures:

Score	Classification (in years)
1	[4, 10)
2	[2, 4)
3	[1, 2)
4	(0, 1)

The CAM-insert is believed to be exchanged every 3 years. For CAM-parts this is often, because this specific insert experiences high wear due to high forced impact. Therefore, the score for the CAM-insert for mean time to failure will be 2.

MTTS

This is the mean time to support of the specific component. This is the mean time (in hours) it takes after a breakdown before the component is identified as the cause of a failure/performance degradation. These scores are based on the time period it takes and how this will affect the production. The longer the MTTS, the more production loss is experienced.

Score	Classification (in hours)
1	0-0.5 (possible during production) No production loss
2	0.5-1 (only possible during long breaks) Minor production loss
3	1-2 (only possible at night or in weekends) Major production loss (including loss of broilers)
4	2-4 (when it takes longer than 2 hours to discover the failure there is no time left to replace the component before production has to be restarted again, therefore it would mean serious downtime)

The CAM-insert can be observed immediately. Nevertheless, the CAM-insert will not be the first component which will be looked at there is a breakdown or performance degradation. Since it is a vital component at an exterior position, it will be looked at fairly quickly. Therefore, the score for mean time to support will be 2.

MTTR

This is the mean time to repair which describes the time in hours it takes on average after a breakdown to repair the component. For Marel a repair is defined by exchanging the broken component by a new one. The ranges are defined by considering the length of time available without hampering production. For example when exchanging a component takes a maximum of half an hour this component can be exchanged without any loss of production. The longer the MTTR, the more production loss is experienced.

Score	Classification (in hours)
1	0-0.5 (possible during production) No production loss
2	0.5-1 (only possible during long breaks) Minor production loss
3	1-4 (only possible at night or in weekends) Major production loss (including loss of broilers)
4	4+ (only possible in weekends) Catastrophic for the production

The mean time to repair for the CAM-insert will take between half an hour and an hour. This is the time because it is an exterior component. It is not a simple replacement since also other components need to be removed before it can be changed. Therefore, to successfully exchange the CAM-insert it will take between half an hour and an hour and the score for this component will be 2.

Component costs

Cost for customer for this component. Costly components require an optimal use of their lifetime. Therefore the higher the cost, the more valuable predictive maintenance can be.

Score	Classification (in Euro)
1	(100-500]
2	(500, 1000]
3	(1000, 2000]
4	(2000, ∞)

The CAM-insert is a relatively expensive component, between the 500 and 1000 Euro, since it is specially designed and manufactured within Marel for a specific piece of machinery. The score for the cost of the CAM-insert will be 2.

Lead Time

Lead time is the time it takes for a component to be delivered by the supplier after ordering. Within Marel these times are unknown so exact decisions cannot be taken. Classification for these components will not be given but the suggestion is that, when the lead time of a component is higher it is more beneficial to consider predictive maintenance, since the reorder moment can better be predicted and less stock has to be held for these components.

In the next section a formula is developed where all the introduced criteria are combined. This formula needs to be created and afterwards tested. To emphasize the importance of certain criteria these criteria will receive a higher weight.

Quantifying the suitability of CBM

To rank the scores, Formula (3.1) is proposed in which each of the criteria is weighted. In this formula, the weight of the criteria is determined by consulting several employees within Marel. Those employees, all involved in the service operations, were asked to distribute 18 points over the previously determined criteria. Additionally, the opportunity was presented to add missing criteria with an explanation and motivation to the list with additional points. This all lead to a distribution of scores over the different criteria as reported in Table 3.4. As shown in this table, the most important criterion for the employees is criticality, and the least important criterion is cost. The total formula would be equal to:

$$S = \sum_{c=1}^{6} w(c) \times v(c) \times u(c) \tag{3.1}$$

With $w(c) = \frac{s(c)}{\sum_{c=1}^{6} s(c)} \times 18$ for which $s(c)$ can be found in Table 3.4 per criterion c, additionally the multiplication with 18 is done for getting significant weights and differences in final scores. 18 originates out of the original points the questioned employees could distribute.

Furthermore, in Formula (3.1), v stands for correction for different scaling within the criteria. This will be 1 except for criticality this will be 2 to correct for the fact that this criterion only can score 1 or 2. The u stands for the score given to the particular criterion.

Criteria	Role 1	Role 2	Role 3	Role 4	Role 5	Role 6	**s(c)**	**w(c)**
Criticality	5	6	7	3	4	6	31	5.17
Skill Level	3	2	3	2	3	1	14	2.33
MTTF	4	3	2	4	3	4	20	3.33
MTTS	2	3	2	4	3	3	17	2.83
MTTR	4	4	3	4	4	4	23	3.83
Cost	0	0	1	1	1	0	3	0.5

Table 3.4: Scores given per criteria

Taking the CAM-insert into account the component will score according to Formula (3.1) to a score of 46 (as shown in Table 3.5):

Criteria	Component Score
Criticality	2
Skill Level	2
MTTF	2
MTTS	2
MTTR	2
Cost	2
Score	**46**

Table 3.5: Score for CAM-insert

When this calculation would be performed for all B- and E-components of a specific machine Marel is able to choose the 10 most important components to evaluate the possibility for predictive maintenance.

So to answer the question “What criteria are relevant for determining components suited for predictive maintenance?”, six criteria have been selected: criticality, skill level of engineer, mean time to failure, mean time to support, mean time to repair, and cost of the component. Furthermore, by using these criteria a quantification is introduced in the form of a formula. Finally, this is all combined within a process to initially start CBM on components and the components beneficial for CBM are selected.

3.4 Case study

This case study will be executed to investigate whether the developed method is suitable for the situation within Marel, and also to check whether the components, which are the result of the proposed method are indeed components of which there is a high interest for executing predictive maintenance. This can be evaluated for this case study, since this machine is currently in use at a customer.

To get acquainted with the TREC, some general facts about this machine are presented here. The TREC consists out of 5808 components distributed over 570 article numbers. The BOM of the TREC consists out of 954 positions which are 39 sub-assemblies and 915 articles.

Taking into account the process of reducing the BOM into a manageable size, first the components are filtered for B & E components which resulted in 124 remaining components. Subsequently, the component with a sales price under 100 Euro were deleted. This resulted in 51 remaining components. 31 of those 51 articles do not have a criticality already, which is subsequently added. 10 out of the 51 remaining articles will be deleted because of not meeting the requirement of being a Vital or Essential critical part. This yields a final list of 41 components that could be ranked using Formula (3.1).

To evaluate the correctness of the method, again some engineers were questioned. Before discussing the method the question was raised which components were found important for predictive maintenance. This had to be answered by taking the TREC in mind. Therefore the engineers which were questioned were employees which are currently involved with setting up maintenance and validating the correctness of the behaviour of the TREC. It was also mentioned that there are no constraints to implement CBM for every component. Furthermore, the test also incorporated randomly selecting positions out of the BOM for evaluation. Out of this it could be concluded that the sample was correct. Nevertheless, when checking the process, if it is appropriate that only B, E components over 100 Euros and with a certain criticality are taken seemed not correct. The reason for this was that certain components were found interesting but had a D-code attached to them. These components were general components which will be left out. The case is that these specific components are part of the base of every rotating machine which Marel produces. Therefore these components will not be considered because the focus will be more on specific components for the function of newly developed machines. The components which are generally important to consider within the machines are ball groove bearings and flange bearings with a minimum inside diameter of 45mm and possess a special lubricating function. For these components it would be better to create a setup which is standardized to be able to monitor these components. Another point to take into account is that some costs are not known after development since these are not sold yet. When a component is sold for the first time a sales price is added. This can result in not selecting the component because the price is too low or not available. Since Marel is only advising in maintenance and not executing the maintenance, the choice was made to take the sales price into account. When Marel would in the near future be responsible for the total maintenance this can be changed to the cost price for Marel. So where no price is filled it should be important to take into account if this price could be over 100 Euros. Filling additional prices is again only needed for the B- & E-components.

Using Formula (3.1), this resulted in the end to monitor the components mentioned in Table 3.6.

As final steps it is questioned if the resulting components can be measured and what the measurement should be. So, it starts with determining the rejection criteria. This step has to be performed individually for each component which was ranked in the top 10. In one case this will be measuring the vibration, in another case it will encompass the position of a specific component. There will also be components who do not pass these tests when it is not possible to measure its condition. This will mean that these components will not be used and will be initially maintained as described within the initial PMS.

Rank	Component	Score	Applicability
1	Gear Wheel z24	58	N
2	Gear Wheel z30	58	N
3	Wheel-drive	51	N
4	Sensor-proximity	50	Y
5	Spring-torsion	48	Y
6	Gear wheel z20	48	N
7	Gear wheel z30	47	N
8	Cam Insert	46	Y
9	Product Carrier	42	Y
10	Guide	40	Y

Table 3.6: Selection of CBM Components

3.5 Conclusion

To answer the first research question it was first considered which component types were interesting for predictive maintenance. The characteristics to which predictive maintenance interesting components have to apply are:

- Random failure pattern
- Critical for the performance of the machine
- Subject to wear

Comparing these characteristics with the characteristics of the different component types within the PMS this resulted in the B and E components.

Next, a method was created to be able to filter interesting components out of the total newly developed bill of material, taking into account the B and E components. Components which have a cost above the 100 Euros and posses a certain criticality (Vital and Essential) were judged on a couple of criteria. These criteria are:

- Criticality
- Skill level needed for repair
- Mean Time To Failure
- Mean Time To Support
- Mean Time To Repair
- Sales costs

As final part of this chapter a case study was performed to verify the method. The method has been approved to find machine-specific components which are suited for predictive maintenance. However, some other components which are standard in every machine produced by Marel might also be interesting. It is advised to design a standardized solution for these components.

The conclusion for Marel is that, during development, it should be tried to focus on specific components which are special for the machine. Besides that, it should be tried to determine common components to be able to introduce CBM for. Furthermore, the lead time of a component (time it takes to get the component supplied from Marels' suppliers to the customer) would be good to take into account but the information about lead time is insufficient in quality at the moment.

Chapter 4

Creating knowledge from data

This chapter discusses the second research question:

How can it be determined which external production factors affect the degradation of a newly introduced machine?

This question is answered through the following sub-questions:

- *Which data is available, and what steps need to be taken to prepare the data in order to be able to use it for determining the external production factors affecting the degradation in performance? (Section 4.1)*
- *Which methods are suited for evaluating which external production factors cause performance degradation? (Section 4.2)*
- *How can these methods be implemented and evaluated by using the available data supplied from the TREC? (Section 4.3)*

In this chapter, first the three sub-questions will be answered. By combining the results of these sub-questions, conclusions will be drawn to answer the second research question.

This question centers around explaining the performance by using production factors which concentrate around the machine and not within. This can be extended with internal factors but this will be out of scope since there is no information available about components of the TREC.

Performance of a machine is measured by concluding if the machine delivered the result which it is intended to do. Considering the TREC, as a transfer system, this means that the performance is the percentage of correctly transferred broilers. A broiler is correctly transferred when it is in the same state as before. E.g. when a broiler is hanging on two legs the broiler is correctly transferred when this broiler is, after passing through the machine, still hanging on two legs.

4.1 Data

4.1.1 Available Data

The available data originates from two IT-systems, both running at the same test customer involved in a special collaboration with Marel. The first system, Innova, is focused on the

Overall Equipment Effectiveness. It measures the performance of the total production line, but also of specific machines. Furthermore, Innova registers broiler demographics and error messages. Innova is closely linked to the production control. Marel explains it as “Innova Food Processing Software enables processors to maximize yield and throughput, conform to quality standards and ensure food safety, with trace-ability built into every process step”. (Marel, 2018).

The second system ChainLive is part of a new IoT based larger project. Within this project the applicability of predictive maintenance is tested. Where the ChainLive project is mainly focused on creating a correct infrastructure for future use, it is also exploring how to use predictive maintenance as a service. ChainLive in particular is interesting because it concentrates around the TREC, the case study of this project. The main data used within ChainLive originates from a setup created by a previous master thesis executed within Marel (van Dorst, 2015). This thesis focused on the applicability of predictive maintenance and showed this by measuring the length between two shackles on the chain (which is used as drive of the machines and transportation of the broilers). Furthermore, within ChainLive both the condition of the shackle on which the broilers hang, and the weight of the broilers are registered.

Within Innova there is a limit on the frequency of registered data. Where it is best to know exactly how every broiler passes through the production line, the registration for monitoring is done in time steps of at most 15 minutes. The most important data is the performance data of the TREC. This data is recorded at several positions throughout a production plant. For the research question the performance around the TREC is interesting. Furthermore, some general production statistics are recorded: the speed at which the line is processing broilers, the specific production moments (including breaks), and some broiler statistics (the weight and the breed). See Table 4.1 for an overview of the available data.

Innova	ChainLive
Performance of machines	Length of shackle
Production moments	Condition of product carrier
Broiler statistics	Product weight
Line speed	Condition of shackle

Table 4.1: Available data

The two projects, previously discussed, capture the most important data sources to evaluate the performance of the machine. Since the primary interest for this question is to find causes of performance reduction, it is important to have this data in a complete and consistent manner.

Some snapshots of the raw data can be found in Appendix A.

4.1.2 Data Preparation

To prepare the data, the first activity is to aggregate all the data in intervals of 15 minutes. 15 minutes is chosen since the performance of the machines, which is registered within Innova, is registered over intervals due to data warehousing limitations. To aggregate data into the 15 minute intervals different actions are taken.

To start, to measure the performance of the machines, a summation of the number of incorrectly transferred broilers is made per 15 minutes. It also has to be filtered so that only the production moments are taken into account. These moments are in general every weekday from 2:30 until 22:00. To adjust for the start-up and shutdown, the interesting production moments will be from 2:45 until 21:45. Additionally, within these production times breaks are scheduled. These breaks are also scheduled during dedicated moments. The previous steps will result in the average performance of the production process during the relevant production times, represented per 15 minutes. Furthermore, per machine it is registered how many shackles were occupied, how many were empty, if both legs of the broiler are present, and if there is a change in the state of the broiler. This change can be, a new missing leg, or a new dropped broiler.

Another special case is the length between two shackles, since these measurements could be improved on sensitivity and correctness. Taking an average of the lengths is sufficiently accurate for the goal. Another thing which needs to be taken into account is that it takes three hours for the chain to make one round through the cooling tunnel. This chain possesses around 45000 shackles. The state of each carrier is represented by the number of missing wheels and if the condition of each carrier is still intact.

For the weight of all the individual broilers it is decided to take a mean, since the production speed and the availability of broilers is not always the same over the whole time.

In the end it is made sure that all data is available as 15 minutes intervals, all beginning and ending at the same moment. This may also mean that data sets with missing data cannot not be used.

4.2 Method Selection

When Marel wants to increase its knowledge about the behavior of the machine and its components, there are a number of ways to achieve this. There are two basic methods to distinguish: qualitative methods and quantitative methods (Creswell, 1994). The first method uses qualitative data and information to analyze past and/or future events. It focuses on concepts, meanings, descriptions of things and not on their quantitative measures (Berg et al., 2004). The second method is about testing objective theories by examining the relationship among variables. These variables, in turn, can be measured so that numerical data can be analyzed using statistical procedures (Creswell, 1994).

To investigate which methods could be useful, first the available data is analyzed. This will be done by discussing the several sources available within Marel. Afterwards, a number of methods that are suited for answering the second research question are discussed.

4.2.1 Method elaboration

As discussed in Section 4.2, there are two main methods to increase knowledge about the behavior of machines and its components. These two main methods were defined as qualitative and quantitative research methods. Since this master thesis is focusing on analyzing data for investigating external production factors affecting degradation in the form of performance of a newly developed machine and judging the available presented data, only the quantitative methods will be further investigated.

When searching for interesting methods it is important that they are able to analyze and interpret data. Generally, statistical procedures are the appropriate quantitative data methods. It is used to answer questions on relationships within measurable variables with the intention to explain a phenomenon (Kumar, 2011). In other words, the method should be able to analyze the data in order to extract meaningful statistics and other characteristics (Wei, 2006). There are many types of appropriate statistical methods that can be found in the literature. However, to make it understandable for Marel and to make it reproducible in the future, it is important to select the method that results in insights that are easy to understand and apply in practice.

Firstly, it is important for Marel to know at what time the performance of a machine was not sufficient. When it is known at what time the performance was not sufficient, Marel is interested in having insight into which factors contributed to that performance degradation at that specific moment. Since the contributing production factors can differ over time it is necessary that Marel is able to select a desired time window to further investigate. Therefore, it is valuable to use a combination of two methods such that Marel can review the performance over time and select a moment in time for analyzing which production factors caused the performance degradation. Summarizing, a combination of two methods will be used:

- One method to determine at what moment the performance of a machine was not sufficient.
- One method to compare this performance with other production factors at that specific time, such that an answer can be given to the second research question.

4.2.2 Statistical Process Control

This section is based on the book by Montgomery and Runger (2010).

The first method that will be applied is SPC, which will be used to determine the moment of insufficient machine performance. In short, statistical process control concentrates on finding process variations by using statistical methods to monitor and control a process (Doty, 1996).

SPC is a method used within Statistical Quality Control. Statistical Quality Control consists of several tools to improve the quality within a company. In this case especially the quality of a production process. It is designed as the process in which statistical and engineering methods are used in measuring, monitoring, controlling, and improving quality. The most interesting implementation of statistical quality control is by using SPC and experimental design (Chandra, 2001). For this research, experimental design is left out of scope since this is executed by testing different designs and continuously changing the environment. This is not the intention because this would mean that the process in which the machine runs is not stable and the prototype is not trusted.

Statistical Process Control is an application of statistical techniques and procedures (such as control charts) to analyze the inherent variability of a process or its outputs to achieve and maintain a state of statistical control, and to improve the process capability. The most important tools which are used within Statistical Process Control are (Fouad & Mukattash, 2010):

- Histogram: Used to show the spread, or dispersion, of variable data.
- Pareto Chart: Used to graph counts of defect data or error types.
- Defect-concentration diagram: Used to visualize all defect or problem areas being analyzed. A cluster of similar defect in the same part of the graph might indicate assignable cause.

- Control chart: Used to analyze process performance (stability) over time.
- Scatter diagram: Used to show the correlation or cause-effect relationship between two data sets.
- Cause-and-effect diagram: Used to document results of root cause analysis. Usually used after identifying a problem with a control chart or other tool.
- Check sheet: Used to accurately collect real time data on location.

This suggests several options to use SPC. For the purpose of SPC in this research, it can be concluded that the control chart fits best. This is because the first method needs to determine at what moment the performance of a machine was not sufficient. Control charts are the usual tool to identify an out-of-control process (Benneyan et al., 2003) and is therefore a very well applicable method.

There are five reasons for control charts being so popular:

- Control charts are a proven technique for improving productivity
- Control charts are effective in defect prevention
- Control charts prevent unnecessary process adjustments
- Control charts provide diagnostic information
- Control charts provide information about process capability

Control charts can be used to indicate variability within a process. Within SPC variability is one of the factors on which decisions may be made. Control charts are characterized by a mean, upper bound, and lower bound to calibrate the data. Within the control chart theory this is called; Central Line, Upper Control Limit (Central Line + 3-sigma), and Lower Control Limit (Central Line - 3-sigma). When between the upper and lower limit it is believed that the process is in-control. Choosing the calibration set is important for subsequently testing newly added data. Taking too much data or a preferred data set into account may result in a total offset of the total chart. Nevertheless, the process can be out-of-control when between the limits due to some extra rules called the Western Electric rules. These rules state that the process is out of control when:

- One point plots outside 3-sigma control limits, or
- Two out of three consecutive points plot beyond a 2-sigma limit, or
- Four out of five consecutive points plot at a distance of 1-sigma or beyond from the center line, or
- Eight consecutive points plot on one side of the center line

This research will only focus on the points that are outside 3-sigma control limits. The reason for this decision is that different studies have shown that when setting the control limit to a lower sigma limit it may detect small shifts from the standard deviation. These shifts might not necessarily signify system instability. The 3-sigma control limit, however, detects larger shifts from the standard deviation and does signify an out-of-control process (Natrella, 2010). Therefore, the decision was made to only focus on moments in time when the system was outside the 3-sigma control limit.

4.2.3 Multiple Linear Regression

After the implementation of SPC which determines at what moment the performance is not sufficient, determining what was the cause of that degradation is of importance. By taking the second method into account, possible statistical data analysis procedures should be reviewed. The most well-known statistical procedures are described and reviewed for their applicability below:

- Correlation: Correlation analysis is a method of statistical evaluation used to study the strength of a relationship between two, numerically measures, variables. It is useful to research whether there are possible connections between variables (Cohen et al., 2014).
- Regression analysis: Regression analysis refers to a group of methods for studying the relationships among two or more variables based on a sample. Although, there are many types of regression analysis, they all examine the influence of one or more independent variables on a dependent variable (Foley, 2018).
- Comparison of means: Multiple tests are available for investigating the difference between the means of variables of two or more groups (Mayers, 2013).

In order to be able to choose the right statistical method for answering the second research question it is important to analyze each method for its applicability. This applicability strongly depends on number of (in)dependent variables in the data. In Table 4.2 an overview is given for each statistical method in terms of the appropriate number of variables and the corresponding research goal.

Method	Applicable for
Correlation	One dependent variable and one independent variable. It can be used to indicate that a relationship or pattern exists, but it says nothing about causation.
Regression analysis	One dependent variable and one or more independent variables. It can be used to determine how strong the relationship is between the independent and dependent variable(s).
Comparison of means	One dependent variable and one or more independent variables in different populations. It is used to determine whether the difference in means (averages) for two groups is statistically significant.

Table 4.2: Applicability statistical methods (Leeper, 2000)

When taking into account the available data and the goal of the research question, the decision is made to use regression analysis as the appropriate method. This decision is based on the fact that the research wants to find factors that cause performance degradation of a newly introduced machine. Correlation is not sufficient for answering this research objective since it is not able to say whether an independent variable is the cause of the dependent variable. In other words, it is not able to say whether an external production factors causes performance degradation. Secondly, the comparison of means is used for investigating differences between the means of variables between groups. This is not the objective of the research and this method is therefore not usable for answering the research question as well.

Since regression analysis is appropriate it is decided to continue with this statistical research method. There are different types of regression methods. The appropriate method depends on the nature of the (in)dependent variables. Since the research question distinguishes one dependent variable (degradation in the performance of the machine) and several interval or normal independent variables (available within the data), the multiple regression method is selected as model type (Leeper, 2000). The results of the analysis can be translated into actions to take to improve the performance of the machine. From now on the method which will be used will be called MLR.

Within MLR, Y is the dependent variable, β_0 the intercept, β_i the regression coefficient of independent variable i, and k the number of independent variables if applicable, the main formula is:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{\mathrm{k}} x_{\mathrm{k}} \tag{4.1}$$

To eliminate variables which are not relevant within the MLR, stepwise regression is used. This is a procedure which creates a sequence of regression models by iteration. The focus lies on adding or removing variables within each step. Within stepwise regression two selection methods are available namely, forward selection and backward elimination. Since backward elimination is less time consuming, this is chosen. Within backward elimination, the process starts with all variables and is continued until all variables left in the model have a significant p-value resulting from the t Test. The t Test is used to check the significance of individual regression coefficients in the multiple linear regression model. When the p-value of the t Test is significant, it means that adding this variable makes the model more effective (Aiken et al., 1991). The majority of analyses uses the cut-off for significance at a p-value of 0.05 (Nuzzo, 2014). This p-value will therefore also be used within this research to include or eliminate independent variables in the model. Afterwards, it is important that if all variables are significant, that the total multiple linear regression is significant by executing a F-test which also results in a p-value which represents the significance. This test indicates whether the regression model provides a better fit to the data than a model that contains no independent variables. When the p-value of this test is significant (< 0.05) it can be concluded that the regression model fits the data better than the model with no independent variables (Montgomery & Runger, 2010). When executing multiple linear regression, it is therefore important to check for significance both using the t Test and the F-test.

Concluding for the second sub-question, several methods were reviewed from which two methods are chosen. One method, Statistical Process Control, which focuses on out of control moments during production. The other method is Multiple Linear Regression which focuses on explaining the relationship between performance degradation found within SPC and external production factors.

4.3 Case study

To illustrate the introduced model, again a case study is performed. This case study has as goal, to show the applicability. In this case the machine around which it is centered is again the TREC. This TREC has the available data described in Section 4.1.1. The generation of results will start, as explained, by creating control charts which are used within statistical process control.

To illustrate, Figure 4.1 shows the overall performance of the rehang performance on the outgoing side of the machine for a certain time period. This is measured within the TREC. This can also be generated per missing leg, or fallen broiler. These figures can be seen in Appendix B. The calibration set will have an average performance of 97.7% which is within the performance agreed with the customer.

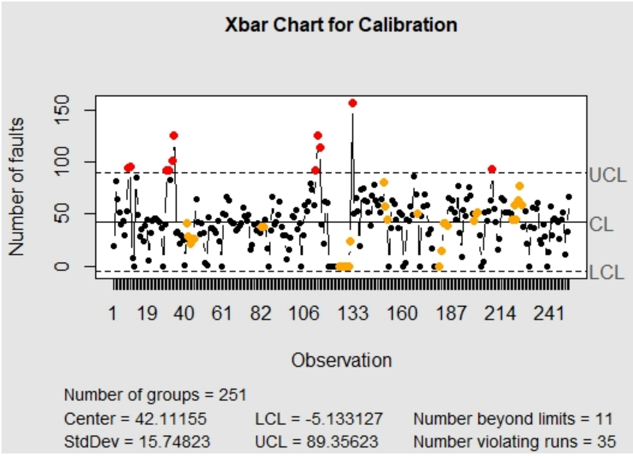

Figure 4.1: Calibration chart for the TREC

Within Figure 4.1 the y-axis represents the number of broilers transferred incorrectly during the 15 minute period. The x-axis represents each 15 minute observation over time. Furthermore, several statistics of the data set are shown. Number of groups being the size of the data set. Center is the mean of the sample, StdDev the standard deviation, LCL is the 3σ lower control limit and the UCL the 3σ upper control limit. The red dots within the figure represent the moments in which the process was out of control due to violating the UCL and the yellow points represent the moment in which the other three SPC rules are violated.

The sequence for finding the variables within MLR is executed by using R as programming language. Eight variables were chosen to assess within the MLR. These variables can be found in Table 4.3. The choice for these was made due to availability within the data and because these variables have a high possibility of influencing the performance.

Table 4.3: Variables used within MLR registered per 15 minutes

Variable	Description
Y	Number of wrongly transferred broilers
x1	Number of arriving incorrectly hanging broilers
x2	Number of empty arriving shackles
x3	Number of arriving broilers hanging on second leg
x4	Number of arriving broilers hanging on first leg
x5	Average length between 2 shackles in the chill line
x6	Average weight of the broilers
x7	Number of broken product carriers in the chill line
x8	Number of broken right wheels of the product carrier in the chill line

The output of all subsequent steps which resulted from backward elimination can be found in Appendix C. For the lack of performance during the time period between observations 1-50, the resulting model looks like:

$$Y = 50.757 + 2.081x_8$$

where x_8 is the number of broken wheels on the shackles on the chill line. With corresponding p-values of the t Test for β_8 and F-test being:

- p-value of t Test of β_8: 0.0472
- p-value of F-test: 0.0472

Since the p-values are below 0.05 it can be concluded that x_8 has a significant influence on the performance degradation. In addition to that, the p-value of the model is significant, hence the F-test.

It is logical that the broken wheels on a shackle has resulted from the regression model. When a wheel of a shackle is broken the position of the shackle will be skewed and the position relative to the machine will be different. With more broken wheels it is logical that this results in worst performance.

In another period it was the case that the machine performed below expectation as can be seen in Figure 4.2. Here, compared to the previous case, new data is added for which the performance has to be validated. The new validation data is compared with the control limits created within the calibration set. Within this figure, it can be seen that there are a lot of out of control measurements within the validation set. For these red clouds it would be beneficial to know what caused this extreme out of control performance.

For the excessive lack of performance during this time period, the resulting model looks like:

$$Y = -35.806 + 0.7043x_3 + 0.049x_6$$

The intermediate steps resulting in this answer are recorded within Appendix D.

In the resulting model, x_3 is the number of broilers of which only the second leg is present, and x_6 is the average weight of the broilers during the 15 minutes. With corresponding p-values of the t Test for β_3 and β_6 and F-test being:

- p-value of t Test of β_3: 0.0119
- p-value of t Test of β_6: 0.0001
- p-value of F-test: $2.57e^{-7}$

Since the p-values are below 0.05 it can be concluded that x_3 and x_6 have significant influence on the performance degradation. In addition to that, the p-value of the model is significant, hence the F-test.

These results make sense for the mean weight since, the rotation and movement during transfer stays the same, the speed of turning is the same so it is likely that for broilers which have a higher weight the transfer is performed too soft. For the incorrect hanging broilers it make sense since, when a broiler is hanging at one leg it is very likely that the broiler in the next phase will drop since the position of the broiler is skewed.

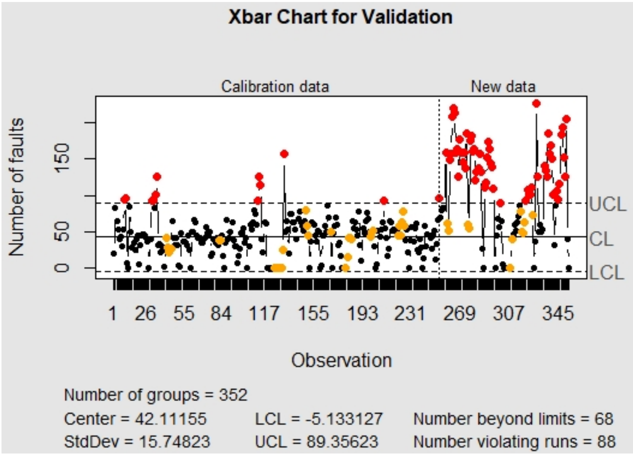

Figure 4.2: Performance chart with bad performed validation for the 1438

As conclusion of the case study it was found that the implementation of the chosen methods was easy to execute and can be used without spending a lot of time analyzing. As results it was found that in the cases for which performance was validated, the weight of the broilers, the state in which the broiler was, and the condition of the shackle was a possible cause of the degradation in performance.

4.4 Conclusion

To conclude, to make use of the outside production factors and find how these factors influence the performance of the machine, a process with two methods was introduced. As a first step, by using statistical process control the performance of the machine can be analyzed. The so-called *out of control* process moments can be filtered from this process. When the timestamps of the out of control process are known, the next method can be applied. This will be Multiple Linear Regression. Within MLR a dependent variable, in this case the performance of the machine, is checked if it can be represented by other independent variables with significant accuracy.

These methods were applied by preparing and analyzing the supplied data and by interpreting the results. During two moments in time the two methods found possible external factors which may underlie the fact that the process was out of control. These factors were the state of the shackle, the mean weight of the broilers, and the total number of missing first legs. The applicability of the methods within Marel can thus be confirmed.

Despite the data limitations it should be noted that the applicability and insights that the two methods can generate are very valuable. The first step of SPC shows in one glance what the performance of the system was. It can support gut feeling by showing the performance of the machine quantitatively. In addition to that, applying MLR as a second step can show which external factors are affecting the performance of the machine. When the data is complete and correct, it may result in insights that have never been conceived before. Besides that, the results may also show important external factors which were thought to be important, but that were never numerically examined.

Chapter 5

Conclusion & Discussion

Within this chapter first a conclusion will be drawn resulting from the answers to the research questions. After this conclusion is drawn, the main research question will be answered. The chapter will continue by stating some limitations of the performed research to Marel. Finally, this chapter ends by giving some recommendations to Marel.

5.1 Conclusion

The two research questions were discussed in Chapters 3 and 4. The results of the research questions will be summarized and the main findings will be presented.

RQ1: How can it be determined for which components it is beneficial to implement predictive maintenance?

To answer this research question, three sub-questions were introduced. Which type of components are beneficial for predictive maintenance was the focus of the first question. Afterwards, criteria had to be determined relevant for predictive maintenance. As final sub-question the implementation within the TREC was researched.

For Marel the main focus to introduce predictive maintenance is on B- & E-components. These components need to be judged on six criteria. A seventh criteria, lead time, may be beneficial. Nevertheless, lead time is currently not accurately registered by the supply chain department within Marel.

The criteria will subsequently be used in formula 3.1 which was also introduced within chapter 3. Using this approach on the TREC as a case study revealed that the approach was applicable and led to valid results.

So to answer the first research question, by performing the introduced model and score the parts on the suggested criteria, components can be selected which can benefit for predictive maintenance. Subsequently, for these components monitoring systems can be set up to start predictive maintenance.

RQ2: How can it be determined which external production factors are of importance in affecting the degradation of a newly introduced machine?

For answering this research question three steps were taken. First the interesting data was found and prepared, by retrieving it from two IT-systems, Innova and ChainLive. Several process variables were taken into account. Next, two data analysis methods were introduced, Statistical Process Control, and Multiple Linear Regression. SPC is used to find out of control production moments by using a 3-sigma limit. MLR is used to explain a dependent variable (in this case the performance) by using several independent variables (process variables). This approach of using the two models was tested on a case study. This test revealed that the approach was applicable and led to valid results.

Main RQ: How can Marel use its data to get faster acquainted with factors affecting performance of its newly introduced machines?

To conclude the main research question, the machines' components are introduced within the first research question by adding predictive maintenance. Interesting components can be determined and these can subsequently be monitored. Furthermore, there is data available about the process within a production plant. Using this data and find out how other machines, broilers, or plant characteristics can be used for finding factors outside the machine influencing the performance. Specifying the degradation, may result into a modification in the design.

The discussed methods can be used for setting up maintenance especially for original equipment manufacturers who also deliver services. Furthermore, the machines of these manufacturers are not stand alone machines. This would especially entail the second part of the project. Hence there are less outside factors which influence the performance of the machine when it is a stand alone machine. For introduction of the first part it is important that there is a similar way of setting up maintenance and some variables are already taken into account. For example, a method for classifying components into maintenance categories.

5.2 Limitations

This research had the following limitations.

- As explained within research question 1, Lead Time could be another criteria to evaluate for predictive maintenance. Nevertheless, this is not known for Marel. With introducing lead time of components within the model it should create better awareness on which components are most difficult to order and therefore be more interesting for predictive maintenance. This could also reduce the inventory for these components. Therefore, recording Lead Time for components can be beneficial for Marel.
- The data quality was a limitation.
  - Inconsistency of measured data was high. For example, a certain variable lacked measurement records for a week. Also the reliability of the measurements are different, due to tests performed on sensors or malfunctioning sensors.
  - Data quality is also limited because of the interval in which the data is recorded. This interval, 15 minutes, makes the performance sometimes too general and many influencing factors can be the cause of the decreasing performance. For example, this time interval makes it hard to determine the exact reasons for a dropped broiler. To better be able to determine reasons for the performance degradation these 15 minutes should be shorter, e.g. 5 minutes. This can be resolved by more frequent registration of data within a safe and secure data registration system.

5.3 Recommendations

From this research a number of recommendations are given:

- Predictive maintenance is not yet a service product which can be offered to the customers. A separate service product needs to be created along with a matching support organization. For example by hiring more data scientists or create a monitoring system which automatically can find explaining variables. Furthermore, by introducing predictive maintenance the period of predicting needs to be established and discussed with the supply chain to be able to detect an error and be on time for delivery of new parts. This will both decrease the inventory and increase the delivery performance.

- For execution of predictive maintenance more knowledge has to be gathered. Especially the knowledge about how certain components behave or measurements can be registered reliably. This is of importance to be able to apply predictive maintenance. After determination if a component is interesting for predictive maintenance the real measurement and setup needs to be created.

- Design a standard monitoring method for the standard components used within the rotating equipment. These components are used very commonly and within many systems therefore this would benefit cost wise. Furthermore, by introducing such a system it may increase the knowledge about these components.

- To be able to implement the mid-term stage, depicted in Chapter 2, put more emphasis on creating a FMECA. This may lead to faster detection of problems. Furthermore, it could increase the knowledge in adding data creating elements to the machine.

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Appendix A

Data Snapshots

	id	DeviceId	ShackleId	ProductPresent	ProductWeight	TimeStamp
1	45442978	ClfgF01Atc	42861	TRUE	2391	2018-05-29 03:19:03.5170000
2	43628569	ClfgF01AtcDance	20766	TRUE	2942	2018-05-25 15:21:33.8570000
3	38115656	ClfgF01Atc	14564	TRUE	1959	2018-05-05 18:20:12.1400000
4	38991334	ClfgF01Atc	33346	FALSE	0	2018-05-09 00:08:05.2500000

Figure A.1: ChainLive, broiler weight

	id	DeviceId	ShackleId	ShacklePitch	LeftWheelPresent	RightWheelPresent	ShackleStateOk	TimeStamp	LineSpeed
1	28209841	ClfgF01Atc	38438	153.69	TRUE	TRUE	TRUE	2018-05-01 00:00:06	247
2	28209842	ClfgF01Atc	38439	153.04	TRUE	TRUE	TRUE	2018-05-01 00:00:06	248
3	28209843	ClfgF01Atc	38440	153.67	TRUE	TRUE	TRUE	2018-05-01 00:00:06	247
4	28209844	ClfgF01Atc	38441	153.69	TRUE	TRUE	TRUE	2018-05-01 00:00:06	249

Figure A.2: ChainLive, shackle length

	id	regtime	modtime	pamid	lotcode	artcode	quality	rangefrom	rangeto	weight	units
1	1	2017-11-03 07:27:58	2017-11-03 09:09:39	1626	2017110302	1	2	1780	1790	55350	31
2	2	2017-11-03 07:27:58	2017-11-03 09:10:17	1626	2017110302	1	5555	1780	1790	317648	178
3	3	2017-11-03 07:27:58	2017-11-03 09:09:57	1626	2017110302	1	0	1960	1970	304464	155
4	4	2017-11-03 07:27:58	2017-11-03 09:10:10	1626	2017110302	1	5555	1960	1970	644326	328

Figure A.3: Innova, broiler statistics

	id	regtime	oeeregistration	pdt	emptycount	addedcount	clearcount	presentcount	legspresentcount	firstlegmissingcount	secondlegmissingcount	firstlegmissingnew	secondlegmissingnew	firstlegisleftleg
2208470	97431106	2018-05-17 13:10:32	21172648	1523	0	0	0	30	30	0	0	0	0	1
2208471	97431107	2018-05-17 13:10:32	21172649	1522	0	0	2	0	0	0	0	0	0	NA
2208472	97431108	2018-05-17 13:10:32	21172649	1438	0	0	0	0	0	0	0	0	0	NA
2208473	97431109	2018-05-17 13:10:32	21172649	1523	2	0	0	0	0	0	0	0	0	NA
2208474	97431110	2018-05-17 13:10:32	21172650	1522	0	0	0	18	18	0	0	0	0	1

Figure A.4: Innova, performance registration

Appendix B

Performance seperated

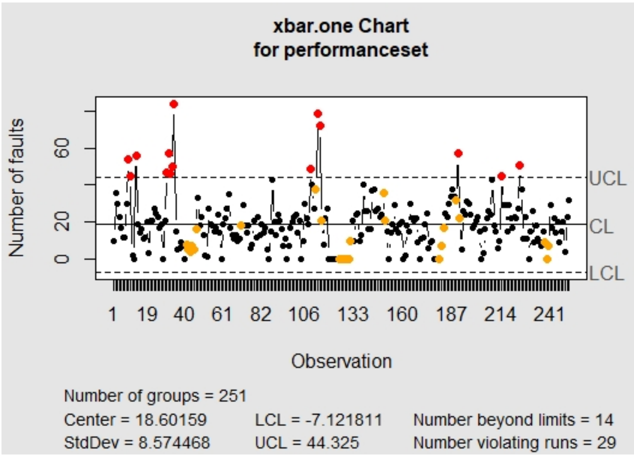

Figure B.1: First leg dropped

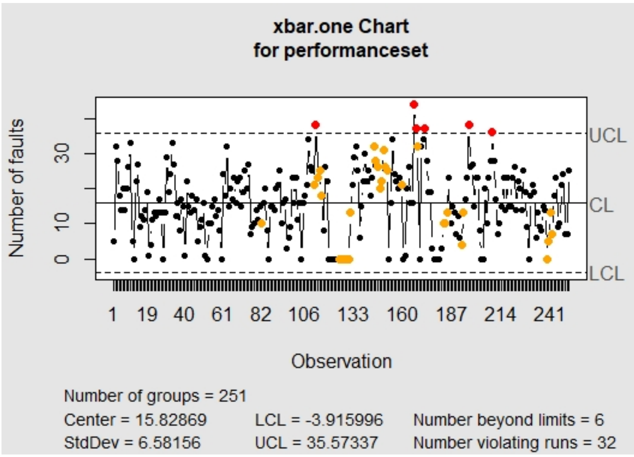

Figure B.2: Second leg dropped

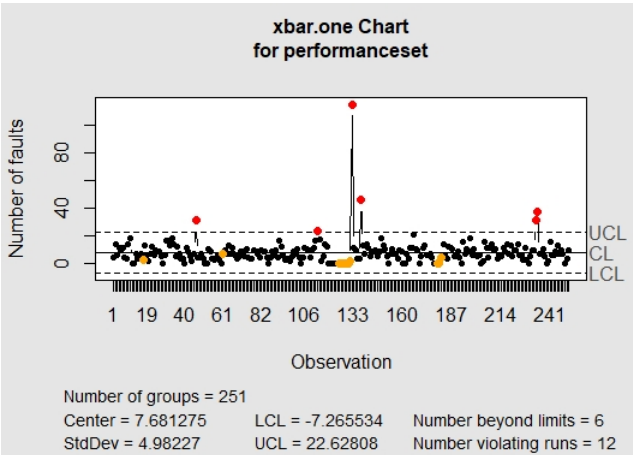

Figure B.3: Dropped broiler

Appendix C

Multiple Linear Regression steps case 1

```
Residuals:
    Min      1Q  Median      3Q     Max 
-49.581 -15.801  -7.176  15.207  82.046 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)  6.246e+03  6.383e+03   0.978   0.3330  
x1           6.919e-01  3.281e+00   0.211   0.8339  
x2          -8.092e-01  3.258e+00  -0.248   0.8050  
x3          -7.215e-01  3.215e+00  -0.224   0.8234  
x4          -7.188e-01  3.239e+00  -0.222   0.8253  
x5          -4.039e+01  4.148e+01  -0.974   0.3352  
x6           8.895e-03  1.058e-02   0.841   0.4047  
x7           2.829e+00  2.867e+00   0.987   0.3289  
x8           2.102e+00  1.071e+00   1.963   0.0557 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 29.12 on 46 degrees of freedom
Multiple R-squared:  0.1702,	Adjusted R-squared:  0.02589 
F-statistic: 1.179 on 8 and 46 DF,  p-value: 0.332
```

Figure C.1: Step 1

```
Residuals:
    Min      1Q  Median      3Q     Max
-49.069 -15.455  -7.377  15.448  81.354

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  6.351e+03  6.299e+03   1.008    0.318
x2          -1.239e-01  2.323e-01  -0.533    0.596
x3          -5.202e-02  4.988e-01  -0.104    0.917
x4          -4.093e-02  3.892e-01  -0.105    0.917
x5          -4.108e+01  4.092e+01  -1.004    0.321
x6           9.169e-03  1.039e-02   0.883    0.382
x7           2.755e+00  2.816e+00   0.978    0.333
x8           2.093e+00  1.059e+00   1.977    0.054 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.82 on 47 degrees of freedom
Multiple R-squared:  0.1694,    Adjusted R-squared:  0.04569
F-statistic: 1.369 on 7 and 47 DF,  p-value: 0.2404
```

Figure C.2: Step 2

```
Residuals:
    Min      1Q  Median      3Q     Max
-48.975 -15.869  -7.026  15.371  81.570

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  6.387e+03  6.224e+03   1.026   0.3099
x2          -1.290e-01  2.247e-01  -0.574   0.5685
x4          -5.552e-02  3.594e-01  -0.154   0.8779
x5          -4.131e+01  4.044e+01  -1.022   0.3121
x6           8.623e-03  8.879e-03   0.971   0.3364
x7           2.743e+00  2.785e+00   0.985   0.3296
x8           2.114e+00  1.029e+00   2.054   0.0455 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.53 on 48 degrees of freedom
Multiple R-squared:  0.1692,    Adjusted R-squared:  0.06536
F-statistic: 1.629 on 6 and 48 DF,  p-value: 0.1596
```

Figure C.3: Step 3

```
Residuals:
    Min      1Q  Median      3Q     Max
-48.749 -15.848  -7.094  15.714  81.874

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  6.500e+03  6.119e+03   1.062   0.2933
x2          -1.354e-01  2.187e-01  -0.619   0.5387
x5          -4.206e+01  3.975e+01  -1.058   0.2953
x6           9.059e-03  8.335e-03   1.087   0.2824
x7           2.742e+00  2.757e+00   0.995   0.3248
x8           2.094e+00  1.011e+00   2.071   0.0436 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.24 on 49 degrees of freedom
Multiple R-squared:  0.1688,    Adjusted R-squared:  0.08398
F-statistic:  1.99 on 5 and 49 DF,  p-value: 0.09664
```

Figure C.4: Step 4

```
Residuals:
    Min      1Q  Median      3Q     Max
-47.256 -16.278  -6.375  16.001  81.002

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  6.692e+03  6.073e+03   1.102   0.2758
x5          -4.331e+01  3.945e+01  -1.098   0.2776
x6           8.529e-03  8.240e-03   1.035   0.3056
x7           2.850e+00  2.735e+00   1.042   0.3023
x8           2.085e+00  1.004e+00   2.075   0.0431 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 28.07 on 50 degrees of freedom
Multiple R-squared:  0.1623,	Adjusted R-squared:  0.09528
F-statistic: 2.422 on 4 and 50 DF,  p-value: 0.06043
```

Figure C.5: Step 5

```
Residuals:
    Min      1Q  Median      3Q     Max
-43.545 -18.435  -7.413  16.470  77.752

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 5620.608   5988.572   0.939   0.3524
x5           -36.225     38.884  -0.932   0.3559
x7             3.140      2.722   1.154   0.2540
x8             2.094      1.005   2.083   0.0423 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 28.09 on 51 degrees of freedom
Multiple R-squared:  0.1443,	Adjusted R-squared:  0.09401
F-statistic: 2.868 on 3 and 51 DF,  p-value: 0.04547
```

Figure C.6: Step 6

```
Residuals:
   Min     1Q Median     3Q    Max
-43.26 -17.04 -10.65  17.36  79.12

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   41.487      6.565   6.319 6.01e-08 ***
x7             4.388      2.367   1.854   0.0694 .
x8             2.032      1.002   2.028   0.0476 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 28.05 on 52 degrees of freedom
Multiple R-squared:  0.1298,	Adjusted R-squared:  0.09631
F-statistic: 3.877 on 2 and 52 DF,  p-value: 0.02694
```

Figure C.7: Step 7

```
Residuals:
    Min      1Q  Median      3Q     Max 
-43.757 -19.257  -6.757  12.847  74.243 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   50.757      4.351  11.665 2.94e-16 ***
x8             2.081      1.024   2.032   0.0472 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 28.69 on 53 degrees of freedom
Multiple R-squared:  0.07226,	Adjusted R-squared:  0.05475 
F-statistic: 4.128 on 1 and 53 DF,  p-value: 0.04721
```

Figure C.8: Step 8

Appendix D

Multiple Linear Regression steps case 2

```
Residuals:
    Min      1Q  Median      3Q     Max
-92.50 -31.86    3.02   23.59  125.27

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -44.63303   32.82435  -1.360    0.177
x1           -1.12896    3.76066  -0.300    0.765
x2            1.16741    3.76228   0.310    0.757
x3            1.75698    3.73002   0.471    0.639
x4            1.64384    3.61154   0.455    0.650
x5            0.04945    0.04098   1.207    0.231
x6            0.04473    0.01315   3.402    0.001 **
x7            1.27230    1.64925   0.771    0.442
x8            5.77731    4.36707   1.323    0.189
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 45.21 on 90 degrees of freedom
Multiple R-squared:  0.3108,    Adjusted R-squared:  0.2496
F-statistic: 5.074 on 8 and 90 DF,  p-value: 3.19e-05
```

Figure D.1: Step 1

```
Residuals:
    Min      1Q  Median      3Q     Max
-94.376 -32.174   2.736  23.750 126.007

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -45.62094   32.49529  -1.404 0.163745
x2            0.03811    0.06157   0.619 0.537428
x3            0.64115    0.31090   2.062 0.042035 *
x4            0.57638    0.62904   0.916 0.361938
x5            0.04993    0.04074   1.226 0.223527
x6            0.04526    0.01297   3.490 0.000746 ***
x7            1.27548    1.64095   0.777 0.439009
x8            5.81221    4.34365   1.338 0.184200
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44.98 on 91 degrees of freedom
Multiple R-squared:  0.3102,    Adjusted R-squared:  0.2571
F-statistic: 5.845 on 7 and 91 DF,  p-value: 1.285e-05
```

Figure D.2: Step 2

```
Residuals:
    Min      1Q  Median      3Q     Max
-93.966 -28.158   4.324  26.812 124.977

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -43.84023   32.25905  -1.359 0.177467
x3            0.64550    0.30977   2.084 0.039953 *
x4            0.56970    0.62684   0.909 0.365804
x5            0.04583    0.04007   1.144 0.255603
x6            0.04556    0.01292   3.527 0.000657 ***
x7            1.08344    1.60595   0.675 0.501596
x8            6.11642    4.30127   1.422 0.158407
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44.83 on 92 degrees of freedom
Multiple R-squared:  0.3073,    Adjusted R-squared:  0.2621
F-statistic: 6.801 on 6 and 92 DF,  p-value: 5.437e-06
```

Figure D.3: Step 3

```
Residuals:
    Min      1Q  Median      3Q     Max
-92.281 -27.839   5.854  24.659 122.361

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -36.06701   30.04280  -1.201 0.232986
x3            0.59861    0.30099   1.989 0.049662 *
x4            0.66140    0.61013   1.084 0.281147
x5            0.05194    0.03892   1.335 0.185257
x6            0.04354    0.01253   3.475 0.000777 ***
x8            5.88697    4.27522   1.377 0.171819
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44.7 on 93 degrees of freedom
Multiple R-squared:  0.3038,    Adjusted R-squared:  0.2664
F-statistic: 8.117 on 5 and 93 DF,  p-value: 2.169e-06
```

Figure D.4: Step 4

```
Residuals:
    Min      1Q  Median      3Q     Max
-86.980 -26.167   3.995  25.956 124.075

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -34.58993   30.03983  -1.151 0.252460
x3            0.72784    0.27663   2.631 0.009946 **
x5            0.05306    0.03894   1.363 0.176262
x6            0.04438    0.01251   3.547 0.000611 ***
x8            5.50960    4.26499   1.292 0.199587
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44.74 on 94 degrees of freedom
Multiple R-squared:  0.295,     Adjusted R-squared:  0.265
F-statistic: 9.835 on 4 and 94 DF,  p-value: 1.087e-06
```

Figure D.5: Step 5

```
Residuals:
    Min      1Q  Median      3Q     Max
-86.469 -22.614   3.644  25.732 123.062

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -36.57596   30.10588  -1.215 0.227411
x3            0.67717    0.27479   2.464 0.015527 *
x5            0.04794    0.03887   1.233 0.220478
x6            0.04637    0.01246   3.721 0.000336 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44.89 on 95 degrees of freedom
Multiple R-squared:  0.2825,    Adjusted R-squared:  0.2599
F-statistic: 12.47 on 3 and 95 DF,  p-value: 6.052e-07
```

Figure D.6: Step 6

```
Residuals:
    Min      1Q  Median      3Q     Max
-87.404 -24.729   2.886  24.953 121.281

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -35.80617   30.18101  -1.186 0.238400
x3            0.70434    0.27465   2.564 0.011883 *
x6            0.04947    0.01224   4.042 0.000107 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 45.02 on 96 degrees of freedom
Multiple R-squared:  0.271,     Adjusted R-squared:  0.2558
F-statistic: 17.85 on 2 and 96 DF,  p-value: 2.572e-07
```

Figure D.7: Step 7