On condition-based maintenance for machine components

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Abstract

The goal of condition-based maintenance (CBM) is to base the decisions whether or not to perform maintenance on information collected from the machine or component of interest. A condition-based maintenance tool should be able to diagnose if the component of interest is in a state of failure but the ultimate goal of a CBM tool is to be able to estimate time until failure, either in terms of remaining useful life (RUL) or estimated time to failure (ETTF). Therefore a CBM tool should have both diagnostic and prognostic features.

This master's thesis was carried out at a company within the packaging industry and the goal was to implement a CBM tool with the possibility to estimate RUL for a set of critical components which could serve as a base for further development within the company. The selection of components to focus on was part of the thesis as well.

The process of implementing CBM with prognostic functionality was more difficult than expected and the goal of estimating RUL was not met for any of the components, but the work that has been done forms a basis for further development. Thus, this thesis will serve as a pre-study on developing CBM and contains information of what is required in order to be successful.

Acknowledgements

First of all we would like to thank Niklas Svanberg for giving us the opportunity of performing this master's thesis at the company and also for giving us a lot of encouragement during the process. We would also like to thank Lukas Karlsson for being a constant support providing both knowledge and time for discussion. Further gratitude goes to all the personnel at the company where the work was performed for helping us with valuable information and the interest shown in our work.

Also we would like to express our appreciation to our examiners, Klas Nilsson and Karl-Erik Årzén, for making time for discussions and for giving both feedback and advice during the work progress.

Abbreviations

ANN	Artifical Neural Network
AR	Autoregressive
ARMA	Autoregressive Moving Average
CBM	Condition-Based Maintenance
ETTF	Estimated Time To Failure
FFT	Fast Fourier Transform
GUI	Graphical User Interface
HMM	Hidden Markov Model
HSMM	Hidden Semi-Markov Model
PCA	Principal Component Analysis
PPM	Parts Per Million
RUL	Remaining Useful Life
SPC	Statistical Process Control
STFT	Short-Time Fourier Transform
TSA	Time Synchronous Average

Contents

1

Introduction

1.1 Introduction to the area

In all industrial machines there are components and modules that eventually will have to be replaced. Components will degenerate and can cause a malfunctioning machine. Some components are more critical than others and if they fail during machine production it can lead to long downtime and high costs. Therefore some of these critical components are replaced on fixed intervals in order to avoid break down during machine production. This can lead to fully functioning components being replaced while they still have several hours of operating time left.

The two traditional ways of machine maintenance are called corrective and preventive maintenance [Coble, 2010]. The corrective approach, also called unplanned or reactive maintenance [Veldman et al., 2011], is based on maintaining the machine when failure occurs and only then. Preventive maintenance is a part of what is called planned or proactive maintenance and performs maintenance on scheduled basis in order to prevent failure from occurring [Veldman et al., 2011]. The corrective approach has the advantage that the maintenance costs are low when no or few failures occur, but the downside is that the components will run until failure and if a critical failure occurs the costs can be immense. Preventive maintenance on the other hand can lead to unnecessary maintenance and replacement of fully functioning components only to ensure that no failure will occur. This causes a trade off between avoiding critical components failing during machine production and the waste that comes of replacing fully functioning components.

Between these two traditional approaches is condition-based maintenance (CBM). The goal of CBM is to be able to make decisions regarding maintenance based on the collected information from the machine. An ideal condition-based maintenance tool should be able to predict failures in time to schedule maintenance and order spare parts leading to a minimization of downtime as well as a reduction of spare parts costs, Figure 1.1.

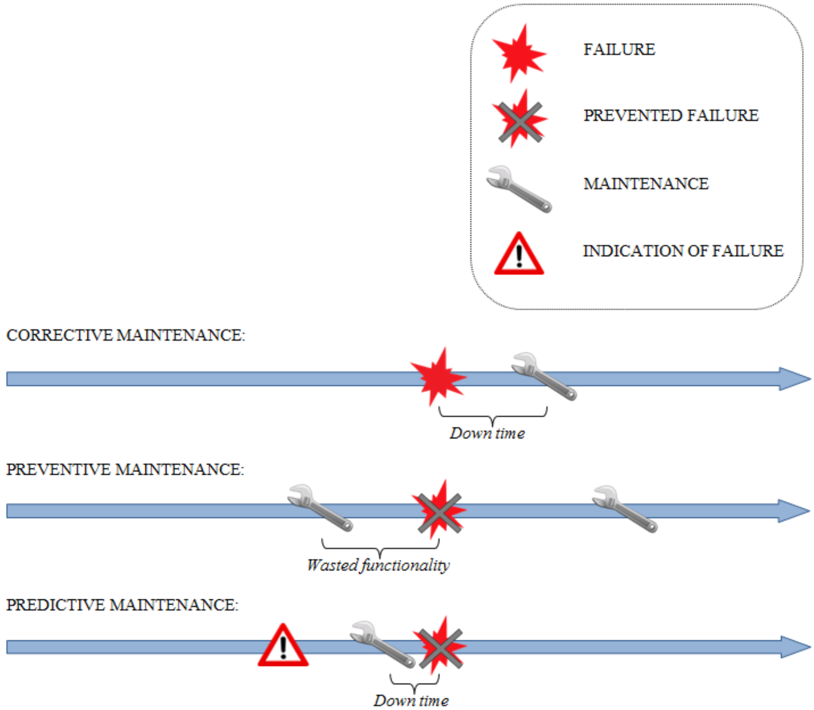


Figure 1.1 Corrective, preventive and predictive maintenance methods.

In order to implement a functioning CBM tool three main steps have to be performed [Jardine et al., 1994]:

1. **Data Acquisition**: Collect information from the equiptment or machine.
2. **Data Processing**: Transform the information into suitable parameters.
3. **Decision Making**: Propose maintenance action based on the information.

Within the area of CBM there are two main categories, namely diagnostics and prognostics. Diagnostics focuses on finding the root cause of a failure when it has occurred while prognostics focuses on predicting possible failures. The goal of prognostic CBM is typically to give an estimate of when the component will fail, this could be given either as an estimate of remaining useful life (RUL) or estimated time to failure (ETTF), but also with associated confidence limit [Sikorska et al., 2011].

With a RUL or ETTF estimate for critical machine components or modules maintenance and replacement of the component or module can be scheduled in time without risking machine faults or wasting of functional components.

The preventive maintenance approach is cost effective when the number of failure events prevented grows large, whereas if the number of prevented failures are low this approach is cost inefficient. The corrective approach is suitable when the failure events are sporadic, keeping the operational costs low, but if the number of failure events grows larger the cost grows as well. When a company decides to integrate a CBM tool the initial cost can be high but if the tool is successful the overall costs will be reduced.

More information regarding condition-based maintenance can be found in Chapter 2.

1.2 Problem formulation

The overall idea for this master's thesis was to develop a tool which can perform a Machine CheckUp, i.e., a health check on the machine and its components. As first idea this could be done by, for example, checking functions before start-up, by applying condition monitoring for health check on critical components and by visualizing the machine health on the operator panel.

Since the time for this work is limited we determined that the main goal should be to study the possibility of estimating remaining useful life for a number of specific critical components or modules. This means that the focus of this thesis is on the prognostic aspect of condition-based maintenance. For each component or module a custom made solution for the specific application should be developed, and not a general solution for all variants of the component, in order to gain the best result. This should also be done only by using the components' own signals and not by adding any hardware in terms of sensors or measurement tools.

This thesis could then serve as a prestudy for the company giving better knowledge of what kind of components or modules are suitable and what information is needed in order to develop a condition-based maintenance tool.

To reduce the workload for this thesis the first step of CBM, i.e., Data Acquisition, was left out of the scope and was therefore handled by other personnel at the company. A logging tool was quite recently developed at the department where the thesis was performed which took care of the data acquisition. The tool contained some limitations which is discussed in the chapters about each component and how it affected the specific component.

1.3 Company

This master's thesis was performed at a world leading company within the packaging industry. The company develops both the packaging machines and the packaging materials. In the thesis the focus is on the components in the packaging machine and not on the packaging material. There exist multiple machine platforms within the company and we have worked with components from different platforms. In the thesis we discuss and explain some of the possible failures in the machine, something that could harm the company if it was released to the public. Therefore the company have decided to remain anonymous in this report. To make sure that the company stays anonymous and that this report is not traceable back to it, all values in this report have been scaled and all units are left out of graphs and tables because of this scaling. The analysis and conclusions are still viable and based on real measurement data.

1.4 SCRUM

We chose to work according to a method called SCRUM [Schwaber and Sutherland, 2013] in this thesis. SCRUM is an agile method where the work is conducted in short sprints, 2 weeks in our case. Each sprint consists of a set of deliverables, also called sprint backlog, that does not change during the sprint. The sprint backlog is decided at a meeting before the start of the sprint, called sprint planning, where the main stakeholder, i.e., the product owner, decides the priorities of the activities and what activities to be completed during the sprint. The SCRUM team then breaks down the sprint backlog into smaller tasks which are easier to handle and complete than a full activity. Every day starts with a short meeting where the project members give brief updates on the work progress and, if problems have occurred, possible solutions are discussed within the group. After each sprint the team holds a sprint review meeting to reflect over what was done and the result during the sprint.

1.5 Individual contribution

Throughout this thesis all work have been planned and discussed together. Since the project was carried out using SCRUM methodology we started each day with a discussion on what had been done and what to do next. Thus, the knowledge and information was always shared between us.

The analysis and implementation of the selected components were divided evenly between us. Dennis focused on the analysis of the rotating spray nozzles and the injection molding unit and Astrid on the gas concentration sensor and the servo motor. However, throughout the project both have been involved with the work for all the components regarding selecting suitable approach and discussions regarding the results and findings. The chapters of the report regarding each component have been divided according to same division as for the analysis and the rest of the report has been divided evenly.

1.6 Thesis outline

This first chapter serves as an introduction to this thesis and contains a short introduction to the area of condition-based maintenance, the problem formulation for this thesis, a short description of the company where the work was performed as well as a section regarding individual contribution. The thesis was carried out using a method called SCRUM which is also explained in this first chapter.

In Chapter 2 the area of CBM is described more in detail. The chapter includes general information, work flow and possible methods to use. References to previous work are integrated in the text regarding the possible methods.

Chapter 3 describes the process of selecting what components to focus on for this thesis.

The components that were chosen are described in Chapter 4-7. These chapters contain a background explaining the component and its application, what method was used for the analysis of the component as well as the results and findings. Each of these chapters are ended with a conclusion regarding the possibility of condition-based maintenance for each specific component.

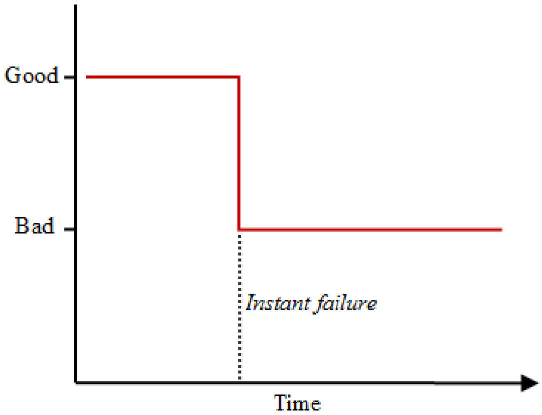
Based on the findings for these components the thesis is concluded in Chapter 8, where some advice for future work also is described.

2

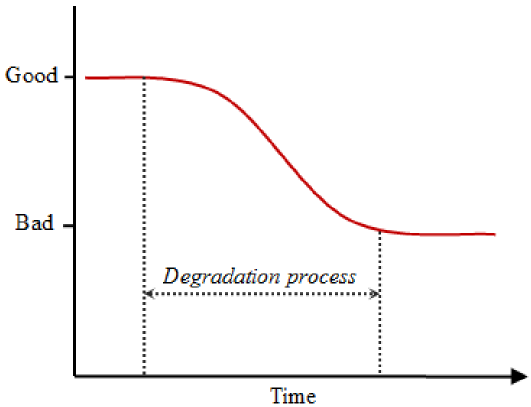
Condition-based maintenance

The idea of condition-based maintenance is to perform maintenance only when it is needed, i.e., use indicators of upcoming failure as markers to schedule maintenance, as opposed to corrective maintenance which performs maintenance when failure has occurred and preventive maintenance which is performed on fixed time intervals. The goal of CBM is to reduce downtime due to failure while at the same time reduce costs of parts being replaced before it is needed, see Figure 1.1. In [Kothamasu et al., 2006] the authors state that for many industries 15-40 % of manufacturing costs are due to maintenance activities. By implementing a CBM tools these costs could be reduced, but the development of a CBM tools can in itself be very expensive. In [McKone and Weiss, 2002] formulation of expected maintenance costs per time unit is given for four different maintenance models which can serve as a base when deciding what approach to use.

Condition-based maintenance is not a new idea and there are a lot of research performed on this subject, though not so much reported from the industry. The reason for this could be that not a lot of companies have developed CBM tools or that it simply is not published due to company policies. In [Martin, 2006] a short historical review on maintenance methods is given. The author distinguishes between hard failures and soft failures, where hard failures occur in an instant and soft failures occur when components deteriorate over time, see Figure 2.1. In [Coble, 2010] hard and soft failures are also discussed and the author compares a hard failure to when a car tire pops and a soft failure to when the tire tread reaches below a minimum allowed depth. Therefore the term failure is relative and needs to be defined for each specific application. Although some research has been performed on predicting hard failures, for example [Son et al., 2013], almost all focus for CBM tools is on soft failures.



(a) Example of hard failure.



(b) Example of soft failure.

Figure 2.1 Schematic representation of hard and soft failures.

The ideal CBM should have both diagnostic and prognostic features. The prognostic part should predict failure which is the main goal, but if not all failures are covered and the prognostic model fails the diagnostic part should be able to isolate the root cause of failure. There are numerous methods to use for diagnostics and prognostics which are more or less suitable to use depending on the specific application. Thus the selection of which method to use is a crucial factor for the success of the CBM tool. As described in [Sikorska et al., 2011] many attempts of implementing prognostic models are terminated due to not reaching the desired results in time, whereas the problem might lie in the selection of modelling method. In order to select a suitable approach solid knowledge, or data, of the application or component to analyze is required as well as mathematical understanding of each model type.

As previously stated a condition-based maintenance program contains three main steps, as can be seen in Figure 2.2. Since the data acquisition is out of scope for this thesis this part will only be described shortly whereas the data processing and decision making will be described more deeply, with main focus on decision making since this part depends on which method that is used.

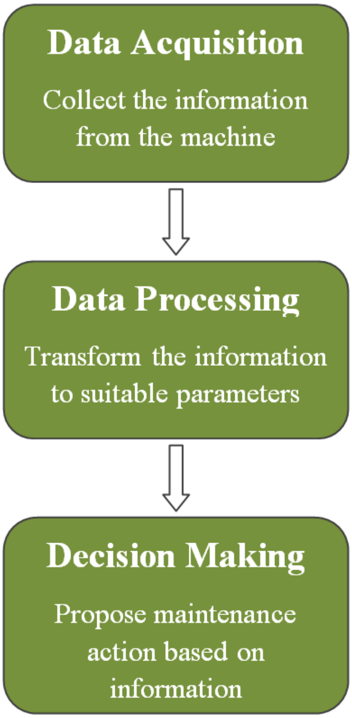


Figure 2.2 The three main steps in CBM.

2.1 Data acquisition

Data acquisition covers the area of collecting information from the process or machine. This could be done by either external sampling tools or integrated in the PLC.

The techniques to collect data will not be covered in this thesis. [Jardine et al., 1994] discusses two types of data used in CBM:

- **Condition monitoring data**: Data or measurements from machine/process such as temperature, pressure, vibration data etc.
- **Event data**: Data of events such as installation, breakdown, minor repair, replacement etc.

The authors raise the importance of collecting both the event data and the condition monitoring data in order to achieve the best CBM tool. The authors point out that in practice the event data is often left out, but that this information is of essence for the whole system.

2.2 Data processing

In order to find the relevant information in the data it needs to be processed. This part of CBM is also called feature extraction. As a start the data has to be "cleaned" so that only correct samples are used in further research. The incorrect data can be caused by faulty sensors or logging tools. A first and simple approach to find incorrect samples of the data is to manually examine the signals to find any extreme outliers and if the cause of these are established to be due to incorrect sampling they can be removed from the data set.

When the data is cleaned the analysis can begin. The suitable method for data analysis depends on the data and its behaviour. In [Jardine et al., 1994] data is categorized into three groups:

- **Value type data**: At each specific time epoch each variable is a single value, such as pressure or temperature.
- **Waveform type data**: At each specific time epoch each variable is a time series of data, such as acoustic data.
- **Multidimensional type data**: At each specific time epoch each variable is multidimensional, such as visual images.

Regarding value type data the analysis can be done quite hands-on when the number of variables involved is small, usually by trend analysis. However, when the number of variables grow large the analysis becomes more complex and some kind of multivariate analysis should be used. Principal Component Analysis (PCA) is a useful method for dimension reduction while keeping the most part of the system's variance [Rosen, 2001].

Processing waveform and multidimensional data is typically called signal processing. There are numerous methods for analyzing waveform data, but the three main categories are time-domain analysis, frequency-domain analysis and time-frequency analysis. Time-domain analysis is based on the time periodic signal and the most basic features that can be extracted is typically mean, peak, standard deviation etc. There are also more advanced methods for analyzing waveform data such as time synchronous average (TSA) [Dalpiaz et al., 2000] or by parametric modelling such as autoregressive (AR) or autoregressive moving average (ARMA).

By transforming the waveform signal to frequency domain the analysis can be done by examining the most interesting frequency regions. The most common approach for frequency domain analysis is to use the fast Fourier transform (FFT). Since the frequency spectrum only covers stationary waveform signals some machine failures, that are expressed as non-stationary, are suppressed by the FFT analysis. This could be avoided by using both time and frequency in the analysis such as the short-time Fourier transform (STFT) or the Wigner-Ville distribution. In [Cohen, 1989] a review of a number of time-frequency distributions are given. Time-frequency analysis is suitable, for example, for vibration data and is commonly used for CBM of gearboxes, such as in [Li and Liang, 2012] and [Omar and Gaouda, 2012].

2.3 Decision making

The part of the CBM tool that handles decision making can either focus on prognostics or diagnostics. As stated earlier diagnostics focuses on finding the root cause of failure whereas prognostics focuses on predicting future failures. The decision of maintenance should be based on the following questions:

- **Diagnostic:** At current time, t, is the component in a state of failure? If yes, what caused it?
- **Progonostic:** At current time, t, when will the component reach a state of failure, i.e., $t_{RUL} = t_{failure} - t$? Is it time to schedule maintenance?

The ideal goal would be to predict machine failure, but the diagnostic of failure is just as important. The possibility of predicting fault or failure is almost always dependent of knowing the cause. The information from a diagnostic tool is relevant when implementing the prognostic tool. Also not all fault cases might be included in the prognostic tool and then diagnostic information can be used as feedback when redesigning the prognostic tool to include the failures that previously were not predicted [Jardine et al., 1994]. The decision making depends entirely on what method is used and therefore the focus of this section will be on what methods are available. Also many methods used for prognostics are based on diagnostic approaches but with the extension of predicting if failure is approaching and therefore the emphasis in this section will be on prognosis methods and the diagnostic approaches are only mentioned briefly.

Diagnostic methods

The diagnostic part of CBM is highly correlated with pattern recognition which is a part of the research area Machine Learning [Huang et al., 2008]. Many diagnostic tools are based on statistical analysis. It can for example be a hypothesis test where H_0 means that a fault is present, H_1 that a fault is not present and by statical testing determine to accept H_0 or to reject it [Jardine et al., 1994]. Another common statistical approach is cluster analysis where multivariate data is grouped into clusters which contain similar information. In the case of diagnostics the clusters can describe different failure cases. Cluster analysis used for diagnostics is described in [Skormin et al., 1999]. Statistical process control (SPC) focuses on statistical pattern recognition through control charts including control limits to detect abnormalities in signals [Fugate, 2001].

Other methods commonly used for diagnostics are hidden Markov models (HMM), artificial neural networks (ANN) and physical models, but since these methods also are common within prognostics they are discussed further in the following section.

Prognostic methods

An extensive evaluation on prognostic modelling options can be found in [Sikorska et al., 2011] where the authors also try to summarize what should be considered when selecting which prognostic model is suitable for different applications within industry. The output of a prognostic model should be an estimate on when failure will occur, either in terms of RUL or ETTF, but also an associated confidence limit. In [Sikorska et al., 2011] several prognostic models are discussed and the authors have categorized the models into four groups based on similarity: Knowledge-based models, Life expectancy models, Artificial neural networks, and Physical models.

Knowledge-based models A well experienced machine operator has a lot of knowledge of previously experienced failure cases and can from the current machine behaviour recognize if some specific failure is about to occur as well as estimated time until occurrence. Prognostic models that are knowledge-based try to mimic the behaviour of these human experts. The model compares the current state of the component with a database containing previously recorded failures. In order to implement this kind of prognostic model a lot of experience and knowledge of the system is needed.

Knowledge-based models can also be divided into Expert systems, used in [Garga et al., 2001] for prognostics of gearboxes, and Fuzzy systems which are discussed in [Cox, 1992].

Life expectancy models Life expectancy models is the category which, according to [Sikorska et al., 2011], contains the largest number of proposed prognostic models, approximately 15 models are discussed in the article. This group can also be divided into stochastic and statistical models.

The stochastic models use probability density functions based on the assumption that RUL for identical components can be treated as statistically identical as well as independent random variables. One of the most commonly stochastic prognostic model used by industry during the last 30 years is Aggregate reliability functions. By using historical failure data the probability density functions and hazard rate are calculated and then modelled by the most suitable distribution, such as Exponential, Gaussian or Weibull distributions. An example of where Weibull distribution is used to estimate RUL can be found in [Banjevic, 2009]. Since the distributions are fitted based on historical information it is fundamental to have enough data available in order to be successful.

An extension of the traditional Aggregate reliability functions is Bayesian models, also called Conditional probability models. The general idea of Bayesian models is to calculate the condition reliability function for an event to happen and for each new observation update the probabilities for future event using Bayes' theorem [Sikorska et al., 2011]. The simplest version of Bayesian models is called RUL probability density function where the probability density function of remaining useful life is the distribution which is continuously updated. Other more complex versions of Bayesian models are Bayesian networks, which in theory are described in [Koski, 2009]. Bayesian networks are graphical models consisting of nodes representing random variables and are used to find statistical dependencies between these variables.

Within Bayesian networks the most common methods used for prognostic modelling are Markov models and Hidden Markov models as well as Kalman filters and Particle filters [Sikorska et al., 2011]. Hidden Markov models will be discussed later in this thesis, see Section 6.2.

As for the statistical methods, which can also be called data-driven models, the current behaviour of the component is compared with a reference behaviour. One way to perform statistical prognosis is by trend evaluation which is done by finding a parameter which corresponds to the degradation of the component. This parameter could be a raw signal or extracted from a raw signal, e.g., mean or peak value, or by multiple signals reduced to one single variable. By the use of historical data for this parameter limits for when failure occur can be established as well as limits for when warning of adjacent failure should be announced. An example of a degradation parameter with limits can be found in Figure 2.3. By performing curve fitting for the degradation parameter observations RUL can be calculated as an extrapolation when the failure limit will be reached.

Other statistical approaches are autoregressive models that are suitable for modelling time series data, as mentioned earlier.

Artificial neural networks When a large amount of data from a system is available but the physical knowledge of the fault causes is lacking it could be suitable to use artificial neural networks, ANN, which is a branch within artificial intelligence that strives to imitate the signal processing of the human brain. An artificial neural

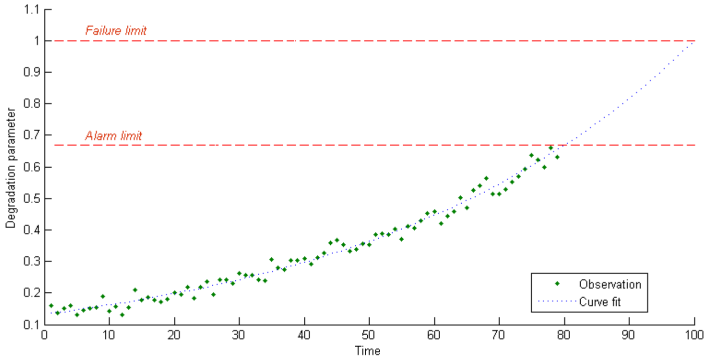


Figure 2.3 Degradation parameter with alarm limits.

network consists of neurons, or nodes, which are located in a desired number of layers. The connection between the neurons are weighted and by using training data with known input and output the weights are adapted to produce the correct output for each input. This training procedure is what makes the model mimic the real physical process without the need of human knowledge. The inputs and outputs can be either single or multivariate. RUL could be the direct output of an artificial neural network as long as there is enough training data with known remaining lifetime as output.

Physical models Prognostics can also be based on physical models where the asset or component is modelled by physical laws for example by ordinary or partial differential equations. This approach requires thorough physical understanding of the component and the possible failure cases and therefore the literature of this approach is limited to specific applications. As an example, in [Luo et al., 2008] differential equations together with state-space representation is used to model crack growth in order to estimate the lifetime of dynamical systems.

3

Selecting components

The first thing that had to be done was to decide which components or modules to work with. To do this we had to find components that broke down fairly often or were being replaced on a regular basis to prevent breakdown and expensive machine stops. The components we were trying to find had to have available logging and data collection available since this was out of scope for this project. To find these components numerous interviews were conducted with persons responsible for different machine components or modules. During the interviews we were trying to get answers to the following questions:

- How often does the component break down?
- Is the component replaced on a regular basis to prevent breakdown?
- Is logged data available?
- Is logged data available for both good and bad cases?
- How do breakdowns express themselves?

After the interviews were completed, a meeting with all stakeholders was conducted. During the meeting the findings of the interviews were presented and the pros and cons of working with each component. The stakeholders then discussed, together with us, and decided which components should be focused on. The following components were selected to be included after the interviews and stakeholder meeting:

- Gas concentration sensor
- Rotating spray nozzles
- Servo motor
- Injection molding unit

These components were selected from a total of 15 components because they suffered from some sort of critical breakdown.

The gas concentration sensor was selected since it showed behaviour that might be useful for lifetime estimate. It was also an expensive component which was replaced frequently which led to it being one of the most costly components on the platform. Additionally, much data was available since a logging tool had been implemented and data had started to be logged a couple of months prior to the start of this thesis.

The rotating spray nozzles were chosen for a different reason and was not that subjective to a lifetime estimate. Instead this component was chosen since it was impossible to detect if the spray nozzles were fully functional without manually inspecting them. The idea with this component was to see if it was possible to detect a malfunctioning spray nozzle by looking at signals in the system instead of a manual inspection. It was a critical component and it was selected for this component since it was a missing function that had to be implemented and the other variants developed to detect a malfunctioning spray nozzle were very costly.

The servo motor was selected because it had to be replaced frequently due to breakdowns. These breakdowns were very costly and by using condition-based maintenance a lot of money could be saved.

The last component we chose was an injection molding unit. It was selected because it had data for both a good unit and a bad unit. As with all the other components this module was also very expensive and monetary gains could be made by using condition-based maintenance on this module.

It is worth noting that there was a lack of knowledge around all of these components and that the causes of the breakdowns were unknown for the most part. That was also a reason for the company to decide on these components since they wanted more knowledge and was hoping that through our work learn more about them. In the end the components were mostly chosen due to the possibilities of saving money, which of course is the whole point of condition-based maintenance.

4

Gas concentration sensor

The gas concentration sensor was chosen since it had been showing some deviating behaviour which might be used for lifetime estimates. The sensor is also quite expensive and needs to be replaced frequently. The recently developed logging tool had been collecting data for two sensors of this kind for several months and therefore a lot of data was available.

4.1 Background

The sensor is designed for measuring the concentration of a certain substance in a gas chamber in parts per million, ppm, using UV absorption spectrophotometry. The sensor is quite complex and consist of approximately 40 signals that are available for data acquisition through external equipment such as the PLC.

Previous analysis of the sensor had showed some indications of component degradation in the signal corresponding to the ppm concentration that was not consistent with the behaviour of the whole system, including the in and out flow of the substance the sensor should measure. During machine production the gas concentration should be constant but the sensor has been showing that the concentration is drifting towards a higher value without changes in the flows. This increased concentration could lead to alarms going off and stopping production. Also before production, when the machine is warming up, the gas chamber does not contain any substance vapor and the concentration should be zero, but sometimes the sensor shows an incorrect value saying that there indeed is substance vapor in the chamber. The control system of the sensor contains a function for zero alignment of the concentration which is used to remove this incorrect offset of the measured concentration before going to production.

A full machine run consists of a number of different machine steps where the production step is the most important. In order to reach production there are a number of warming up steps and there are also cooling down steps after production.

The data that was available for the analysis was from two different sensors in the same machine which were sampled with a fixed sample period whenever the machine was operating by the recently developed logging tool. The data set consisted of 44 machine runs with a mean length of 15 hours.

In Figure 4.1 an example of the described behaviour of the increasing concentration can be observed where the upper concentration limit is exceeded. During machine warm up, in machine step 60, the zero alignment of the concentration offset is performed just before transition to machine step 65. This can be observed in Figure 4.2. Please note that the alarm limits have been switched off for the plant where the data were collected and that is why the machine is still running even though the alarm limits for the ppm values are exceeded.

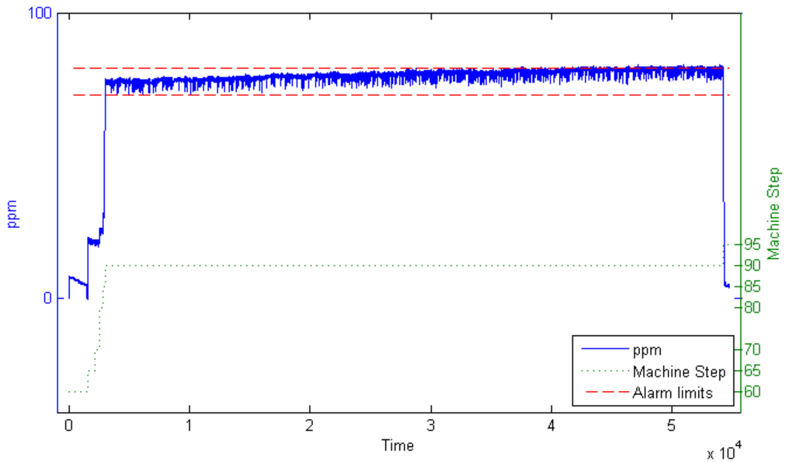


Figure 4.1 Full machine run with ppm limits.

4.2 Method

The idea for this component was that the offset during warm up could be caused by degradation and therefore be used to predict if the alarm limits would be exceeded during machine production. Based on the analysis of these predictions for each machine run the remaining useful life could later be estimated.

In order to get the long term degradation process we decided to classify each machine run and from there determine the behaviour of the system when reaching the alarm limits. The classification was made by extracting a number of characteristics from each machine run. These characteristics can be found in Table 4.1. There were also a few more characteristics that were extracted for each run but did not affect the classification and are therefore not published out of respect for the

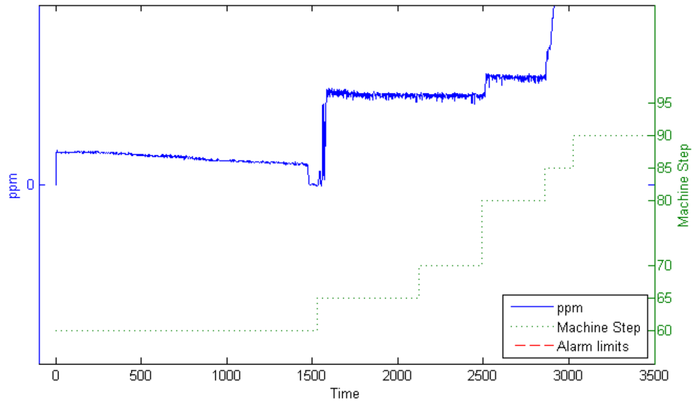


Figure 4.2 Zero alignment during machine warm up.

manufacturer. We decided to use the following five different classifications for the machine runs, which are described in Table 4.2.

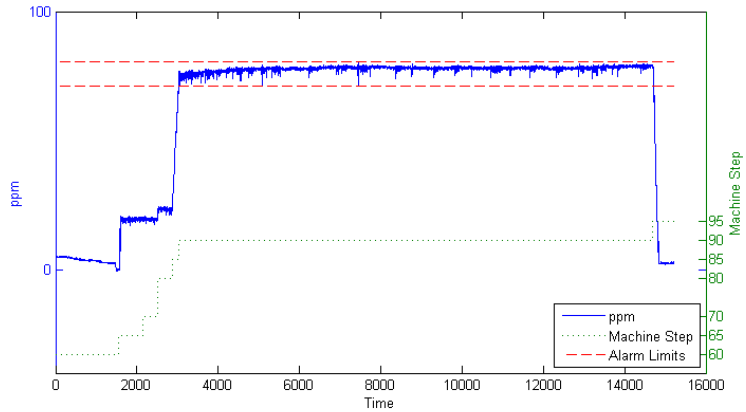
Table 4.1 Characteristics used to classify each machine run.

What	Definition
length	Total length of machine run
ppm offset init	Mean value of the first 150 samples of first machine step
ppm offset after	Mean value of all except first 150 sample of last machine step
ppm prod start	Mean value of the first 150 samples during production
ppm prod end	Mean value of the last 150 sample during production
product temp	Mean value of the product temperature
lower alarm	Alarm for lower limit triggered = 1
upper alarm	Alarm for upper limit triggered = 1

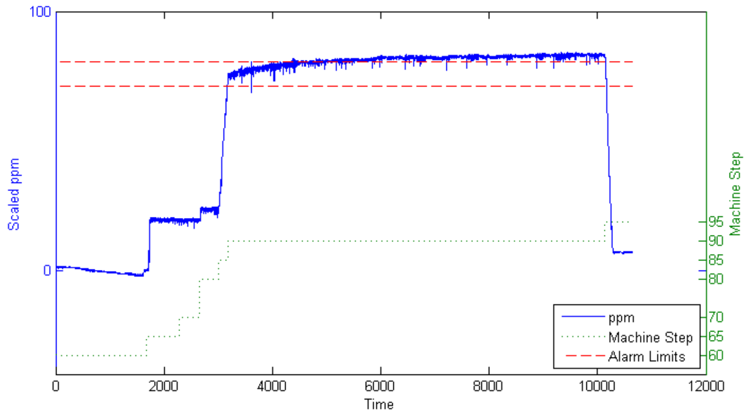
Table 4.2 Classifications of machine run.

Classification	Description
GOOD	The machine performs all the machine steps and never violates the concentration alarm limits.
SHORT	A normal machine run but only in production for a few minutes.
WRONG	Something happens that affects the concentration that is not intended.
ALARM	Alarm should have been triggered.
INCOMPLETE	Not performing all the machine steps.

In Figure 4.3 there are examples of the classifications GOOD and ALARM. The machine steps that correspond to warming up are 65-85, production is 90 and cooling down is 95.



(a) GOOD.



(b) ALARM.

Figure 4.3 Examples of classification GOOD and ALARM.

4.3 Results

The first idea was to look at the concentration offset during warm up for each machine run against the classifications and look for correlations. The result of this analysis can be seen in Figure 4.4, where the initial ppm offset is on the horizontal axis and the classifications on the vertical axis. The most important information is the difference between GOOD and ALARM but unfortunately no clear relations could be extracted for any of the two sensors.

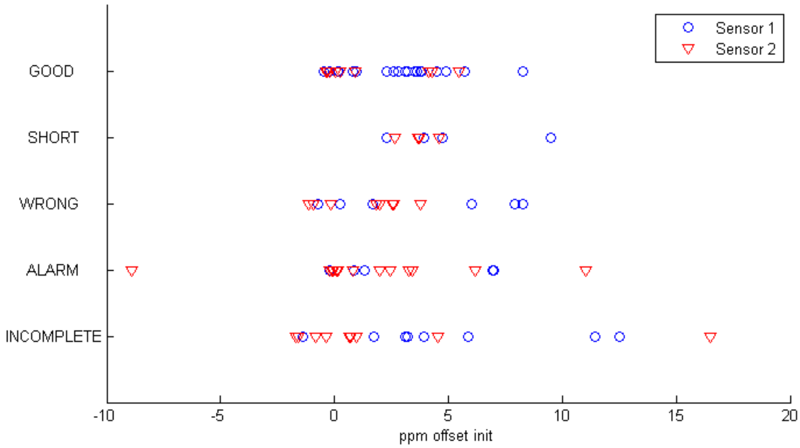
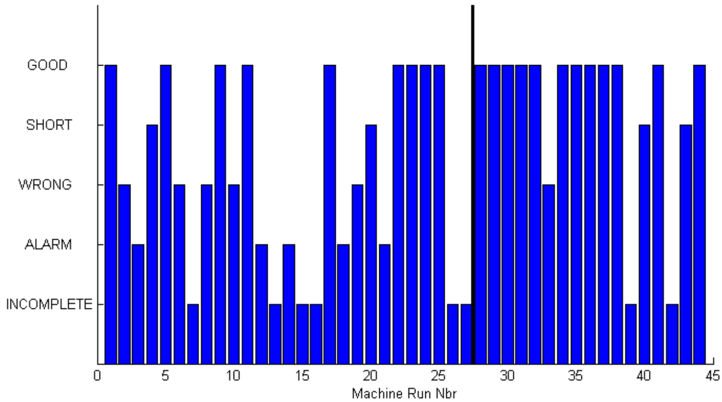
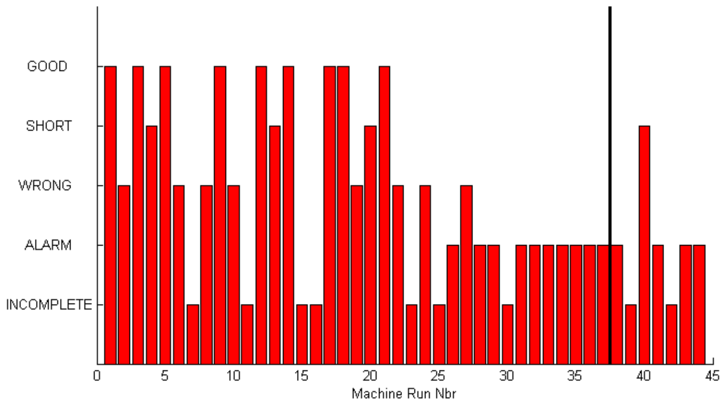


Figure 4.4 Classification and ppm offset init.

Both of the sensors from which data had been collected had been replaced during the logging period so we decided to look at the classifications for each run together with the time of replacement. In Figure 4.5 the classifications of each machine run are shown as bar plots and the time of replacement as a thick black line. For sensor 1 there is a clear improvement of the machine runs when the sensor is replaced with no machine runs reaching the alarm limits after replacement. For sensor 2, however, the malfunctioning behaviour continued also after replacement.



(a) Sensor 1 - classification of each machine run.



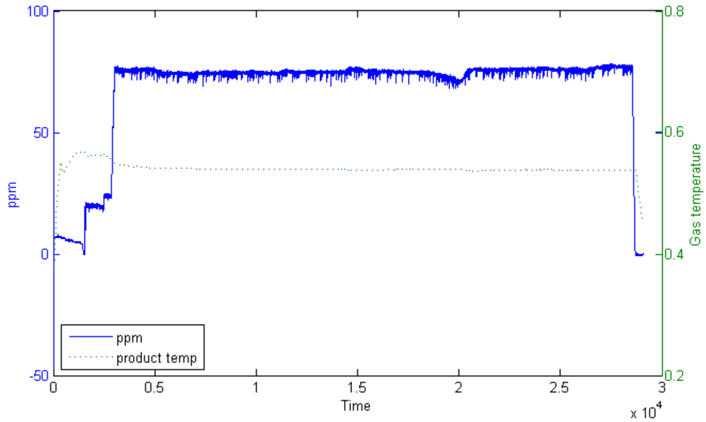
(b) Sensor 2 - classification of each machine run.

Figure 4.5 Mean Position Error for Test Case 1.1.

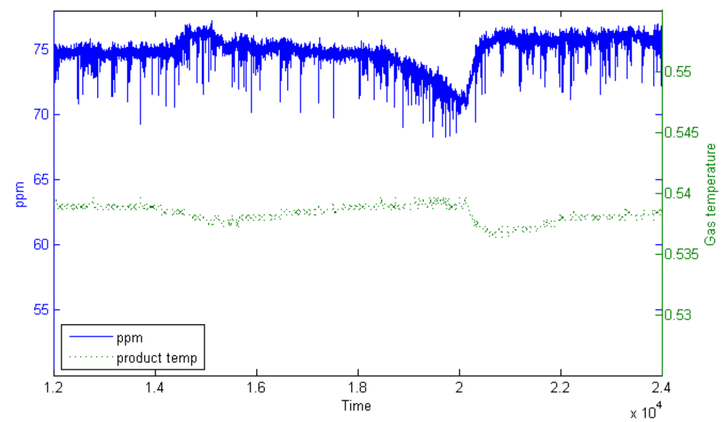
The data analysis that was performed during this thesis raised some questions for the personnel involved with the sensor. This led to a parallel investigation of the behaviour of the component and an alarming discovery was made. From the ideal gas law, Equation 4.1, it is known that the concentration of substance in a gas is dependent of the temperature. In this equation P is the pressure of the gas, V the volume, n the amount of substance, R the universal gas constant and T is the temperature of the gas.

$$P \cdot V = n \cdot R \cdot T \tag{4.1}$$

As described earlier the sensor uses UV absorption spectrophotometry to calculate the substance concentration. These calculations use a compensation factor to compensate for changes of the substance temperature according to the ideal gas law. Recent discoveries showed that this compensation factor is incorrect which leads to substance concentration varying with the temperature. The effects of this can be seen in Figure 4.6, where Figure 4.6(a) shows the full run and Figure 4.6(b) a close up of where the effects of the incorrect compensation factor can be observed.



(a) Full run.



(b) Close up.

Figure 4.6 Product temperature and ppm concentration.

Because of the discovery of the compensation factor being incorrect the configuration of the component will be modified until the proper behaviour of the sensor is achieved. This discovery also made all the collected data unreliable and therefore we decided to not work any further with this component in the thesis.

4.4 Conclusion

The analysis of the gas concentration sensor showed a stochastic behaviour. No clear correlation was found between the ppm concentration during machine warm up and the alarm limits being exceeded. The discovery of the incorrect compensation factor and therefore the absence of reliable data caused us to not work any further with this specific component in this master's thesis.

5

Rotating spray nozzles

The second component we decided to work with was two rotating spray nozzles. Even though no practical data existed and that it was not lifetime estimation that would be the goal for this unit, it was still chosen since it was a critical component for the company. Different solutions had been developed to solve the problems with this component, however these were very expensive and therefore a large monetary gain could be made.

5.1 Background

The two rotating spray nozzles were located inside a container in a cleaning system, designed to clean the interior of said enclosed container. In the cleaning system a separate tank was used to hold the cleaning liquid. During cleaning the cleaning liquid was sent from the separate tank into the container to be cleaned by a pump. The pump built a pressure in the system which was used to spray the inside of the container by two rotating spray nozzles to hit all surfaces. The spray nozzles rotated because of the pressure of the cleaning liquid that passed through small slits in the nozzles. A cleaning sequence consisted of multiple rinses, both with and without chemicals, and for each rinse there were a number of steps to be performed, for example filling the separate tank and spraying the inside of the container.

The problem with the system was that the spray nozzles could fail to rotate and thereby not spray the complete interior of the container. A non-rotating spray nozzle could for instance be caused by dirt entering the nozzle and blocking it. Since the spray nozzles only rotated by the pressure from the cleaning liquid and were not controlled in any way, there was no direct feedback from the nozzles whether they rotated or not. Our task with this module was to see if it was possible to diagnose if the spray nozzles rotated or/and had been blocked, so they could not spray, by looking at signals outside the container. A number of signals were available for consideration but we concluded that only a few were possible as measurements for detecting a rotating spray nozzle. The signals we decided to look at can be seen in Table 5.1

Table 5.1 Signals in cleaning system.

Signal	Description
Frequency	Inlet pump frequency
Tank level	Level of cleaning liquid in tank
Pressure	Pressure of cleaning liquid in the system
Temperature	Temperature of cleaning liquid

5.2 Method

Since the recently developed logging tool did not cover the cleaning system data was needed. Data existed from previous test, but from those tests everything went well so we could not observe anything abnormal with those that would indicate a non-rotating nozzle. So new tests, where bad performance was forced, had to be run. The interesting parts of the rinses were the spraying steps since it was then the nozzles should rotate. Due to time constraints tests were only performed for the first two rinses where the nozzles should rotate, 1st and 2nd rinse. We decided on five test cases as can be seen in Table 5.2. All test cases were run three times to make sure that the data was accurate. All alterations were only made on one of the two spray nozzles.

After half the tests were completed we found out that the logging time was 1 s despite the fact that the logging could be done with a sample time of 25 ms. Since half of the test were completed with 1 s sample time, we decided to continue with the same sample time for all tests. However, new test were conducted on test case 1, 2 and 5 in Table 5.2 with a sample time of 25 ms.

Table 5.2 Test cases for the rotating spray nozzles.

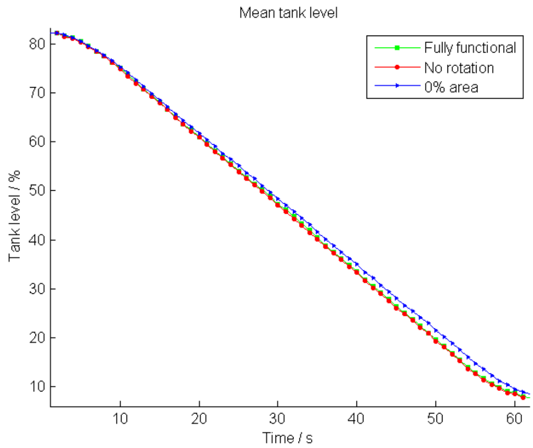
Test #	Description
1	Perfect condition of spray nozzles
2	No rotation of one nozzle
3	No rotation and 50 % slit area of one spray nozzle
4	50 % slit area of one spray nozzle
5	0 % slit area of one spray nozzle

5.3 Results

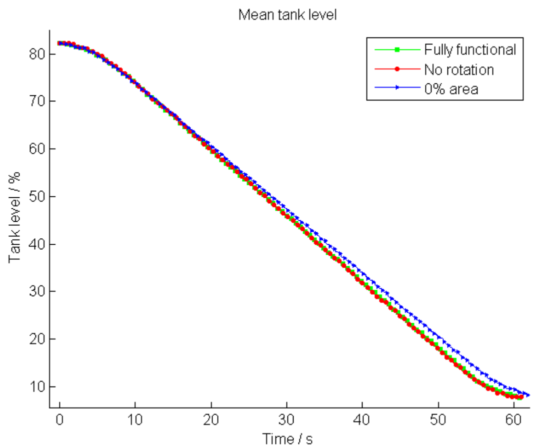
The significant data from the tests can be seen in Figure 5.1, Figure 5.2, Figure 5.3 and Table 5.3. The variables where data is not presented did not show any difference between the test cases or showed extremely stochastic behaviour. The data presented is from test cases 1,2 and 5 in Table 5.2, since these can be seen as the extreme cases. The other cases (test number 2 and 3 in Table 5.2) are left out since they did not provide any meaningful insight and the data from the extreme cases are easier to observe on their own. Additional figures can be found in *Appendix A*. Figure 5.1, Figure 5.2 and Figure 5.3 show the calculated mean of the multiple tests performed on each test case; three for the slow logged tests (1 s sample time) and two for the fast logged tests (25 ms sample time).

In Figure 5.1 the level of the cleaning liquid during the first rinse is presented. The level is represented as percentage of a full tank. The level is plotted against time.

The graphs of the frequency in Figure 5.2 and Figure 5.3 represent the inlet pump frequency during the two rinses. The frequency is in Hz and this is plotted against time.

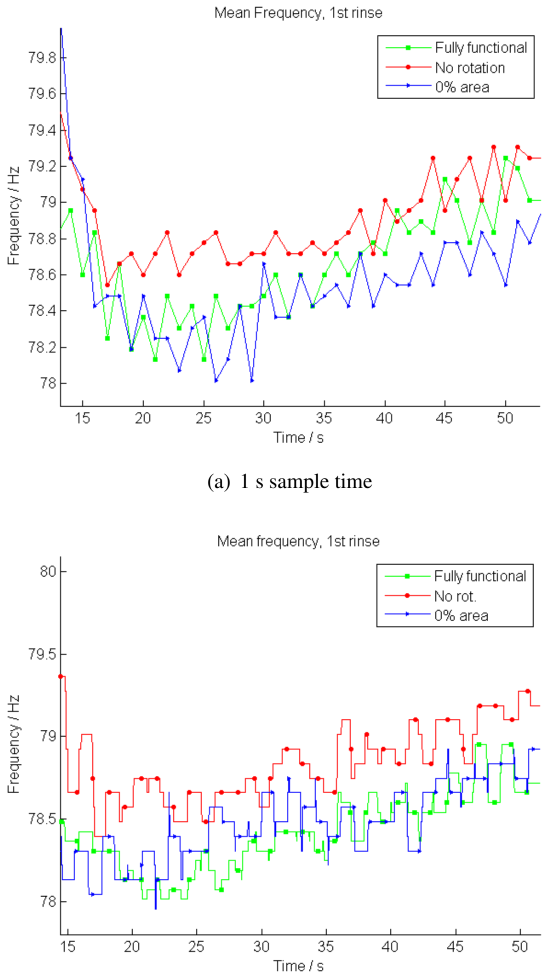


(a) 1 s sample time



(b) 25 ms sample time

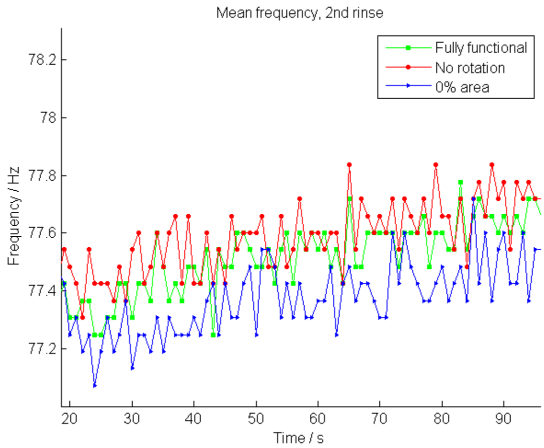
Figure 5.1 Clean system tank level during spraying, 1st rinse.



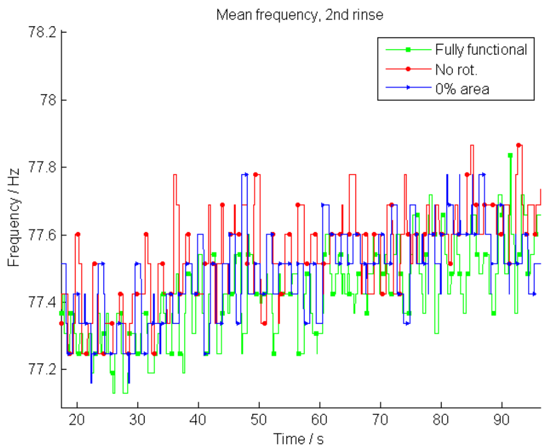
(a) 1 s sample time

(b) 25 ms sample time

Figure 5.2 Inlet pump frequency during spraying, 1st rinse.



(a) 1 s sample time



(b) 25 ms sample time

Figure 5.3 Inlet pump frequency during spraying, 2nd rinse.

The mean frequency presented in Table 5.3 is calculated as the mean of the values between 15 and 50 seconds in *Figure 5.2(a)* and *Figure 5.3(a)* for rinse 1. For rinse 2 the frequency is the mean of the values between 20 and 90 seconds in Figure 5.2(b) and Figure 5.3(b).

Table 5.3 Mean frequency in tests.

Rinse #	Sample time	Nozzle condition	Mean frequency
1	1 s	Fully functional	78.62
1	1 s	No rotation	78.85
1	1 s	0 % area	78.48
1	25 ms	Fully functional	78.41
1	25 ms	No rotation	78.81
1	25 ms	0 % area	78.47
2	1 s	Fully functional	77.51
2	1 s	No rotation	77.58
2	1 s	0 % area	77.37
2	25 ms	Fully functional	77.41
2	25 ms	No rotation	77.53
2	25 ms	0 % area	77.48

5.4 Discussion

When we started to analyze the data from our tests we noticed that the test length varied. This was due to the fact that a cleaning was performed until the separate tank holding the cleaning liquid had been emptied to a preset level. When the nozzle was blocked the tank emptied slower than when the nozzle was clean. The rotation did not matter for the time it took to empty the tank as can be seen by the same figure. However, the time difference is really small between the two cases. In reality the nozzle probably will not be blocked 100 %. Instead it will probably just be blocked by a small percentage of the whole slit area. This makes it hard to detect a clogged nozzle since the small difference will be even harder to detect with a partly clogged nozzle. Clogging of two nozzles may be detectable since this might lead to drastic increase in the time it takes to empty the tank. However, this scenario is very unlikely and would most likely only happen if the nozzles had been tampered with manually. It is also notable that our way of blocking the nozzle may not reflect the reality and thus it is even harder to analyze the data correctly. Therefore it seem unlikely that we would be able to detect a spray nozzle failure by looking at the tank level signal.

By looking at the frequency for both the first and second rinse it is very clear that there is no correlation between the inlet pump frequency and a malfunctioning spray nozzle. The frequencies are very stochastic and the only thing that can be considered to stand out is that the non-rotating spray nozzle requires a slightly higher pump frequency. However, as with the tank level, the differences are minimal between the tests and to predict a malfunction nozzle would be very hard, to not say impossible. It is strange that a blocked nozzle requires as much frequency from the pump as a clean nozzle. A clogged nozzle should generate a high pressure in the system and therefore make the pump work at a lower frequency, but the data in Table 5.3 shows differently. It can be seen that the mean frequency of the completely clogged nozzle is both higher and lower than a fully functional nozzle during both the first and second rinse. This is a very undesired behaviour from our point of view as we would have liked to see a clear difference and presumably a lower frequency for the clogged nozzle.

In both cases minimal differences can be observed but no clear correlations between signals and malfunction can be found. To be able to detect a malfunction, clearer differences would be needed. Even with small differences it might be possible to perform statistical analysis on the data, but in that case, much larger data sets are needed. Since we used really extreme test cases and still can not see a sufficient difference between good and bad cases, it seems very unlikely that it will be possible to detect if a nozzle is partly jammed or clogged.

5.5 Conclusions

The rotating spray nozzles showed a random behaviour and only small differences could be found in the signals from the different test cases. Those small differences showed to be too small to work any further with and in combination with the stochastic behaviour it was decided that this was not a component to work any further with in this thesis.

6

Servo motor

An AC linear servo motor was also a subject for this thesis even though it did not fulfill all the desired requirements in terms of available data and clear failure causes. The reason for selecting this motor was simply that it needs to be replaced frequently because of breakdown during production and if condition-based maintenance were to be established it could save the company a lot of money.

This chapter will start with a background section that describes the servo motor and its application. In the next section previous work related to this component is presented. In the Section 6.3 the approach used for this component is described and the results and findings are presented in Section 6.4. Based on the findings a Matlab based analysis tool was implemented and is presented in Section 6.5.

6.1 Background

The motor is installed vertically inside a machine and the purpose of the servo motor is to apply a cap on to the package the machine is producing. In Figure 6.1 is a schematic sketch of the positions of the motor axis and in Figure 6.2 the motion profile, also called cam curve, can be observed. The homed position is where the motor axis meets a mechanical stop inside the motor and the start position is at an offset distance from the homed position in order to avoid wear of the mechanical stop when the motor is in operation. The application of the cap takes place when the motor axis is at its end position.

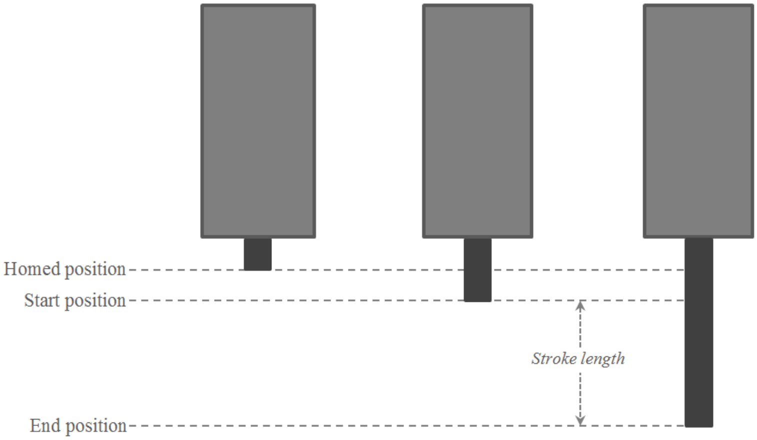


Figure 6.1 Positions of servo motor axis.

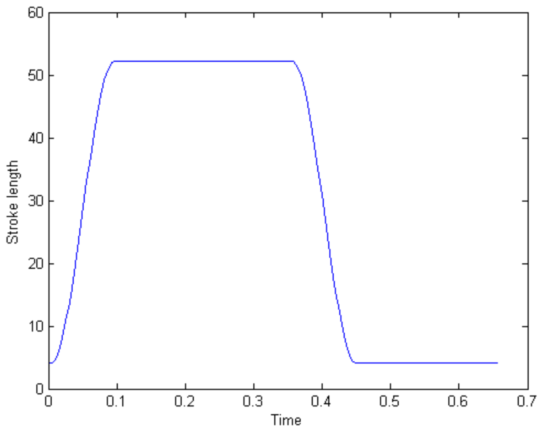


Figure 6.2 Cam curve of servo motor.

The servo motor is being replaced more frequently than the manufacturer suggests. In some cases the motor had to be replaced because the machine operators had detected, by visual observation, that the caps were being applied too high up on the package.

The reason for this degradation was not established and a number of failure causes were discussed. The first cause that was discussed was that the motor's internal linkage or lubrication was deteriorating making the motor unable to reach the full stroke length, causing a large position error at the end position. This was not noticed by the PLC since the alarm limit for the position error was set to an unreasonable high value. This case was supported by the fact that some motors that had to be replaced were examined and some of them showed that the lubrication inside the motor had changed colour. This might have been caused by substances inside the machine. Another fault cause up for discussion was that the motor during homing sequence did not reach the correct mechanical stop and instead homed before reaching the innermost position. However, if this would have been the fault cause the caps would have been applied too low on the package and therefore this fault cause was ruled out. The last cause that was discussed was if the encoder was malfunctioning and not giving the correct position feedback to the servo drive. If this was the case the feedback signals actual velocity and actual acceleration would show strange behaviour with discontinuities. This had not been detected by the personnel, and therefore the fault cause that became focus for this analysis was that the motor was unable to reach the full stroke length.

The servo motor is controlled by a servo drive produced by a different manufacturer than for the motor itself making it difficult to involve the manufacturer in the lifetime estimation. The controller in the servo drive uses cascaded control with an inner control loop for velocity and an outer for position control. Both the inner and outer controllers are PI-controllers with feed forward ability both for velocity and acceleration. A simplified block diagram for the controller can be seen in Figure 6.3. For this specific servo motor the integrators were turned off but with 100 % velocity feed forward.

The machine in which this servo motor is installed did not have any automatic logging tool and therefore no continuous data was available. Some data existed but the information regarding the motors was sparse.

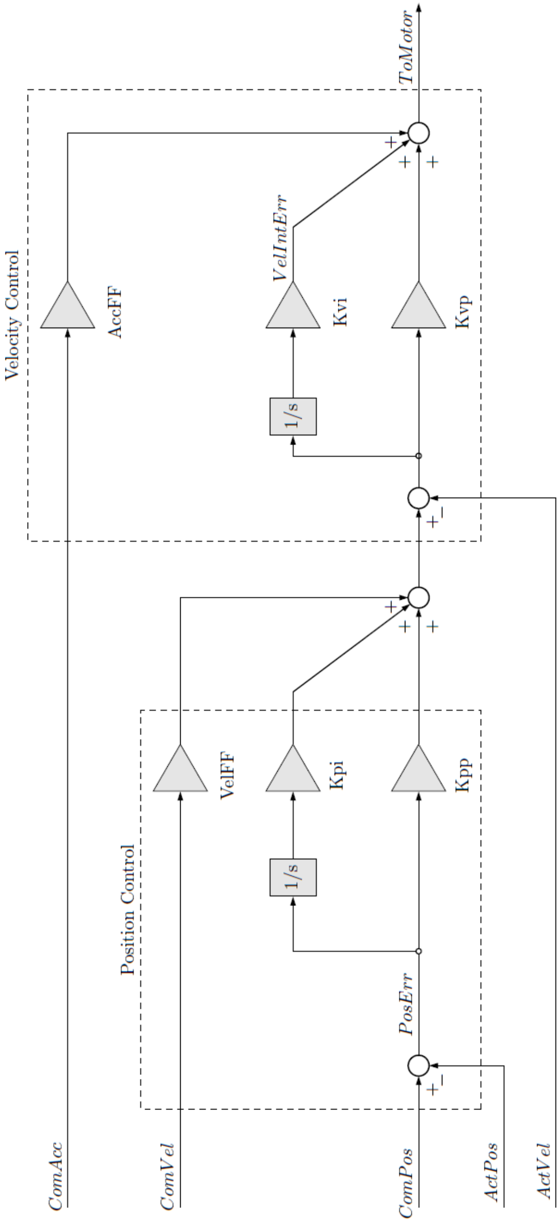


Figure 6.3 A simplified block diagram of the servo drive controller.

6.2 Previous work

In [Wu et al., 2009] the authors propose a method for estimating RUL for an AC servo motor driven linear actuator by using Hidden Semi-Markov Models (HSMM) based only on existing signals from the motor drive, in this case current feedback and position sensing. When the linkage components wear the internal friction will increase which will affect the closed-loop control effort while keeping the same motion profile which is why the authors chose to use current feedback for this research.

A traditional Markov model is a statistical model of a stochastic process which contains a number of specific states and probabilities of transferring between these states. A hidden Markov model (HMM) is a form of Markov model where the current state is not observable but the output of the system has to be evaluated in order to estimate which state the system is in. Both Markov models and hidden Markov models satisfy the Markov property which declares that they are time independent and only depend on the current and previous states, but not on how long the system was in each state [Ghahramani, 2001]. The difference between hidden Markov models and hidden semi-Markov model is that the for HMM the output is one single observation whereas for HSMM the output is a segment of observation, making the model time dependent.

The goal is to maximize $P(O|\lambda)$, where O is the observation sequence and λ is the model. The model can be denoted $\lambda(\pi, A, B, D)$. π is the initial state distribution, i.e., the probability of starting in each state. A is the transition matrix, where $a_{i,j}$ corresponds to the probability of moving from state i to state j. An example of a transition matrix for a simple Markov model can be found in Equation 6.1 and in Figure 6.4. B is the observation model which is only present for hidden Markov models and D is the state duration distribution which is only modelled by the time dependent hidden semi-Markov models.

$$\mathbf{A} = \begin{pmatrix} 0.1 & 0.8 & 0.1 \\ 0.9 & 0 & 0.1 \\ 0.2 & 0.2 & 0.6 \end{pmatrix} \tag{6.1}$$

In [Wu et al., 2009] the authors propose a method where the model parameters are obtained by using the Expectation-Modification method, described in [Dempster et al., 1977], applied to a set of training sequences. Also a modified Forward and Backward method was used to avoid computational underflow [Dong and He, 2007]. In the presented simulation study the authors used four states which correspond to the health state of the motor: Excellent, Good, Fair and Worst. They used three training sequences with known output and tested the model on a validation sequence. The remaining useful life of the simulated validation sequence was 405.33 days and when tested on the model the estimated RUL, including 95 % confidence limit, was 387 ± 145.54 days.

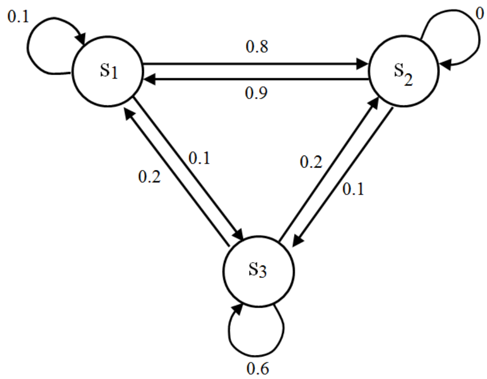


Figure 6.4 Example of Markov transition model.

6.3 Method

Even though the method proposed in [Wu et al., 2009] was promising for estimating RUL, this solution was not possible for this thesis since there were no training data or validation data available.

Instead the goal was set to find deviations within a number of signals between well performing motors and motors that are deteriorating. However, for a servo motor containing approximately 250 signals there was first an discussion on what signals to analyze. Since the failure cause to focus on was due to growing position error this signal was given, also the signals command position and actual position. In order to rule out encoder failure the signals actual velocity and actual acceleration were also selected. As described in [Wu et al., 2009] the friction within a motor increases with the wear of linkage components, and when friction increases more current is needed to perform the same motion profile which generates more feedback current. The servo motor in this thesis did not have current feedback signals, instead the focus was on the torque feedback signal. Current and torque are highly correlated for a servo motor since the torque is generated by the current and the more torque is needed the more current is fed. Therefore the torque feedback signal should be analyzed as well.

As described earlier the integral action for both the position and velocity control were turned off but there was a question on whether the signal called velocity integrator error, i.e., the output of the integral part in the velocity loop, see Figure 6.3, would be more suitable to use for lifetime estimates. Since the integral part of a PID controller will remove stationary errors this signal would increase if the motor is unable to reach its command position. However, since the integrator part of the velocity loop was turned off this signal would be constantly zero until the regulator parameters were changed. Optimizing the control parameters for the servo motor was not part of this thesis and therefore no effort was made to adjust the other parameters accordingly. For tests regarding the velocity integral error signal a non-zero value for the integral gain was simply added.

Finally the signals that were used in the analysis can be found in Table 6.1.

Table 6.1 Signals to analyze for the servo motor.

Signal
Command Position
Actual Position
Actual Velocity
Actual Acceleration
Position Error
Torque Feedback
Velocity Integrator Error

Method Test 1

In order to compare the signals, healthy motors and motors close to failure needed to be located and data collected. Three machines in the machine hall at the company contained this specific servo motor that had been running relatively few hours and were performing well, therefore these three motors could be used as reference motors. Locating motors close to failure was more difficult. Since the company has machines all over the world identifying a motor which should be close to failure is not done easily and collecting data from such a machine is even more difficult since no automated logging system was at hand. Data needed to be collected by service technicians that would connect to the PLC and manually start a logging session. Three motors were located and data collected. Unfortunately two of these motors were installed in machines running with different machine capacities, i.e., producing a different amount of packages per hour. When the capacity is modified all signals show different behaviour making the comparison of the signals impossible. The capacity affects the time for the cam cycle with the effect of different velocity, acceleration as well as torque feedback. The third motor which was running with the same capacity as the reference machines did not show any clear deviations, as is described in Section 6.4.

Method Test 2

Since Test 1 did not produce any results which could prove degradation of the motors a new approach was developed. From the help of personnel at the company six claimed servo motors were located. By claimed it means that they have been installed and running in a machine but have been replaced due to malfunctioning. The information regarding these motors was sparse. The reasons for them being claimed were not entirely known, only one of them had a full description on what fault that had caused the replacement. The number of hours of production was known for three of the six motors. The fact that the reasons for replacement were unknown is a major factor for uncertainty for this analysis.

With these six claimed motors available the next step was to install them in the machine and collect data for analysis. First of all the motors were tested in a test rig to see whether they were operational or not. One of the claimed motors were unable to run but the other five did not show any indications of failure. The motor which was already installed in the machine was used as reference and the overall information on the motors can be found in Table 6.2.

Table 6.2 Information on motors used in Test 2.

Motor	Claim cause	Operating hours	Operational
Reference	Not claimed	Few	Yes
Claimed 1	Fault related to position error	Above average	Yes
Claimed 2	-	Above average	Yes
Claimed 3	-	-	Yes
Claimed 4	-	Above average	No
Claimed 5	-	-	Yes
Claimed 6	-	-	Yes

Two different test cases were specified, the first with focus on collecting data with the original regulator parameters and the other with integral action for the velocity loop added. During the test a new test case was added where the stroke length was increased in order to produce a larger position error. Due to mechanical components inside the machine the motor axis is not able to move past a certain length leading to an increased position error. In this last test case the signal called Velocity Integrator Error was unfortunately missed during the logging session. The test cases are listed in Table 6.3.

Table 6.3 Test cases for servo motors.

Test case	Description	Goal
2.1	Original regulator parameters	Find deviations between signals
2.2	Integrator for velocity loop added	Analyze velocity integrator error
2.3	Stroke length increased	Larger position error

The operational motors were installed in the machine and the first two test cases were run for all motors including the reference motor. Test case 2.3 was only run for one of the motors since the test case was added after starting the tests. For each motor the machine was run for only a short time period compared to normal production period. This should also be kept in mind when evaluating the results.

The signals were analyzed mainly by visual observation. In the results signals are presented both as raw values but also as mean values which is described in Section 6.4. For some signals the frequency spectrum was also analyzed. The frequency content was calculated by discrete Fourier transform. The Fourier transform allows to analyze the frequency content instead of looking at discrete time signals. The frequency that is of interest is mainly the cam cycle frequency since at this frequency the frequency amplitude describe the content for the whole cam cycle. In order to calculate the cycle frequency the cycle period had to be identified. This was done by extracting the lengths of the cam cycles in number of samples. Due to the manual trigger of the logging not all cycles have the same lengths but are varying with one or two samples. The most common length is chosen as the cycle period and the cycle frequency as its inverse.

6.4 Results

Data processing

In order to analyze the data it had to be processed so that the cam cycles were matched. This was done by an automatic script which located the start vector index for each cam cycle and then removing all samples before first cam cycles and after the last cam cycle, for all the signals. This could only be done for the cases where the machine capacity and sample period were identical which was a criteria for the analysis. The logging of data was triggered manually and therefore the number of captured cam cycles varied. Also the cam cycles could not be exactly matched since the triggering of the logging session was done manually, the signals could deviate with half the sample time in both directions, as can be seen in Figure 6.5. In this figure motor 1 and 3 are well matched but motor 2 is slightly ahead. This should be considered when observing graphs with time on the horizontal axis.

In the following sections some of the results are presented by the mean value of a number of consecutive cam cycles. The reason for this is that by looking at one single cam cycle there could be small deviations from the normal performance which could be caused by something else than the servo motor itself. For all cases where mean value has been used the same number of cam cycles was used for averaging.

Results Test 1

As described earlier two of the test motors, i.e., motors that should be close to failure, were installed in machines running with different machine capacities. This can be seen in Figure 6.6 where the command position is plotted against time. The reference motors and test motor 1 are running the same capacity while test motor 2 and 3 different machine capacities. Not only does the machine capacity deviate but also the offset start position and for test motor 3 the sample time was different compared to the reference motors. Because of this mismatch test motor 2 and 3 were excluded in this analysis.

For test motor 1, that had the same setup as the reference motors, the focus was on the signals position error and torque feedback during application, i.e., at

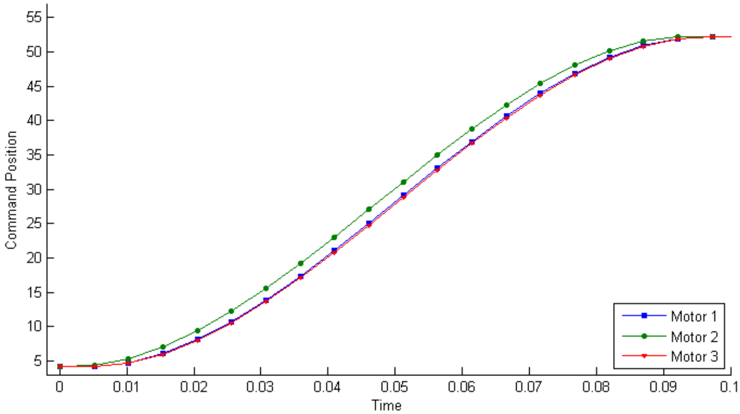


Figure 6.5 Mismatch of cycles due to sampling.

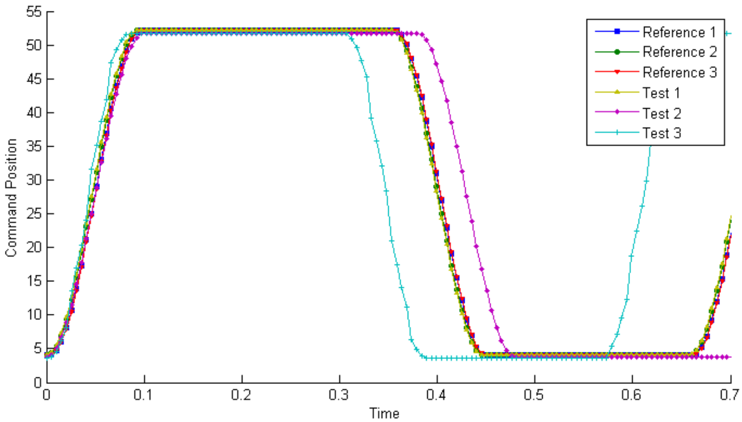


Figure 6.6 Problem with different machine capacities.

the end position. In Figure 6.7 the mean value of the position error for a number of consecutive cycles can be observed as well as the signal actual position for reference of the cam curve. The same plot can be sen in Figure 6.8 for the torque feedback signal.

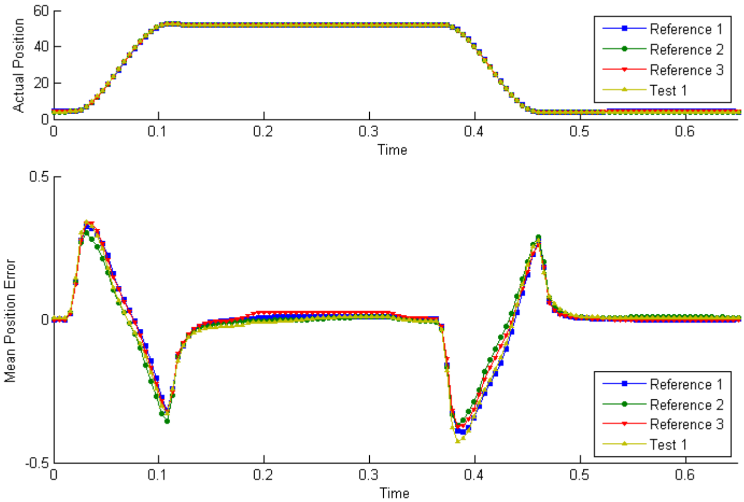


Figure 6.7 Mean value of position error for reference motors and test motor 1.

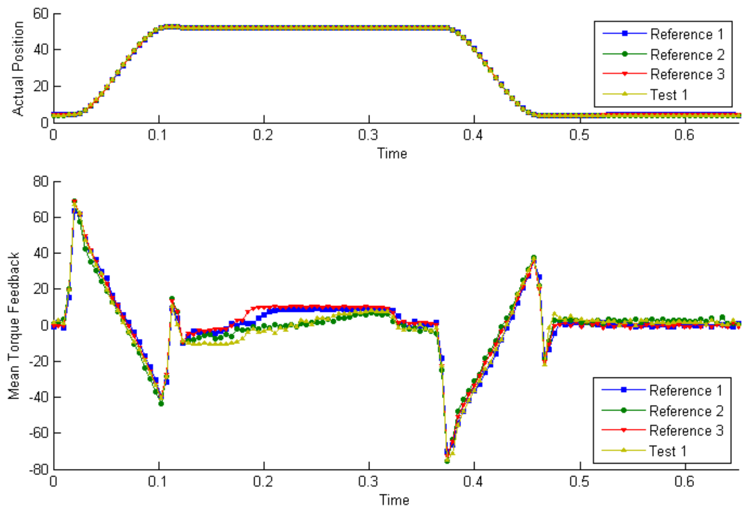


Figure 6.8 Mean value of torque feedback signal for reference motors and test motor 1.

As can be seen in the previous figures the test motor does not show any deviating behaviour compared to the reference motors. There are small differences but they are also expressed among the reference motors. This test motor does not show any indication of applying the cap incorrectly on the package. The conclusion from this test is simply that more tests have to be performed.

Results Test 2

The five claimed motors that were operational were installed in the machine one by one and all of them were able to run during full machine production without raising any machine alarms. This supported the idea of the motors being claimed due to misplacement of the caps detected by the machine operators.

Test Case 2.1 This was the test were the original regulator parameters were used and a reference motor was compared to five claimed motors. The signals of interest for this test case for five successive cam cycles are presented in Figure 6.9. Note that Claimed motor 4 is not present since it was not operational. The focus for this test case was to find differences of the Position Error signal during the application period. To our surprise the results were similar to the ones in Test 1, i.e., there are no significant differences between reference motor and the claimed motors. In Figure 6.10(a) the mean value of the position error for the six motors can be compared.

During the application period, i.e., when the motor axis is at the end position, the position error for the claimed motors does not deviate from the reference motor's position error. First when the motor reaches the end position there is a negative position error but a negative position error would lead to the cap being applied too low on the package and not too high. Therefore there was no way to verify that the problem operators had been detecting with caps being applied to high was caused by large position error by this test. But again, it was not certain that this had been the failure case for these claimed motors. During the rest of the application period the position error is so small that it cannot cause any displacements of the cap on the package.

However, some differences between the motors were discovered. During movement from start position to end position the position error is varying between the motors. This could not affect the application of the cap to the package but could indicate wear of the motor. By looking at a mean value of the position error a specific order of the motors was established where the reference motor seemed to produce the smallest position error. This can be seen in Figure 6.10. The same order was confirmed when looking at the mean value of the torque feedback, as can be seen in Figure 6.11. To avoid problems with mismatched cam cycles the same observations can be presented as in Figure 6.12 where the actual velocity is used on the horizontal axis and the torque feedback signal on the vertical axis.

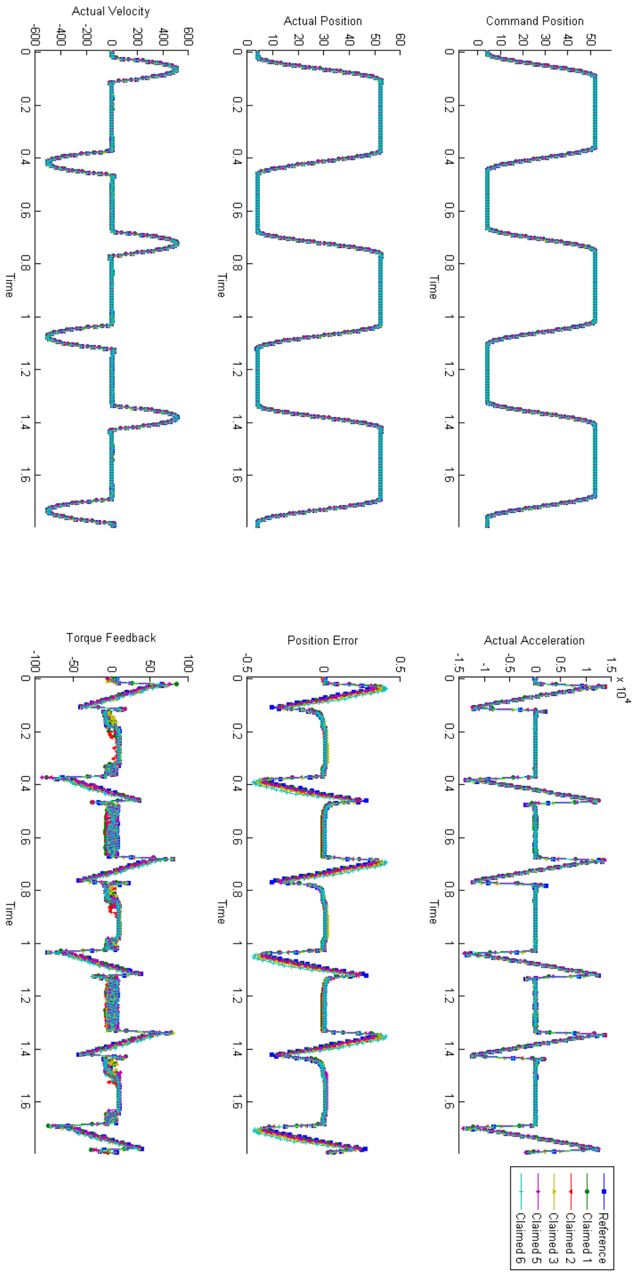
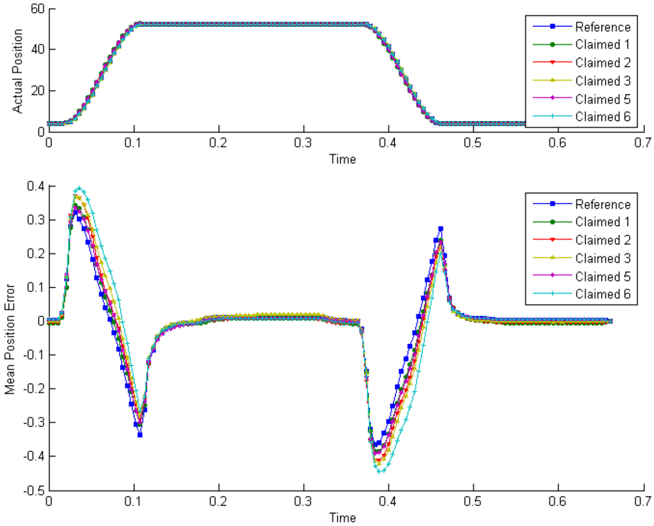
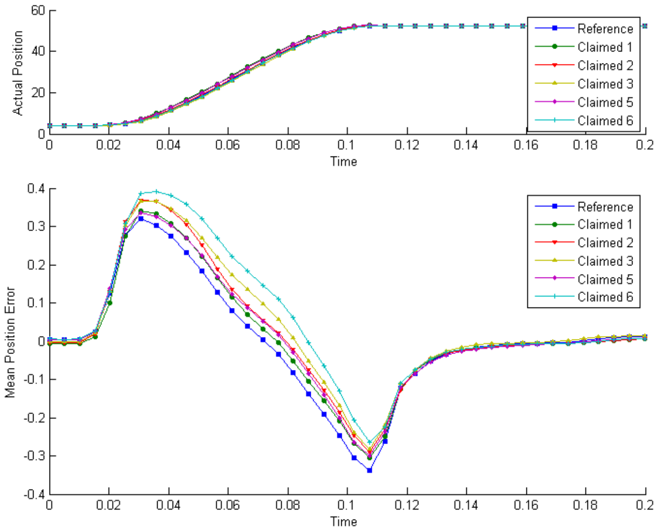


Figure 6.9 All signals in Test Case 2.1.

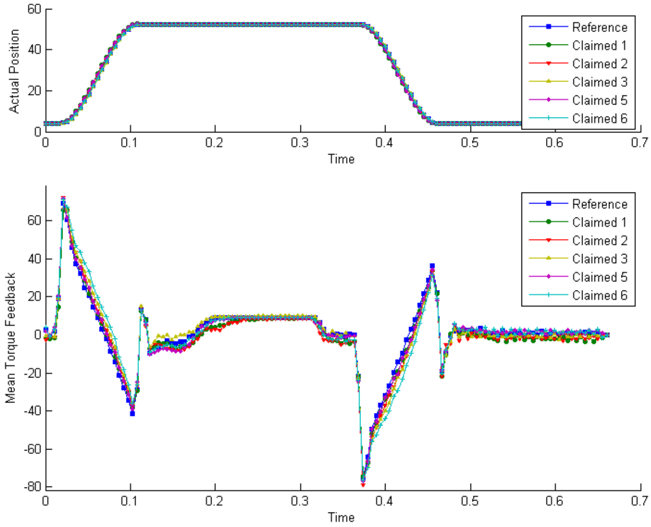


(a) Whole cam cycle.

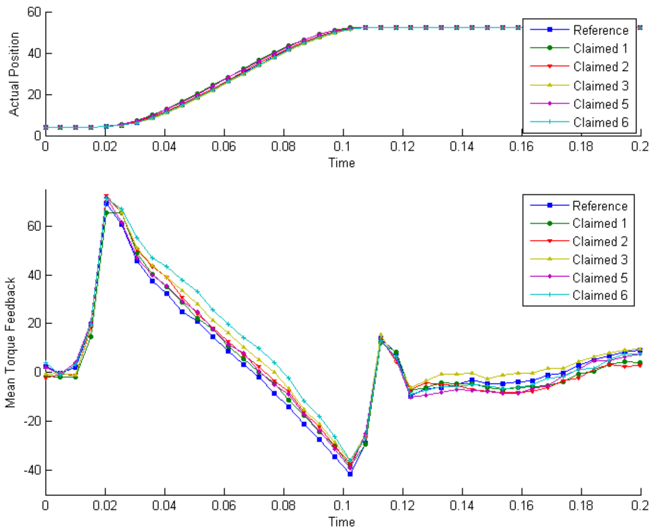


(b) Close up during movement.

Figure 6.10 Mean value of the position error for Test Case 2.1.



(a) Whole cam cycle.



(b) Close up during movement.

Figure 6.11 Mean value of the torque feedback signal for Test Case 2.1.

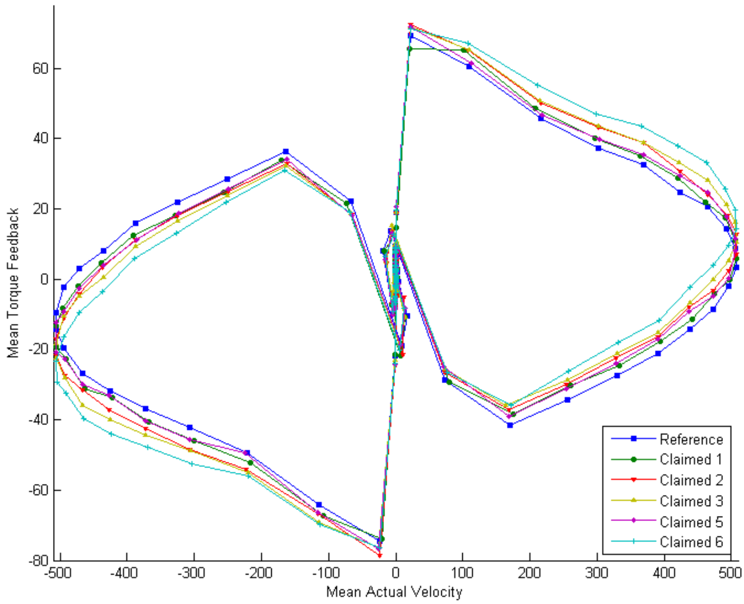
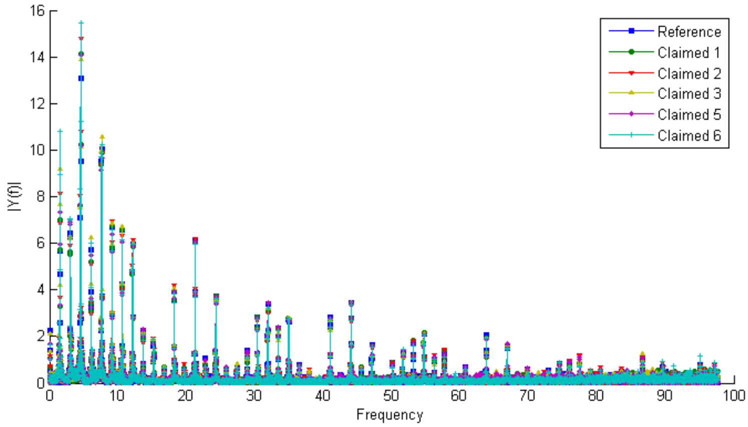
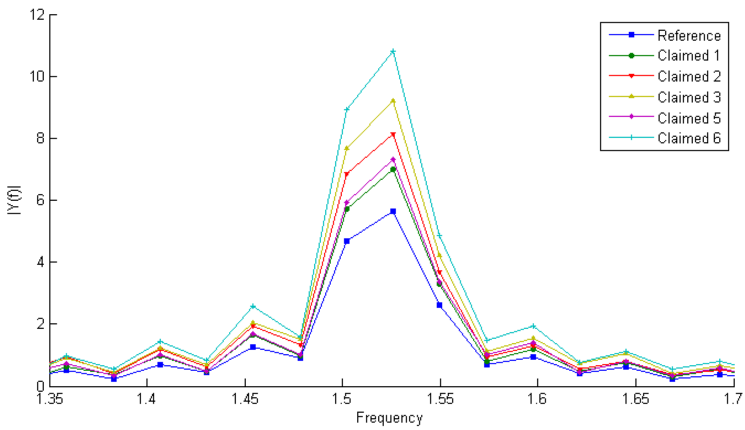


Figure 6.12 Actual velocity vs torque feedback for Test Case 2.1.

As stated previously this could indicate degradation of the motor and that this order was the order of health between the motors, where the reference motor was the most healthy and claimed motor 6 was the most unhealthy. Since the motors are operating in the same environment with the same configuration increased torque feedback should indicate that the motor has to work harder to perform the same motion profile. This could be caused by a degraded motor and more specifically that the internal linkage or lubrication is degraded. In the previous figures the differences of torque feedback can only be observed during certain parts of the cam curve. Thus, in order to get a measurement of how the signal is varying for the whole cam cycle the frequency spectrum is analyzed. The full frequency content and a close up at the cam cycle frequency can be seen in Figure 6.13. The peak in Figure 6.13(b) is distributed over two successive frequencies and this is caused by cam cycles having different lengths. 58 % of the cam cycle lengths correspond to the most common frequency which generates the maximum amplitude and 42 % correspond to the second most common frequency which generates the second highest amplitude. The other peaks of the frequency spectrum are multiples of the cycle frequency. From the close up figure it is possible to see the same order of the motors appearing once again.



(a) Full frequency spectrum.



(b) Close up on cycle frequency.

Figure 6.13 FFT spectrum of the torque feedback signal.

Based on this test there is no way to verify that this order is really the order of health for the motors, it is purely an assumption. To really verify this order the motors should be run in the machine until complete failure, which for this project was not possible. However, if this order were to be explained by the health of the motors it would be possible to get a measurement of how degraded a test motor is by comparing the amplitude of the frequency spectrum at the cam cycle frequency with the amplitude of a reference motor. This measurement could be a percentage of how much more torque feedback the test motor generates compared to the reference motor. From here on this measurement is called the *Rating* of the motor and it is calculated as in Equation 6.2, where Y_{Test} and Y_{Ref} are the amplitude of the test and reference motor and f_c is the most common cycle frequency.

$$Rating = 100 \cdot \left(\frac{Y_{Test}(f_c))}{Y_{Ref}(f_c))} - 1 \right) \tag{6.2}$$

The ratings of the motors in this test can be found in Table 6.4 and in Figure 6.14 is the assumed health order of the motors according to this test case presented. Based on these findings an idea of implementing a Matlab based tool for this kind of analysis emerged. This tool was implemented and is presented in Section 6.5.

Table 6.4 Ratings of servo motors according to Test Case 1.1.

Motor	**Rating**
Reference	0.00%
Claimed 1	23.79%
Claimed 2	43.72%
Claimed 3	62.59%
Claimed 5	29.23%
Claimed 6	90.93%

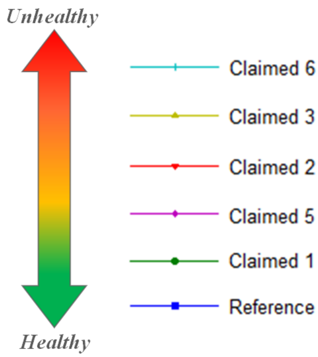


Figure 6.14 The assumed health order.

Test Case 2.2 This test case was performed to investigate if the signal called velocity integrator error would be more suitable for lifetime estimates based on the assumption that the motors were unable to reach the full stroke length. Figure 6.15 confirms that the velocity integrator error will increase the control signal to the motor in order to remove stationary errors. Since the position error during application is so small it is negligible, approximately 0.0002 % of the full stroke length, nothing can be said of the health status of the motors based on this test. If there are problems with servo motors not being able to reach to full stroke length it could be suitable to use Velocity Integrator Error to estimate health or RUL, but since Test Case 1.1 showed that this was not the case for the claimed motors this method was excluded.

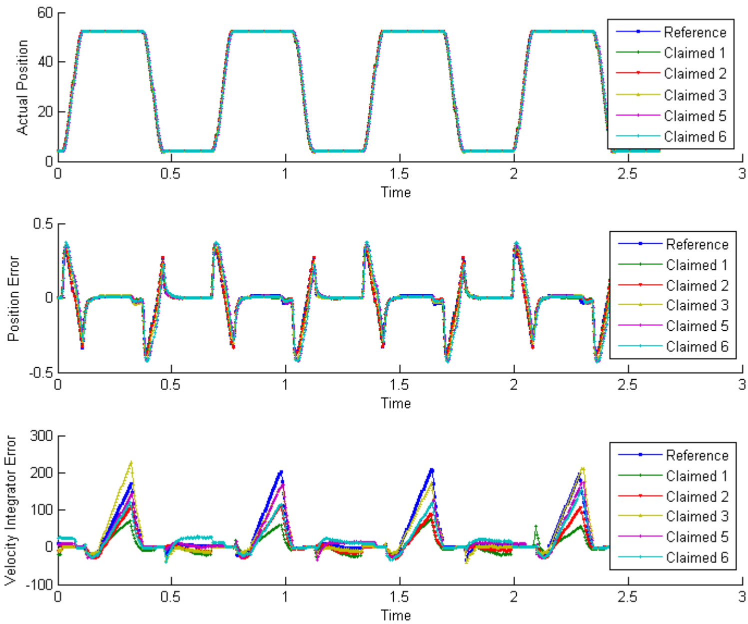


Figure 6.15 Test Case 2.2.

Test Case 2.3 This test case was added during the tests since Test Case 2.2 did not show a clear effect of Velocity Integrator Error due to the non-existing position error. The mechanics inside the machine prevent the motor axis from moving much further than the original stroke length, therefore if the stroke length is increased by a small factor it will generate a larger position error. This test were performed on only one of the claimed motors since the test was added during the test session and the velocity integrator error signal was unfortunately not recorded, but Figure 6.16 shows that the position error is better compensated for when integral action is added to the control loop. As can be seen in the figure the Position Error with integral action added causes a dip which is not present for the signal without integral action. This is due to the regulator parameters not being optimized for this servo motor application, a non-zero integral gain for the velocity control loop was simply added.

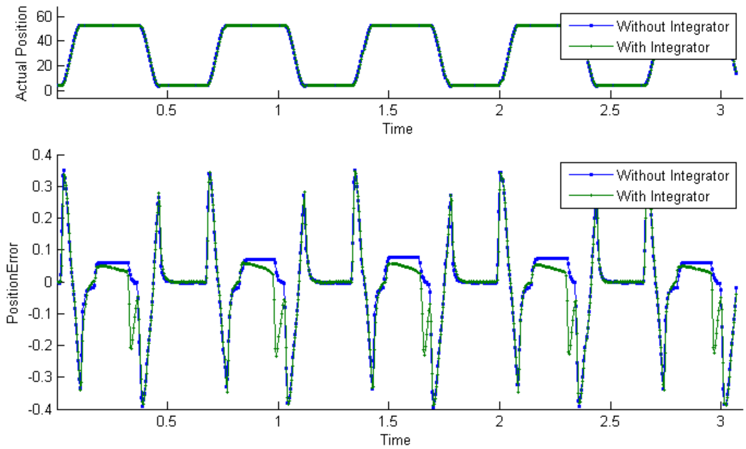


Figure 6.16 Test Case 2.3.

6.5 Servo Motor Compare Tool

Based on results in Test Case 2.1 in Test 2 the idea of implementing a Matlab based servo motor compare tool emerged which could be used for further analysis in order to establish a condition-based maintenance program. This tool should focus on comparing signals between one reference motor and one test motor operating under the same conditions and data collected with the same sample time.

In Figure 6.17 the GUI of this tool can be seen. On the top left the .csv-file of logged data is selected for both reference motor and test motor. When a file is imported some useful information regarding the data will be displayed, such as filename, number of cam cycles, cycle time and as well the offset start position. Comparison is only possible if the machine capacity and sample time is identical for the two motors. Since the reference and test motors may have different number of logged cam cycles the user can select the number of cam cycles to use for averaging and the FFT analysis.

On the top right is the plot settings where the user can select which signal that should be used for the axes. It is also possible to plot the mean values by ticking the checkbox "Plot mean value" as well choose if the plot should be in lines or with markers.

On the lower part of GUI the FFT analysis can be performed by clicking the "Calculate FFT" button. The cycle frequency and the amplitudes at the cycles frequency is then displayed and the frequency spectrum is presented in a figure, either as a full spectrum or just as a close up around the cycle frequency. The rating of the test motor is presented in the result box.

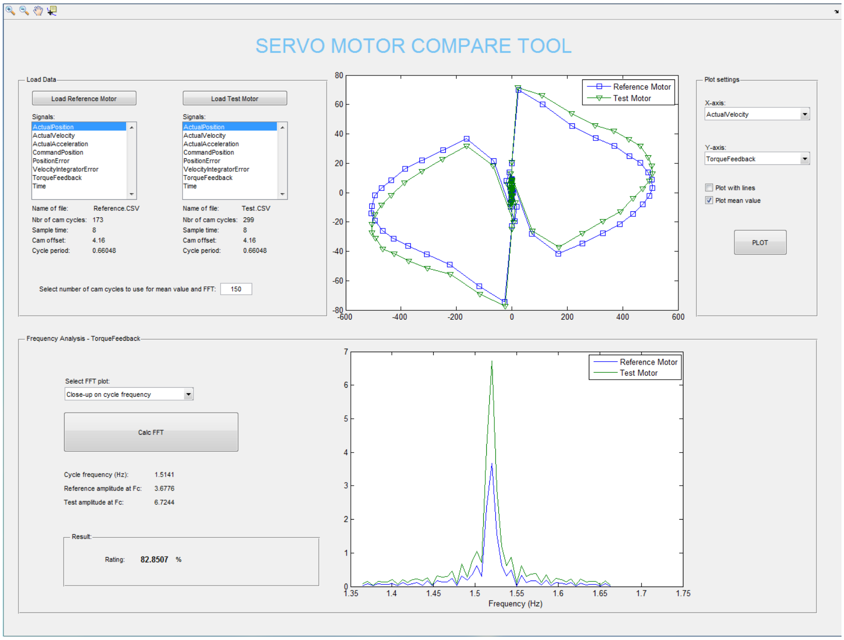


Figure 6.17 Servo motor compare tool.

6.6 Discussion and future work

Due to the fact that there was no run-to-failure data, no historical information on how long the components have been operational, no clear failure cases, and sparse information regarding the motors in this analysis, there is no possibility to estimate the RUL. In order to be able to implement a functional condition-based maintenance algorithm further analysis on this servo motor is needed.

Based on the assumption that the degradation of the motor is expressed as increased torque feedback the implemented compare tool can be useful in further analysis. Data from more motors should be collected and compared, not only test motors but also reference motors. As a first approach a number of healthy motors should by analyzed in order to evaluate the natural variance between healthy motors. Based on the outcome if this analysis a reference rating for the healthy motors including confidence limits could be established. This should be performed for all machine capacities. In order to define a threshold for signaling to the operators that the motor is close to failure, data from a number of motors should be collected for the whole life cycle. This could be done by adding a logging tool for this machine as well or by scheduling logging sessions at fixed intervals, e.g., the signals should be logged every x hour of production.

Since the rating of the motors are in percentage compared to the reference motor the most important thing is to be consistent, but the number of cam cycles used for averaging and the FFT analysis should also be evaluated go gain the best result.

7

Injection molding unit

The fourth component we studied in this thesis was an injection molding unit. This component was selected since we had access to a unit with bad performance as well as a unit with good performance. A lot of logged data was available from those units from the recently developed logging tool. The unit is very expensive and an implementation of condition-based monitoring would save the company much money. On the downside, there were no clear failure cases and the involved personnel did not know why one of the units was performing badly. However, all the pros was sufficient for this component to be selected and the company also thought that much information regarding the failures of the unit could be gained through our analysis.

7.1 Background

Injection molding is a manufacturing technique where a material is melted and shot into a cavity to form a desired shape. This is done by melting small granulates of the material to be shaped, e.g., plastic or glass. The melting procedure is done in an extruder and the melted material from the extruder is then stored in an accumulator to build pressure in the system. This pressure from the accumulator is used to push the melted material into the cylinders through hoses, with surrounding heating elements to keep the material hot. When a cylinder is fully loaded it shoots, using hydraulics, the melted material into a cavity which cools the material and it becomes solid in the desired shape. When a shot is done the pressure from the accumulator starts to refill the cylinders again. A schematic figure of an injection molding unit can be seen in Figure 7.1.

The company's injection molding unit consisted of two cylinders that shot into two separate cavities. The problem the company had with the injection molding unit was that during start-up, the time it took to refill the cylinders after a shot increased during the first shots. After some shots the refill time decreased and stabilized around an accepted level. Since the cylinder shoots at fixed intervals it is crucial that the cylinder has been fully refilled before it shoots so that the shape is made of the right amount of material. Too little material can lead to holes and other faults in the formed shape. A typical curve of refill time during one production run can be seen in Figure 7.2.

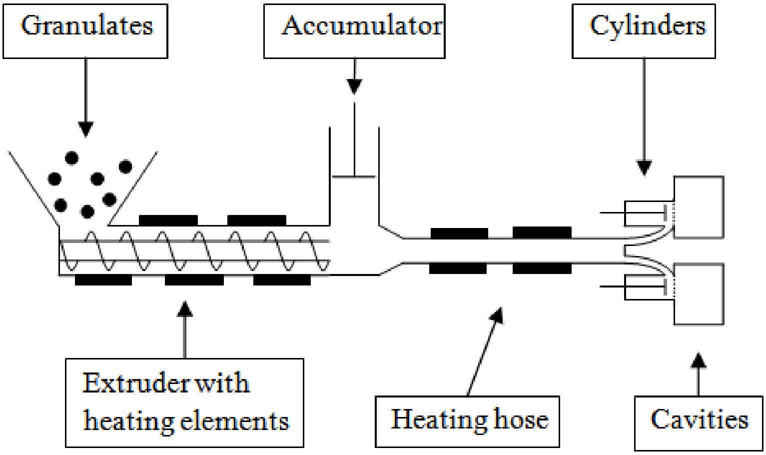


Figure 7.1 Schematic figure of an injection molding unit.

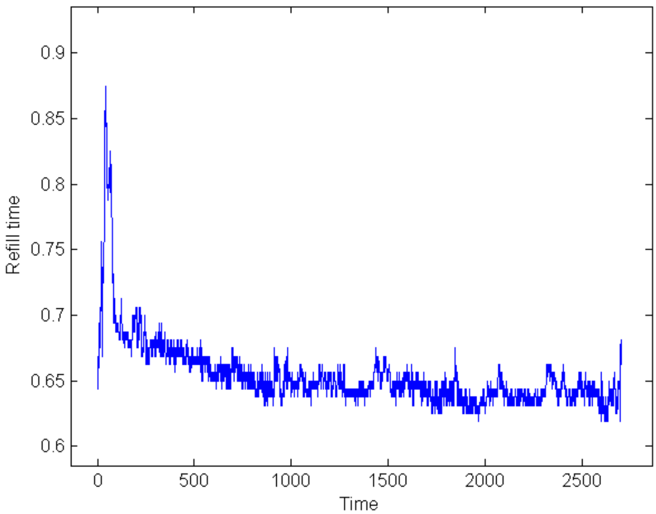


Figure 7.2 Typical refill time for a production run.

To the company it was obvious that the problem was increased refill time in the injection cylinder during start-up. The refill time is not allowed to increase over a certain threshold since that would lead to non-full cylinders performing shots with the wrong amount of material. But the cause of the increased refill time was unknown. Several different scenarios were discussed with involved personnel of the injection molding unit. The first cause of increased refill time could be caused by seized cylinders. This would cause one cylinder to refill faster since the cylinders are filled by the same pressure from the accumulator and if one cylinder is seized, it would require higher pressure to refill at the same time as a non-seized cylinder. The second possible cause for increased refill time might be when the system is halted for a while and melted material was standing still and being kept warm inside the heating hoses. When material is kept warm inside the hoses without any movement the material closest to the hoses might become too hot and burn solid and stick to the surface of the hoses. If too much material is burnt solid it leads to a smaller sectional area in the hoses which in turn leads to a decreased throughput of material. A decreased throughput of material will lead to longer refill times in the cylinders since less material is being pushed through by the same pressure from the accumulator. A third possible failure mode was the hydraulics controlling the injection cylinders. The hydraulic motor could cause increased refill times by not opening the valve fast enough after a shot from the injection cylinder.

7.2 Artificial neural networks

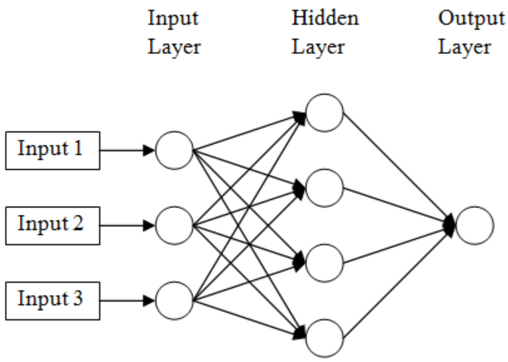


Figure 7.3 Layout of artifical neural network with three inputs, one hidden layer consisting of four neurons and one output in the output layer.

Artificial neural network (ANN) is a model that aims to mimic the human brain. ANNs are data-driven models and thus no particular domain knowledge is needed since the model is built using observation data. The purpose of an ANN is to map given inputs (observation data) to outputs. An ANN model consists of inputs, neurons and outputs. The input is simply the signals to be monitored. The outputs is what the network should calculate. This can be several things, for instance RUL, health percentage, ETTF, etc.. The neurons are the calculating units of the ANN. Multiple neurons make up a neuron layer and an ANN consists of a number of neuron layers. Each neuron in the ANN consist of inputs from the previous layer (or the monitored input if the neuron is in the first layer), input weights, a bias (threshold) and an output. The output from neurons in a layer is fed as input to the neurons in the next layer (if it is not the output of the network). A schematic of a neural network can be seen in Figure 7.3. The weighted input to a neuron is called the activation and is defined by Equation 7.1, where a is the activation, i is the i:th input to the neuron, x is the input, w is the input weight, and b is the bias of the neuron.

$$a = \sum_i x_i w_i + b \tag{7.1}$$

To calculate the output of a neuron the activation is sent through a transfer function. The most common transfer function is the Sigmoid (logistic) function [Priddy and Keller, 2005]. The Sigmoid function is defined in Equation 7.2, where y is the output and a is the activation.

$$y(a) = \frac{1}{1+\mathrm{e}^{-a}} \tag{7.2}$$

To be able to compute the correct output, the ANN is trained with observation samples. The most well known training algorithm is the backpropagation learning algorithm [MacLeod, 2011][Kaastra and Boyd, 1996]. The backpropagation algorithm adjusts the weights and biases using the gradient descent method where a cost function is minimized. A cost function used by many is the squared error given by Equation 7.3, where m is the number of training samples, x is the training samples, o is the desired output, and y is the actual output [Priddy and Keller, 2005; Smith et al., 2003; Tian, 2012; Nielsen, 2014].

$$C = \frac{1}{m} \sum_x \left\| o(x) - y(x) \right\|^2 \tag{7.3}$$

When the actual output is the same as the desired output the cost is zero and the network is fully trained. In practice the cost function never becomes zero but it can come close to it. To adjust the weights and biases, and thereby minimize the cost, the error of the output layer is sent backwards to the previous layer to calculate its error, since there is no target for the hidden layers neurons. This is where the name backpropagation comes from. Equation 7.4 shows the equation for error in the output layer, where E is the error, y is the output from the network, and o is the desired output from the network. Equation 7.5 shows the equation for error in the backpropagation, where y is the output from the neuron, i is the number of feedforward neurons, E is the error in the feedforward neuron, and w is the weight of the feedforward neuron. Both Equation 7.4 and Equation 7.5 are for a network with a Sigmoid activation function.

$$E = y\,(1-y)\,(o-y) \tag{7.4}$$

$$E = y\,(1-y)\sum_i E_i w_i \tag{7.5}$$

The weights are then adjusted (the learning of the network). Equation 7.6 shows how this is done for a network with a Sigmoid activation function, where E is the error of the neuron, and a is the input activation to the neuron.

$$w^{+} = w + (Ea) \tag{7.6}$$

Local minima

The purpose of training an ANN is to minimize a cost function. In some cases the ANN might get stuck in local minima in which the ANN thinks it has found an optimal solution since it cannot adjust the weights in any way to reduce the cost. This is a well known problem with ANNs and there is no universal solution to it. So to overcome it ANN with the same settings are trained multiple times with randomized initial weights and biases. Therefore it is likely that some of the initializations lead to the global minima and not get stuck in local minima. The more complex the structure of the network is (i.e. more layers or more neurons in each layer) the more likely the network is to get stuck in local minima during training.

7.3 Previous work

In [Smith et al., 2003] the authors have developed a prototype system to predict failures in doors at airport ground transportation vehicles. Their prototype system collects real-time data from the doors and analyzes them using a neural network to determine the condition of the door. Three types of neural networks are tested, a backpropagation, a cascade correlation, and a radial basis function. The data that is used is from the doors where twelve levels of degradation are simulated. The results show that the backpropagation network performs best on test data. Their conclusions are that more data with known degradation is needed to build reliable predictive models, each door set would need a customized predictive model, and that much of the time and cost of the project was on data acquisition.

In [Ahmadzadeh and Lundberg, 2013] an ANN is designed to predict RUL in mill grinders without stopping the grinder and perform manual measurement of the mill wear. The ANN used in the study is a two layer backpropagation network with several input and outputs. Principle component analysis is used to reduce the number of input parameters. Two ways of training and testing the network are proposed.

One where the test set of 434 sample points is divided into two groups, one is training data and one is test data. The other way is to train the network on a complete life cycle of all 434 samples and test it on new, unknown, data from another life cycle. Both ways show an accuracy of more than 90 %. Their conclusions are that neural networks are a good way to predict RUL when the input / output pattern is complex and unknown and that much data is needed for training and tuning the network.

7.4 Case study

Since the injection molding unit is a complex system with lots of failure modes and where the cause of the failures is unknown it is hard to analyze the data and draw any conclusions from it manually. Therefore we decided to perform a case study where an ANN was used. We decided to use an ANN since it excels when the system is complex and the relationship between the input and output is hard to map.

Data processing

The data which was analysed came from two different injection molding units. One of the units performed well whereas the other did not perform well enough and were scheduled for replacement. To determine whether an injection molding unit performed well or not we were told, by involved personnel, to look at the maximum refill time of the complete run. The involved personnel also told us to categorize the runs into three categories according to the maximum refill time where the first category was considered good (green), the second OK but not good (yellow) and the last one bad (red).

The injection molding units that we looked at had over 140 logged signals available to consider. In an ANN it is important to not include redundant signals and information since this will impact negatively on the performance of the ANN. Therefore we decided to use the available signals from the injection molding unit that we thought directly had an impact on the injection cylinders. The signals that were selected can be seen in Table 7.1 and the signals were sampled / calculated once per production run.

Table 7.1 Signals to analyze for the injection molding units.

Signal
Max refill time cylinder 1
Max refill time cylinder 2
Mean refill time cylinder 1
Mean refill time cylinder 2
Mean accumulator pressure
Heating power cylinder 1
Heating power cylinder 2

The refill times were an obvious choice since this was the factor that the company used to decide whether the unit was performing well or not. We also choose the accumulator pressure since this was directly tied to the refilling of the cylinders and a higher pressure should lead to faster refill times. Lastly we added the heating powers of both cylinders due to the fact that low heating power could be seen as an indication of a seized cylinder. This was because a seized cylinder would develop heat as its friction increased and thereby the heating elements would not have to add so much heat.

There were possible other signals that would be suitable for the ANN that were also considered for fault detection. A signal that was considered was the position of the cylinders. The position was left out of the network since the sample time of the logging system was too slow and differences between different cylinders would be hard to see. Another signal that was considered was the heating power of the heating hose. This was left out since we wanted to reduce the number of signals to the network and chose to only use signals that were directly tied to the cylinders.

Since we decided to use a feedforward backpropagation network which used the Sigmoid function as activation all input values had to be scaled to the interval [0,1]. To do this all values were scaled using Equation 7.7, where e is the value to be normalized, $E_{\min}$ is the smallest logged value of that signal and $E_{\max}$ is the largest logged value of that signal.

$$e_{\text{normalized}} = \frac{e - E_{\min}}{E_{\max} - E_{\min}} \tag{7.7}$$

As output of the network we used the health status, where 0 was perfectly healthy and 1 where the worst case. To label each run with this output the runs were sorted by the higher of the max refill times. Once these were sorted we tried to categorize them into three categories according to information gathered by involved personnel. Once the runs were categorized it was clear that most of the runs were in the first group and only a few were sorted in the other two groups. To map the runs to an output value between 0 and 1 where most were located around 0 (first group) and only a few that were not we decided to use an ad-hoc formula, Equation 7.8, where x is the vector of the sorted machine runs and N the number of runs. The graph of the formula can be seen in Figure 7.4. This formula gives a exponential growth for the last values and the first becomes very close to 0, exactly what we wanted.

$$o(k) = \frac{e^{0.1 \cdot x(k)} + 1}{e^{0.1 \cdot N}} \tag{7.8}$$

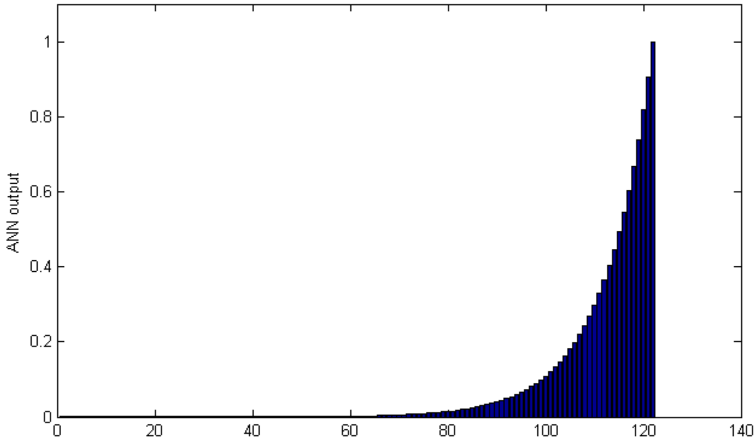


Figure 7.4 Generated output of ANN for the sorted machine runs.

ANN structure

We decided to use a feedforward backpropagation network since it seemed simple but still could perform well as shown by [Smith et al., 2003]. To decide which structure that would be the best for the injection molding unit, a number of tests were performed with different settings of the network. The different settings can be seen in Table 7.2. All combinations of the settings were tested 20 times to achieve maximum cover and avoid local minimas and unlucky random initializations. Settings outside of the testing range (more layers, more neurons or more iterations) showed to always get stuck in local minimas and were therefore left out.

Table 7.2 Network test settings.

Setting	Variants
Layers	1, 2, 3
Neurons	1-21
Iterations ($\cdot 10^3$)	5, 20 , 50, 100, 150, 200

To train and test the network 158 samples were available. We decided to split them into two groups where 122 were selected as training data and the other 36 were selected as testing data.

To evaluate the results of the setting we used a standard mean squared error as measurement. The equation for mean squared error can be seen in Equation 7.9, where m is the number of test samples, o is the desired output and y is the actual output.

$$MSE = \frac{1}{m}\sum_{i}(o_i - y_i)^2 \tag{7.9}$$

RUL

The output from the network only tells the health status of the unit according to the last run, i.e. diagnostics. What we were looking for in this thesis was prognostics and therefore the output from the network had to be processed. Since the output from the network is current health status, trend analysis, see Section 2.3, of this signal could be used to determine RUL. As can be seen in Figure 7.5(a) and Figure 7.6(a), where the output from the network is ordered in chronological order, the outputs from the cylinders differ a lot. The output from the unit with bad performance oscillates after run 40 and has a small peak at run 15. Only small peaks occur in the output from the good unit. Therefore it was tempting to assume that the bad unit started to degrade after run 40. However, no confirmation of this could be made and therefore we could not make this assumption.

Since this was a case study, we still wanted to try some sort of prognostic method on the injection molding unit. Therefore the most simple form of trend analysis we could think of was used, namely a low-pass-filter with limits. This was used to remove the small peaks that seem to occur in both units' performance. The equation for the used low pass filter is given by Equation 7.10, where y is the new output, α is a scaling factor of how filtered the signal should be, a is the old value, and i is the current run in the series. To detect when a unit is starting to perform badly, this low pass filtered value could be used to trigger alarms when reaching certain levels. To determine the alarm levels, historical data from many different injection molding units would have to be analyzed and it should be determined how bad a unit can perform before alarms should be triggered. Note that this is an approach that is suitable for the two units worked on in this thesis and as more data is added from other units it is possible that this approach does not work.

$$y_i = \alpha + o_i \cdot (1-\alpha) \cdot y_{\text{i-1}} \tag{7.10}$$

7.5 Result

Table 7.3 shows the result of the five best network settings acheived from the tests.

Table 7.3 Results of network tests.

#	Layers	Neurons	Iterations	Train MSE	Test MSE
1	3	5	100 000	$5.76 \cdot 10^{-4}$	0.047
2	2	6	200 000	$3.54 \cdot 10^{-4}$	0.053
3	3	4	200 000	$3.86 \cdot 10^{-4}$	0.058
4	2	5	200 000	$2.37 \cdot 10^{-4}$	0.059
5	3	8	150 000	$2.63 \cdot 10^{-4}$	0.061

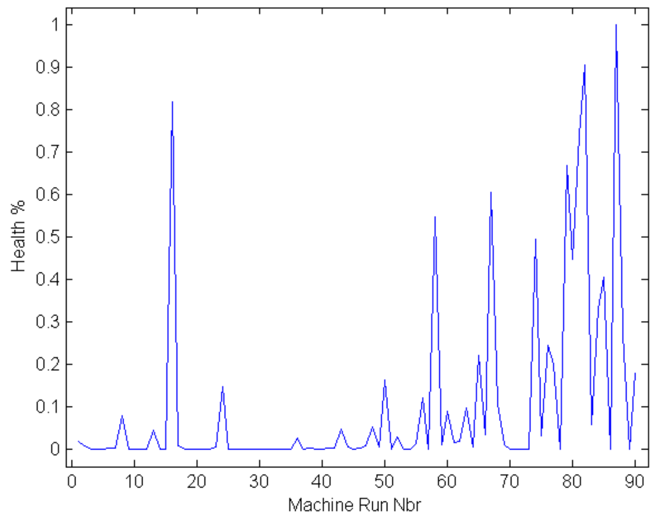
Figure 7.5 and Figure 7.6 show the output from the network compared to low pass filtered outputs with $\alpha = 0.1$ for the good and bad unit.

7.6 Conclusions

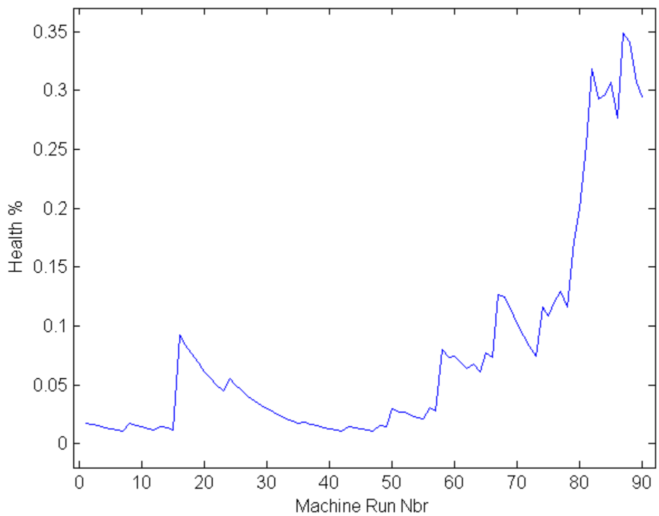
As with the servo motor in Chapter 6, no run to failure data or historical data exists for this component. To make things even worse there was no clear failure modes, just some possibilities that involved personnel thought could be a cause of failure. Therefore we had to use a data-driven model where knowledge of all failure modes was not needed.

The data-driven model shows promising results with the best result showing less than 5 % mean squared error in its classification of previously unseen data. However, it is very uncertain how accurate this is in reality. First of all, the training data is only from one failing unit and one well performing unit and therefore it is most likely only able to detect failures similar to the failing unit's. To avoid this more data from other failing units would have to be added to the training set to learn the model more failure modes. Another factor that makes the model uncertain is in the way the output was calculated. Since it is only based on the maximum refill time it would be possible to only look at the maximum refill time and get the same result. However, this would only detect increasing refill times and no other failure modes.

The ANN only outputs the current health status of a unit. To predict RUL the degradation parameter would have to be added in combination with historical data from multiple units.

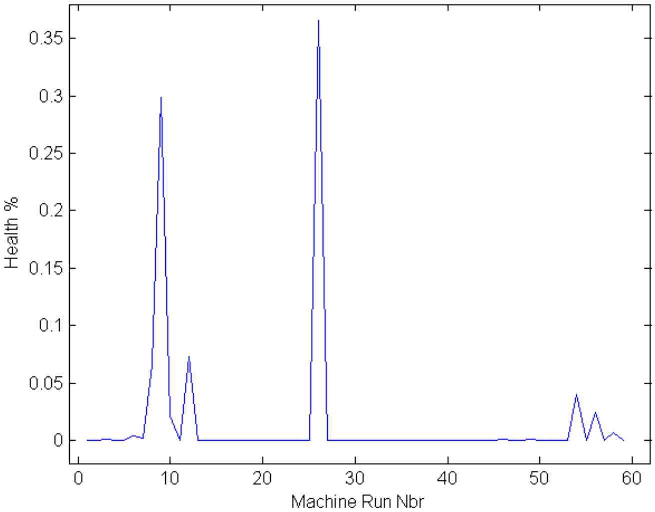


(a) Before low pass filtering.

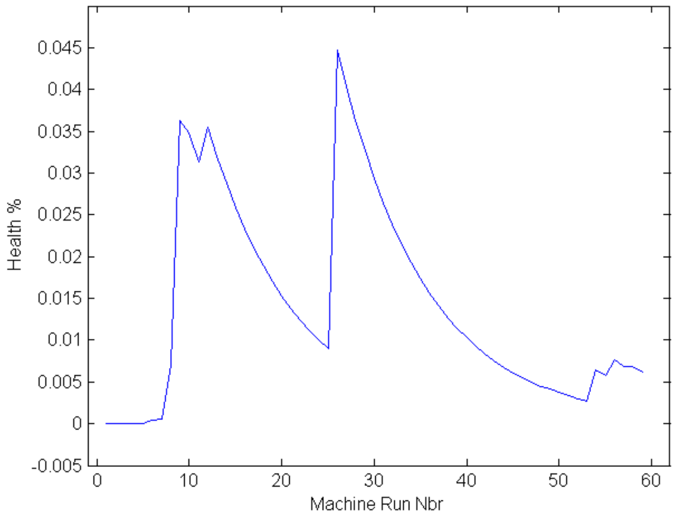


(b) After low pass filtering.

Figure 7.5 Low pass filtering of output from unit with bad performance.



(a) Before low pass filtering.



(b) After low pass filtering.

Figure 7.6 Low pass filtering of output from unit with good performance.

8

Conclusions

8.1 Conclusion regarding results

The goal for this thesis was to implement a tool for determining the health of a set of machine components. The ultimate goal was to be able to estimate remaining useful life of these components and to present this estimate on the machine panel so that the operators could get a useful indication on when it is time to schedule maintenance.

With the information and resources that we had at hand during this thesis we were not able to reach the complete goal for any of the selected components. For some of them, however, the work that have been done can be used as a base for further development.

Regarding the gas concentration sensor there was no possibility of estimating lifetime. An immense amount of data was available but due to the discovery of the incorrect configuration the data was unreliable and the analysis terminated. Therefore it is not possible for us to comment on whether this kind of component is suitable for condition-based maintenance.

From the analysis of the rotating spray nozzles small differences within the signals for the extreme failure cases can be seen but they were not significant enough to use for diagnosis of the component's functionality. Since it is not possible to detect failure there is no way to foresee failure and estimate RUL. Thus, components of this kind are not suitable for condition-based maintenance.

Although no algorithm for calculating lifetime for the servo motor was implemented this component shows some promise regarding prognostics. If the assumption concerning the increased Torque Feedback is due to degradation is correct it will be possible to estimate remaining useful life when further analysis has been made. The implemented compare tool could be useful in this analysis.

The injection molding unit did not have clear failure cases and was therefore modelled by data driven artificial neural networks. In order to really estimate health and remaining life further analysis and development is needed for this component as well. Since there were no clear failure causes for our analysis the output of the training data for the networks was only based on one of the unit's signals. The process of defining the output should be done with more knowledge of the failure cases and causes. The networks will also be more successful in producing the correct output if more training data is available.

8.2 Reflections

Since the results of this project did not reach the intended outcome of implementing CBM for a number of critical machine components some reflections regarding the process should be made. The first reason to discuss is the lack of knowledge regarding the fault causes. Without physical understanding of the degradation process of a component it is very difficult to analyze data and foresee when failure will occur. This problem correlates to the company's handling of claimed components. Today the components that are claimed are simply replaced and in general no further investigation of the fault cause is performed. Thus, the root cause of the replacement and failure is not fully established. In order to locate the root cause and gain more knowledge of each component's degradation the company needs to change the handling of claimed components and invest in the analysis of the failure causes.

The analysis of the degradation process would also be facilitated by the possibility to collect data remotely. The recently developed logging tool only covers a small set of machines and have only been in place for a few months which for some components is an insignificant time period. As earlier described, in order to collect data from machines that are not covered by the new logging tool a service technicians have to connect to the PLC and manually start a logging session. Since the company have machines installed globally this can be a difficult task. The difficulty of collecting data leads to limited possibility to analyze the data which prevents the development of physical understanding of the failure causes. The analysis would be easier to perform if the data was more accessible by collecting data remotely.

The data discussed above is mainly the condition monitoring data, or raw signals, but the event data, for example time of last service or replacement, is also in need of systematic handling. Event data is today, to our knowledge, not handled systematically for each specific component, but to some extent on machine level by the personnel in charge of that specific machine. If event data was stored in a database accessible for more personnel it would be easier to locate useful information during the analysis of the degradation process.

Another matter up for discussion is that in this project the signals that were used were raw signals from the PLC and they were more or less processed and analyzed individually. With a more profound physical knowledge of the degradation process it might be possible to calculate more suitable parameters inside the PLC even before the data is collected. For example, for the servo motor in this project the signal that became focus was the torque feedback signal since it was a signal that was normally sampled and can to some extent express the changes of the internal load and friction. However, by analyzing the control loop of the regulator it should be possible to calculate a parameter that represent the degradation behaviour more distinctly. This would lead to less data processing for the CBM system and would make the decision making easier. Overall regarding the signals that were used in this project they were chosen quite arbitrarily, meaning that it was the signals that were usually used for analysis by the personnel. However, the selection of signals or parameters used for CBM should be chosen with more profound knowledge of the component.

Overall, for this company, in order to implement a CBM tool much larger preparation is needed than what is at hand today.

8.3 Future work

If the company wants to implement CBM with prognostic features in the future there are some things that need to be done before this is possible. In general, for a CBM system, a lot of data as well as knowledge about the specific components is needed. So the first step necessary to implement CBM is to decide on which signals that should be logged, i.e. what should be considered as data in the CBM system. In this step it is important to get a thorough understanding of the component in question and decide whether the currently logged signals is enough for lifetime estimation or if new signals needs to be logged. This can be seen in our analysis of the spray nozzles where we could not find any correlations with a malfunctioning spray nozzle and the current signals behavior. In this case it might be needed to install additional hardware to be able to log other signals that are not available today. In the case of the gas concentration sensor and the injection molding unit a lot of data was available for analysis but not enough knowledge about how the data should be interpreted. This could be called “data rich – information poor” and should be avoided when analyzing machine data. In this first step it is also important that not only signals from that component are logged but that event data is logged as well. This was something that was missing when we analyzed the servo motors and thus made the analysis very hard and unreliable.

The second step towards a CBM system should be to start logging the signals that were decided in the first step. To be able to analyze the components and detect patterns when a component is starting to degrade run-to-fail data is needed. Optimally data from when the component is installed to when it fails is logged and how the component fails is “attached” to the data. This makes is possible to analyze the data for the failure cases, after all it is impossible to predict a failure where the signal pattern is unknown. Another point that is important to make in the data logging step is the possibility to remotely log data and analyze it remotely. All components considered for CBM should have automatic data logging and there should not be a need for technicians to be on site for logging. Ultimately all logging should be stored in a database where all information is gathered and easily available, both raw signals and event data.

Once necessary data is logged the data should be analyzed. This can be seen as the diagnosis step and here patterns for the failure are detected. When this step is complete there should be enough knowledge to be able to distinguish a healthy component from a faulty one. To be able to do this, tools like the “Servo motor compare tool” can be used.

When the proper diagnosis has been made it should be possible to develop a prognostic model that estimates RUL. To be able to develop this model all previous steps should be complete. If the wrong signals are logged some failures might be undetectable and therefore unpredictable. If there are not enough data logged the analysis could be wring and all of the failure cases might not have expressed themselves if data is logged for a too short period or on too few components. If the diagnosis is not performed thoroughly, wrong patterns for the different failure cases might be discovered and therefore wrongly predicted in the prognostic model. It is tempting to just jump to this step and develop the prediction model, but to be able to do this all previous steps needs to be in place and performed correctly.

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A

Rotating spray nozzles

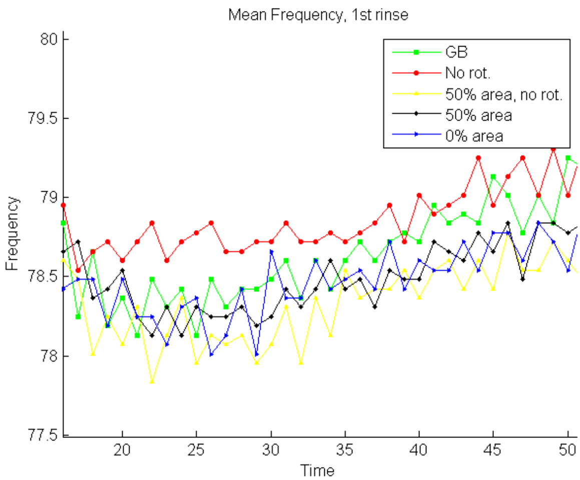

Figure A.1 Frequency during 1st rinse with all test cases, 1 second sample time.

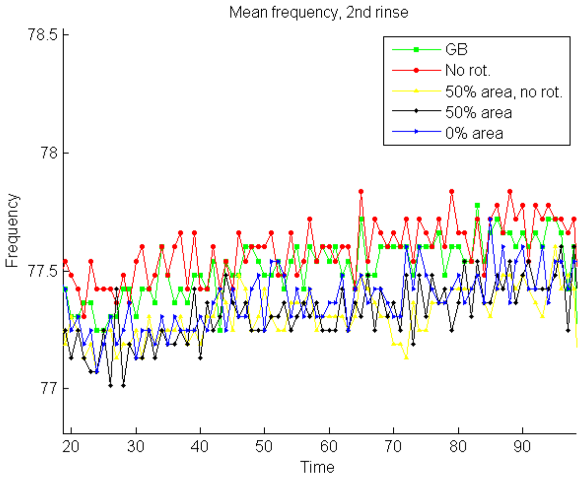

Figure A.2 Frequency during 2nd rinse with all test cases, 1 second sample time.

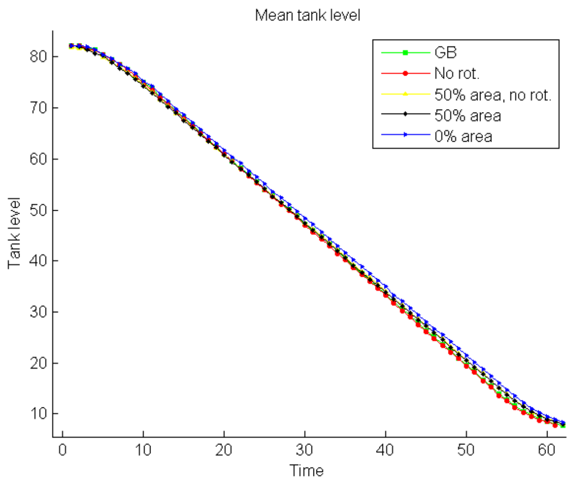

Figure A.3 Tank level with all test cases, 1 second sample time.

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Title and subtitle

On condition-based maintenance for machine components

Abstract

The goal of condition-based maintenance (CBM) is to base the decisions whether or not to perform maintenance on information collected from the machine or component of interest. A condition-based maintenance tool should be able to diagnose if the component of interest is in a state of failure but the ultimate goal of a CBM tool is to be able to estimate time until failure, either in terms of remaining useful life (RUL) or estimated time to failure (ETTF). Therefore a CBM tool should have both diagnostic and prognostic features.

This master's thesis was carried out at a company within the packaging industry and the goal was to implement a CBM tool with the possibility to estimate RUL for a set of critical components which could serve as a base for further development within the company. The selection of components to focus on was part of the thesis as well.

The process of implementing CBM with prognostic functionality was more difficult than expected and the goal of estimating RUL was not met for any of the components, but the work that has been done forms a basis for further development. Thus, this thesis will serve as a pre-study on developing CBM and contains information of what is required in order to be successful.

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