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The quantified effect of an active maintenance strategy on the Overall Equipment Effectiveness in dairy production lines

A case study at FrieslandCampina Maasdam

The quantified effect of an active maintenance strategy on the Overall Equipment Effectiveness in dairy production lines - case study at FrieslandCampina Maasdam

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Preface

This thesis project is the last part of my master Multi-Machine Engineering (MME) at the University of Technology in Delft. From wanting to be a vet to realising much more exiting things happen in the field of technology, due to going to the Harry Potter studio's, to finally finishing this degree.

In my bachelor Mechanical Engineering I already found that maybe designing machines was not really the way I wanted to go. When I started looking into the different master of ME, I soon found that optimisation, logistics and coordination between machines was something I was much more excited about. This was how I ended up at MME.

For this thesis project I did an internship at FrieslandCampina Maasdam. I became a part of their continuous improvement (CI) team and the task to find a suitable way to improve the OEE of their newest dairy cup line was placed upon me. I want to thank Emina, the CI manager but also my supervisor during my internship. I could always discuss my ideas, curiosities, dilemmas and frustrations with her. Besides helping me with the research part of the project, she also was able to help and make me see the academic importance.

Besides Emina, I want to thank my supervisor from the TU Delft, Yusong Pang. Yusong always challenged me and never gave the easy way out. I really think due to this that I challenged myself more and a better project came from this. I also want to thank Dingena Schott for being supportive, critical and for me most importantly, clear in what she expected from the project and from me.'

Of-course I would also like to thank my friends and family. My board members I would like to thank for being very patient when I would go on about everything that I encountered and the frustrations that I had. Just being able to blow off some steam helped a lot. I would like to thank my parents for the great interest and support they gave me during this project but also during my whole education, it made it all possible. And finally I would like to thank Wouter, who put up with me having to leave the house at 7 every morning and my late night stress moments. Thank you all very much.

I hope you will enjoy reading my thesis report.

E.R. Mooldijk
Delft, September 2022

Summary

In this thesis, a production line simulation model and a predictive maintenance model are developed. With the simulation model the effect of preventive maintenance on the Overall Equipment Effectiveness can be found. The interaction between the simulation model and predictive maintenance model will give an insight into the quantified effect on the Overall Equipment Effectiveness when implementing a predictive maintenance strategy in a dairy cup line. This research will be conducted as a case study of the dairy cup line at FrieslandCampina Maasdam.

In the production industry it is very important to achieve the World Class Manufacturing standard [1]. World Class Manufacturing strives towards achieving the zeros state [2]. Implementing an effective maintenance strategy is one way a lot of companies try to achieve this standard [1]. Effective maintenance can extend equipment life, improve equipment availability and retain equipment in the proper condition. Poorly maintained equipment may result in breakdowns, malfunctioning or slower production [3]. Some active maintenance strategies, like predictive maintenance, can even help reduce the amount of maintenance performed.

To see how well a company is doing, the Overall Equipment Effectiveness can be used. The Overall Equipment Effectiveness is a quantitative metric defined by Nakajima [4]. The Overall Equipment Effectiveness can be used by companies as a tool to see where improvements can be made but also as an indicator as to how the plant, production line or machine is operating. With the indicators in a percentage of the total effectiveness, the availability rate, performance rate and quality rate the different losses can be identified [5].

In the dairy industry achieving this zero state is very important [6]. To see how an advanced maintenance strategy will effect the OEE in the dairy industry, a case study at FrieslandCampina Maasdam is conducted. FrieslandCampina Maasdam wants to ensure a high OEE for their dairy cup lines, which is currently at an average of 23.94%, taken from October '21 until February '22. Currently this is done with the implantation of preventive maintenance on a part of the production line, but mostly corrective maintenance is done. This means that when a part breaks down or causes a lot of unplanned stops, maintenance will be performed. These strategies mean that a lot of losses still occur. To see if the OEE can increase when implementing a more advanced maintenance strategy this research is set up.

With this research the following research question is answered: **To what extent can an active maintenance strategy improve the Overall Equipment Effectiveness of a dairy cup line?**

To answer this question first a literature survey was conducted into the connection between the OEE and maintenance. The Overall Equipment Effectiveness is the product of the availability rate, performance rate and quality rate. These three factors are effected by the *six big losses*. In table 1, the losses contributing to the factors can be seen.

Table 1: OEE factors and the corresponding losses [7]

Availability rate	**Performance rate**	**Quality rate**
Breakdown losses	Minor stoppages	Quality and rework losses
Set-up and adjustment losses	Reduced speed losses	Yield losses

Maintenance strategies have developed from corrective maintenance to preventive maintenance to predictive maintenance and according to some even to process oriented maintenance [8]. A difference can be made between reactive and active maintenance. In this project there will be looked at preventive and predictive maintenance as active maintenance strategies. Preventive maintenance aims at reducing unplanned stops by performing maintenance on equipment before it breaks down [1, 9]. The maintenance is performed at a certain interval, which can be determined by the manufacturer of the equipment, probability and statistics or experience with the equipment [9].

Predictive maintenance aims at only performing maintenance if it is needed [1]. The condition of different parts is used to indicate if maintenance is needed [9]. Predictive maintenance consists of the following steps [10–12]:

1. Determining vital components to be monitored
2. Determining parameters that indicate deterioration
3. Setting critical thresholds for each variable
4. Data acquisition
5. Data processing
6. Fault detection
7. Prognosis
8. Maintenance decision making

Predictive maintenance is said to have an effect on the environmental safety, reliability. availability, product quality, costs for parts and labour and waste regarding raw materials and consumables [10, 13].

The link between the OEE and active maintenance can mainly be found in the improvement of the availability rate when implementing predictive maintenance. With predictive maintenance, maintenance is only performed when needed, resulting in less planned stops. With both preventive and predictive maintenance less unplanned stops, like breakdowns, are supposed to occur. These factors lead to a higher availability rate.

In the performance rate and quality rate the effect of preventive and predictive maintenance is mostly secondary. For the quality rate in the dairy industry a reason for quality losses is if the dairy stood still for too long in the production line and has perished. These produced cups have to be thrown out, resulting in quality losses. If less stops and also the duration of stops is reduced this problem will occur less.

To see which part of the production line in scope is most suited for active maintenance, an analysis of the OEE and unplanned stops is made. The analysis of the OEE of the production line shows that the availability rate is not up to the world class standard determined by Nakajima, see table 2.

Table 2: OEE values for production line 14, (average over October'21 - February'22) vs. World Class values

	Availability rate	Performance rate	Quality rate	OEE
Average	**24.6%**	**98.22%**	**99.09%**	**23.94%**
World Class	90%	95%	99%	85%
Difference	- 65.4%	+ 3.22%	+ 0.09%	- 61.06%

This shows that the implementation of active maintenance could theoretically lead to an improved OEE. To see which part of the production line is most suited for the implementation of active maintenance an analysis of the breakdowns occurring is made. From this analysis it is evident that the sections which have suction cups are responsible for the largest number of stops occurring but also for the largest total time spend on stops. Within these sections it is checked what causes these stops. The largest part of the stop and also the biggest contributor in time is the fact that cups, seals or lids are missing. The suction cups in these sections extract the cups, seals and lids from the holders and place them in/on their designated place. If these cups, seals or lids are not extracted the error message: cup/seal/lid missing shows.

The missing of these materials was found to be due to the following reasons:

- Jamming of material
- Deterioration of suction cups
- Holder empty

If the stop is due to the jamming of the material only one stop occurs, if it is due to the deterioration of suction cup the stops will increase with time, if the holder is empty another error message saying the magazine is empty will show. If the stops are caused by deterioration it is something that could be prevented with predictive maintenance. It was checked if this could really be helped by replacing the suction cups. From historic data the number of stops prior to replacement and after replacement were compared, this showed a reduction of 8 times.

From here an indicator for the deterioration of the suction cups is chosen. The suction cups create a vacuum when touching the to be extracted material, this vacuum is set at -0.75bar. If this -0.75bar is achieved, production continues as normal. If the achieved vacuum is equal to or above -0.65bar, the production line will stop due to not being able to extract the material. From historic data the change in the achieved vacuum due to deterioration for all sections is constructed.

To see what the effect is of implementing active maintenance on the suction cups, a simulation model of the production line is made. This simulation simulates all the stops that occur in the production line. This simulation model follows the production of 1 row of cups in the production line, one row equals 6 cups being produced in parallel. This is done for the stops of all the different sections, the stops due to maintenance, the changeover stops and stops due to factors outside of the production line. The distributions for all these stops, how often they occur and how long they take, are determined from the historic data of October '21 until February '22. The achieved vacuum of the cup, seal and lid vacuum is also simulated for every row produced. The final output of the simulation model is the availability rate, as this is the factor of the OEE that will be influenced by predictive maintenance. In figure 1 the outputs of the simulation model can be seen, this also shows which outputs are used by the advanced maintenance model as inputs.

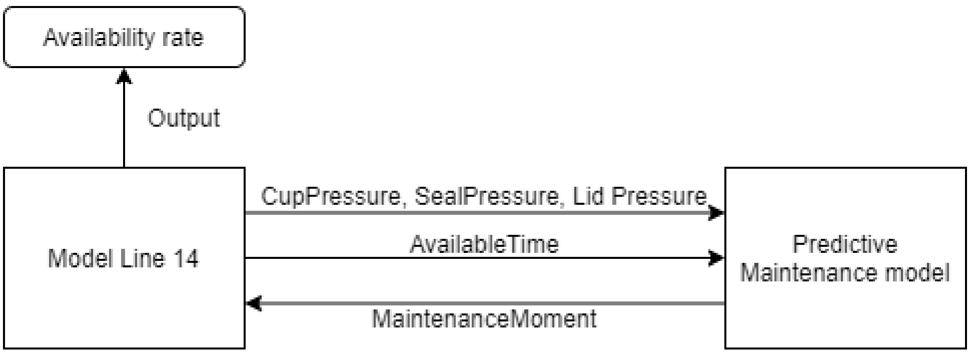


Figure 1: Interaction between Model Line 14 and Advanced Maintenance Model

The predictive maintenance model uses the achieved vacuum of the cup, seal and lid section, as can be seen in the figure above, as well as the available time for maintenance from the simulation model as inputs. In figure 2 the steps in the predictive maintenance model with the corresponding inputs and outputs can be seen.

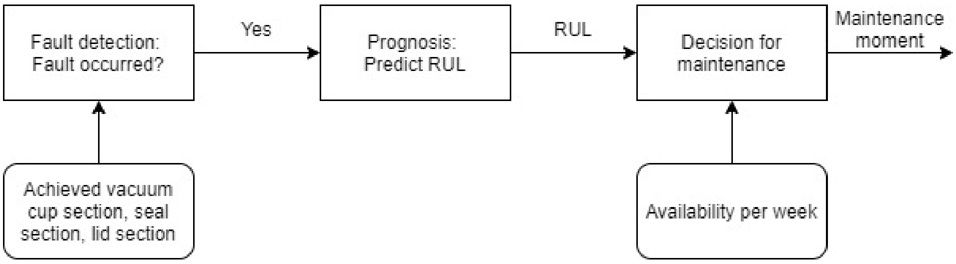
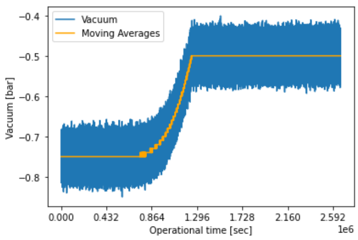
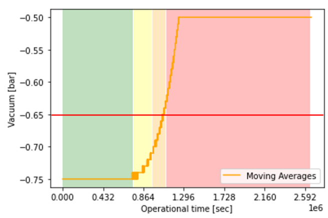


Figure 2: Interaction of different parts of predictive maintenance model

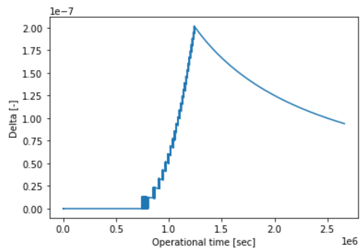
As can be seen for the fault detection the input is the achieved vacuum of the three sections. In figure 3a the achieved vacuum (in blue) can be seen with it's corresponding moving averages (orange). The moving averages is used for the fault detection of the suction cups. In figure 3b the different stages of deterioration are seen. In green is the normal operations, the moving averages is here constant at -0.75bar. In yellow is the start of deterioration seen, no real problems are caused yet, the achieved vacuum starts increasing. in orange is the deterioration at such a point that more stop start happening, the achieved vacuum starts increasing towards the threshold of -0.65bar. The red part is when the achieved vacuum is above -0.65bar and operations with these suction cups are no longer possible.



(a) Achieved vacuum (blue) and moving averages (orange)



(b) Stages of deterioration seen in the changes in the achieved vacuum



(c) Computed delta of the moving averages of the achieved vacuum

Figure 3: Achieved vacuum, deterioration stages and the computed delta

In figure 3c the computed delta of the moving averages is seen. This delta together with the moving averages is used to determine if deterioration has set in or if a stop happens due to another reason. If the moving averages is no longer a constant -0.75bar and the delta is no longer 0, it means deterioration has set in, this will activate the next step: the prognosis.

The prognosis step makes a prediction of the Remaining Useful Life left of the suction cups. It does this based on the current and past values of the achieved vacuum for each section. With a machine learning library developed for python a neural network is trained to make a regression analysis of the RUL of the suction cups. In figure 4, the determined RUL with the corresponding achieved vacuum can be seen, see orange graph. The current achieved vacuum, from the simulation model, is used as input of the regression analysis and the RUL at that moment is predicted.

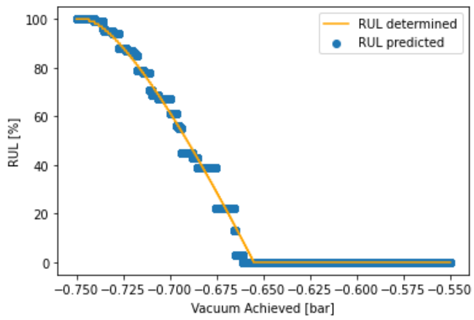


Figure 4: Determined and predicted RUL set out on the achieved vacuum in bar

Based on this, a prediction of the RUL corresponding with the current achieved vacuum will be made. This is shown by the blue dots. With this predicted RUL an advised maintenance moment is decided upon. If the RUL is below 60%, a moment for maintenance needs to be planned within a certain time frame, this time frame differs for the sections. This is decided upon with the use of an equation which maximises the available time per week. The output of this is the advised maintenance week per section.

A few experiments are conducted to see what the quantified effect is of implementing an active maintenance strategy on the OEE. First a base scenario was run, in this scenario normal degradation periods are used and the maintenance strategy implemented is corrective maintenance, resulting in an OEE of 24.13%. Then an experiment with the comparison of preventive and predictive maintenance was conducted. This experiment will show how the two different methods respond to different scenario's of degradation and how this translates into the OEE of the production line. In table 3 the results of these experiments are visible.

Table 3: Results expressed in OEE of the different experiments with different deterioration rates

	Base	**10 weeks**	**20 weeks**	**30 weeks**	**Worst case**
Preventive Maintenance	27.51%	27.46%	27.48%	27.46%	2.54%
Predictive Maintenance	27.88%	27.86%	27.91%	27.96%	27.3%

From these results it is concluded that the biggest effect on the availability rate is due to the reduction of stops and not due to the reduction in maintenance activities. This can be seen in the experiment with a degradation period of 30 weeks, with the implementation of predictive maintenance there are only 3 maintenance actions needed for the scenario of degradation of 30 weeks, while with preventive maintenance still 9 moments are used. However, the difference in OEE is statistically insignificant. In the worst case scenario the reduction in stops with predictive maintenance is very good, but more maintenance moments are needed. With preventive maintenance, the actions are only performed at the set moments, resulting in a lot of stops and even not being able to operate, resulting in an extremely low OEE. In real life this would be prevented by switching to corrective maintenance. This could then result in an increase more than 3% OEE, while the switch from preventive to predictive maintenance in a normal, or 'better' scenario does not not result in an increase.

Contents

Abbreviations

World Class Manufacturing	WCM
Total Productive Maintenance	TPM
Overall Equipment Effectiveness	OEE
Preventive Maintenance	PM
Predictive Maintenance	PdM
Artificial Intelligence	AI
Remaining Useful Life	RUL
Sensitivity Analysis	SA
Polyethylene Terephthalate	PET
Cleaning in Place	CIP
Neural Networks	NN

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1 Introduction

In the production industry productivity is very important. To achieve World Class Manufacturing (WCM) is something that a lot of companies strive towards [1]. WCM strives towards achieving the zero state; zero waste, zero accidents, zero rejects, zero failure, and zero stock [2]. To be able to achieve this, measures have to be taken.

Implementing effective maintenance is for a lot of companies a way of achieving WCM [1]. According to Swanson, effective maintenance can extend equipment life, improve equipment availability and retain equipment in the proper condition. Poorly maintained equipment may result in breakdowns, malfunctioning or slower production [3]. Active maintenance can help reduce breakdowns and failures. Some active maintenance strategies, like predictive maintenance, proactive maintenance, and condition based maintenance can even help reduce the amount of maintenance performed. These types of maintenance strategies can be defined as 'as needed' types of maintenance [13]. This means that maintenance is only performed when it is indicated based on the condition of the equipment that maintenance is needed.

One of the methods for reaching WCM is Total Productive Maintenance (TPM). TPM was first defined by Nakajima, who also defined a quantitative metric together with this method [4]. This quantitative metric is called the Overall Equipment Effectiveness (OEE). During the years OEE has developed into a tool that can be used on its own [4]. The Overall Equipment Effectiveness is a tool companies use for improvement, to see how far from WCM they are. One way the tool can help is by identifying losses, it can show which losses occur[14, 15]. Another way the OEE can be used as an indicator, expressed in a percentage, of how well the equipment operates[4, 5]. These losses contribute to the availability rate, performance rate and quality rate [14]. If the OEE value is high, it indicates that the equipment effectiveness is good [5]. However, with OEE, there is not one way defined as to how to improve the low OEE value or how to reduce the losses.

1.1 FrieslandCampina

In the dairy industry, the zero status is very important [6]. Dairy products are perishable products. For example, if long failures occur in the dairy production line it may cause the in-process product to be scrapped due to quality deterioration during the stoppage [6]. Contributing to 14% of the global agricultural trade, the global dairy market in 2019 had a value of 719 billion US dollars [16, 17]. The dairy industry is a very important and large industry worldwide.

FrieslandCampina is a Dutch dairy production company. They produce dairy consumer goods, like milk, yoghurts, quark, custard, porridge, etc. They also produce ingredients for medicines and nutritional supplements. FrieslandCampina is a worldwide company, with factories all over the world. They own different brands but also produce for supermarkets like the dutch Albert Heijn and Jumbo.

FrieslandCampina has a production plant in Maasdam. At the Maasdam plant, special products are produced. Special products are products that contain extra ingredients, like fruit, flavouring or nuts and grain fibres. At the plant they handle 260 million kgs of raw milk, this is processed into 4 million units per week. All these units are produced across 12 production lines. At the plant of Maasdam, the Overall Equipment Effectiveness is monitored for all these production lines. Every production line has its own OEE target, based on the planned stops due to preventive maintenance (PM) and changeovers and a margin for unplanned stops and speed losses.

One of these production lines is Line 14. Line 14 is a new line. It is a flex line, which means it can produce different types of products and also in different packaging configurations. For example, the line can produce porridge in 95mm base cups of 450g, but also quark in 112mm base cups of 500g.

The OEE target for line 14 is 45%. However, currently this production line has an OEE value of roughly 25%. For dairy cup line 14 to reduce the breakdowns preventive maintenance is implemented to part of the production line, but corrective maintenance, a reactive type of maintenance, is still the dominant strategy applied for this production line. Meaning equipment on the line is not kept up to standard and breakdowns occur often, being a contributor to this low OEE. If equipment fails, corrective maintenance actions have to be taken. The practical problem here is that the OEE of line 14 is beneath the target and needs to be improved.

1.2 Problem definition

As mentioned, using the Overall Equipment Effectiveness is a way for companies to monitor their level of World Class Manufacturing. It is also a tool for finding improvement areas. Advanced maintenance is a good fit for trying to reach the zero failure state.

Often companies already make use of an active maintenance policy, like (condition based) preventive maintenance or predictive maintenance, and also use the OEE value to monitor the productivity of their machines, production lines or whole plants. However, the direct effect is not always quantified. Also, the decision of implementing an active maintenance strategy can be a difficult one to make for companies. Implementing a strategy like predictive or condition based maintenance does bring costs with it [18]. If there is no knowledge about what the quantified effect of an active maintenance strategy is on the Overall Equipment Effectiveness in a dairy cup line, the decision to implement this type of strategy can be a difficult one.

From literature, it can be found that an active maintenance strategy has a positive effect on the OEE [19]. This has been researched widely in different types of industries. There has also been research into the effect of maintenance strategies on the performance of companies [8]. However, a model or tool which can be used to determine the quantified effect on the OEE value if an active maintenance strategy is applied in the dairy industry is not available.

At FrieslandCampina Maasdam this can be seen as well. The company uses preventive maintenance, they know that this type of maintenance can reduce unplanned stops, like failures. But, it is not taken into account how much this factors into the OEE value. Implementing a more advanced maintenance strategy, like PdM, can bring many costs with it, it can also take quite some time to train the staff properly in working with the strategy [18]. However, it is found that with the use of an active maintenance strategy the OEE can increase. Increase in the OEE means better productivity, which can save a lot of costs due to, for example, less breakdowns and equipment failures which need to be restored [1]. So for a dairy company it would be interesting to see what the quantified effect on the OEE of a dairy cup line is if a more advanced maintenance strategy were to be implemented, like predictive maintenance. This way, decision making into the implementation of this maintenance strategy is better grounded.

1.3 Aim of the research

With this research the aim is to show what the effect of an active maintenance strategy is on the OEE in a dairy production line. With this the following research objectives are set:

- A production line simulation that can generate the OEE based on different influences on the production line.

- Provide a predictive maintenance model that can decide on the maintenance actions that have to take place and when.
- A quantified answer on to what the effect of an active maintenance strategy is on the OEE for the dairy cup line at FrieslandCampina Maasdam.

As academic contribution this will be a two models that can interact with each other. These can be used to determine the effect on the OEE of an active maintenance strategy. Providing insight into where this effect is largest and quantify this effect. It will also be a methodology of implementing a maintenance model on a production line simulation model and how to use this effectively.

As a practical contribution for FrieslandCampina, the predictive maintenance model can be used in combination with the simulation to see what the increase in OEE might be after implementation. With this information, a cost-benefit analysis can be made by the company to decide upon implementation.

1.4 Scope

For this research the following scope will be used to give boundaries to the research.

The type of maintenance used in this research is a more advanced maintenance type than the one currently used at FrieslandCampina Maasdam. Currently mainly corrective maintenance is used on the production line, but a start has been made for planned preventive maintenance. The next, more advanced, step would be predictive maintenance. The OEE will be the tool used to quantify the changes made. The OEE tool has been widely used, in different industries, and is proven to be a good tool for monitoring changes and if these changes lead to improvements or not. The model will be a generic model, however, the model will be implemented on a simulation of Line 14. One part of the production line will be used to implement predictive maintenance on. The most suited part will be chosen and the parameters indicating the degradation of this part will be simulated.

1.5 Research questions

From the problem statement and the research objectives the following research question and sub-questions have been set up. The main research question will be answered during this thesis by answering the sub-questions. The main research question for this research is:

To what extent can an active maintenance strategy improve the Overall Equipment Effectiveness of a dairy cup line?

To be able to answer this question the following sub-questions have been drawn up:

1. On which aspects of the Overall Equipment Effectiveness does an active maintenance strategy have an effect?
2. What active maintenance strategies will be used to analyse the effect on the OEE?
3. What critical part of production line 14 will be used to analyse the effect of active maintenance?
4. How will the active maintenance strategies be modelled?
5. What is the difference in effect from the different active maintenance strategies on the OEE?

1.6 Methodology

To be able to answer the research question and sub-questions two different models will be build in this project. One predictive maintenance model and one simulation model of the dairy cup line.

The answer to the main research question will be a quantified answer. Meaning, it will be an indication in a percentage of how the OEE is affected by active maintenance. To be able to give this quantified answer, experiments with active maintenance strategies on the production line will have to be conducted. Within active maintenance there is preventive and predictive maintenance. Because a predictive maintenance strategy is not easily or quickly implemented on the physical production line [20], it was chosen to make a simulation model of dairy cup line 14. This model that will be build will have to include different sections of the production line, production runs, stops in the sections, routine stops, other stops, maintenance performed and will have to generate the to monitor parameter.

A predictive maintenance model will be build that can be implemented on the simulation. The model will have to be able to use the outputs of the simulation for decision making about the maintenance to be performed. Different experiments which represent different scenarios which can occur regarding the degradation of the monitored parts will be executed. The results from these experiments will give a quantified outcome into the increase or decrease in the OEE of the production line.

1.7 Outline

The sub-questions and main question mentioned above will be discussed in different chapters of this report.

Sub-question 1 will be discussed in chapter 2. A literature survey will be conducted to find the link between the OEE and active maintenance, with the main focus on predictive maintenance as this is new for the production line. Case studies into the dairy industry will be surveyed to see how the OEE can be used in practice. The effect on production of predictive maintenance will be researched, this gives information about how predictive maintenance can lead to improvements. From this information links between the improvements which can come from predictive maintenance and the improvement areas which are indicated by the OEE are made.

Sub-question 2 will also be discusses in chapter 2. The different types of maintenance strategies will be discussed. Also how the development of these maintenance strategies works and how they became more advanced than the previous one. An in-depth analysis of predictive maintenance will also be given as this is needed for the predictive maintenance model.

Chapter 3 will give some background on modelling. Since two different models will be made, a survey on how to do this will be conducted. In this chapter the fundamentals of a simulation model will be discussed. How predictive maintenance can be modelled will also be discussed. As well as how to verify, validate and analyse the sensitivity of a model. This information can later be used when building the models.

In chapter 4 sub-question 3 will be discussed. Here an analysis of the working of the production line will be given. The current situation regarding the line OEE and maintenance performed will be explained. From this information, it can be seen what the critical losses are in the production line. Failure analysis into these critical losses will provide an insight into the most critical part of the production line which can be used to implement predictive maintenance on. The decision into what parameters will have to be included into the line 14 model and what these parameters represent.

In chapter 5 the model which will be used to simulate the critical part of the production line will be explained. This will contribute further to the answer of sub-question 3. Here more in detail data is explained about the breakdowns and the parameters which indicate these breakdowns. It is explained how the critical component will be modelled and how the rest of the dairy cup line is modelled. Sub-question 4 will partially be answered. In this chapter it will be discussed how maintenance can be Incorporated into the simulation model.

In chapter 6 the predictive maintenance model will be explained. This will be a partial answer to sub-question 4. In this chapter the predictive maintenance model's used components will be introduced and discussed. The methods used for fault detection, prognosis and decision making will be discussed. The modelling of these will be explained and how the model can be implemented on the simulation model of Line 14.

Sub-questions 5 will be discussed in chapter 7. In the results chapter the outcomes of the implementation and simulation of the models will be discussed. Several experiments will be conducted to visualise the quantified outcome of the increase or decrease in the availability of the production line. The difference between the different active strategies chosen will also be discussed. The difference in the initial state and the state after the implementation will be discussed. The quantified difference in the OEE values will give an insight into the effect active maintenance has on the OEE in a dairy production line.

In chapter 8 the conclusion will be drawn. Here all the sub-questions will shortly be discussed and the answer to the main research question will be stated. Recommendations for further research will also be made in this chapter.

2 Survey on OEE and maintenance connection

To find out to what extent an advanced maintenance strategy has an effect on the Overall Equipment Effectiveness in a dairy production line, first some literature has to be found about the link between these two. In this chapter the following will be discussed:

- General understanding of the OEE
- Maintenance strategies
- General understanding of predictive maintenance
- Effect of predictive maintenance on OEE

2.1 Overall Equipment Effectiveness

The Overall Equipment Effectiveness is a quantitative metric provided by Nakajima in combination with Total Productive Maintenance [4]. Total Productive Maintenance is a strategy for productivity and effectiveness improvement [21]. According to Sowmya and Chetan (2016), the OEE can measure the gap between the actual productivity and the potential productivity of a manufacturing unit [22]. This means, it measures the degree to which the equipment does what it is supposed to do. It is used to identify and measure losses of important aspects of manufacturing, these are availability, performance and quality [14, 22, 23]. This can then be used for the improvement of equipment effectiveness and thus the productivity [4].

2.1.1 OEE value

The OEE tool can be used to identify losses which reduce the equipment effectiveness [14]. Losses are activities which cost time and resources but do not create any value [4]. To monitor how the equipment is operating, the OEE value can be used. This value is calculated using three values, availability rate, performance rate and quality rate [14]. The OEE is calculated as follow:

$$OEE = availability\% \, * \, performance\% \, * \, quality\% \tag{2.1}$$

These values can in their turn be calculated from the different losses. According to Nakajima (1988) there are six different types of losses, the six big losses [7]. In table 2.1 these six big losses can be seen with their corresponding OEE value.

Table 2.1: OEE values and the corresponding losses [7]

Availability rate	**Performance rate**	**Quality rate**
Breakdown losses	Minor stoppages	Quality and rework losses
Set-up and adjustment losses	Reduced speed losses	Yield losses

The availability rate is calculated as follow [14]:

$$Availability = \frac{Actual\ operating\ time}{Planned\ operating\ time} * 100\% \tag{2.2}$$

$$Actual\ operating\ time\ = Planned\ operating\ time - Down\ time$$

The performance rate is calculated as follow [4]:

$$Performance = \frac{Theoretical\ cycle\ time * Actual\ outputs}{Operating\ time} * 100\% \tag{2.3}$$

The quality rate is calculated as follow [4]:

$$Quality = \frac{Processed\ amount\ -\ Defect\ amount}{Processed\ amount} * 100\% \tag{2.4}$$

Nakajima has suggested the ideal values for the availability rate, performance rate, quality rate and the OEE. These values are:

Availability rate	90%
Performance rate	95%
Quality rate	99%
OEE	85%

These values are now considered to be the World Class OEE factors [7, 24]. However, Dal, Tugwell and Greatbanks (2000) found that in practice this OEE performance number is almost never reached. Instead, they propose a more realistic OEE of 50% and higher [14].

2.1.2 OEE use in dairy production lines

To see the current situation of using the OEE in the dairy industry found in literature a few case studies have been surveyed. Dal, Tugwell and Greatbanks said that one way of using the OEE is to indicate improvement areas [14]. In the case studies performed by Tsarouhas in the dairy industry, it can be clearly seen that this is the way the OEE was used for that research. The availability rate, performance rate and quality rate were calculated. Those values were set out against the world class value and it was determined which factor needed most improvement. From here the losses contributing to that factor were found and those were improved upon.

The second way of using the OEE, according to Ljungberg, is to monitor the dimensions of effectiveness of the implemented improvement strategy [5]. This could be seen in the case study performed by Ihueze and U-Dominic. The OEE values were calculated at the start of the case study. It was shown that the improvement areas were the availability rate and the performance rate but no direct actions on this were taken. TPM was implemented and after this the new OEE values were calculated. In this case, the OEE was used to monitor the improvements made.

From other studies it also became clear that when using a different method for improvements, like TPM, the OEE was most of the time used as an indicator or measure for improvement and productivity. TPM does not focus on only one improvement area but wants to improve in different areas [9]. If no other method or tool was used, it was more like for the OEE to be used as an indicator of improvement areas. It can be seen that in the studies that use TPM as an improvement method, like in [25],[5],[21],[26],[27], the OEE is used as an indicator of productivity and reliability than an indicator for improvement areas.

In the studies [28],[29],[30],[31],[15],[14], it can be seen that the OEE is used to show the improvement areas. The biggest contributor to the low OEE value is found and from there the biggest loss is determined. For these areas recommendations are then made as to how to reduce the losses.

From the case studies read, it can be seen that there is not a very big difference between the use of OEE in any other industry and the dairy industry. This could be because OEE can be applied to many different types of industries and the usage of the tool is defined in such a way that the implementation does not have to be very specific [4]. Another reason why this could be the case is because of the person who conducted the research. The studies in the dairy industry were both performed by the same researcher, this may lead to having the same methodology in both studies. This will lead to very similar usage of the tool and outcomes. However, the similarities could also be due to the fact that when using the OEE tool, it has become clear that it is either as an indicator of improvement areas [14] or as a measure of productivity and effectiveness [5]. Which type of production industry might not make such big of a difference in *how* the tool is used. How the value of the OEE is calculated is for every industry the same.

From the studies it also became visible that methodologies for improving the OEE value in the dairy industry are limited to either just looking for the improvement areas and analysing how those can be improved by means of machine improvements, training or improving maintenance actions or scheduling. It is not explicitly defined which method works best in which case. Using TPM is also a commonly used method for improving the OEE value. The values are used to compare the before and after of implementing TPM.

2.2 Maintenance strategies

Maintenance plays an important role to keep availability, reliability, product quality and safety requirements to the desired level cite wang2007selection. The purpose of maintenance is to extend equipment lifetime [32]. The definitions of the different maintenance strategies can differ between researchers. For this research the strategies used can be seen in figure 2.1.

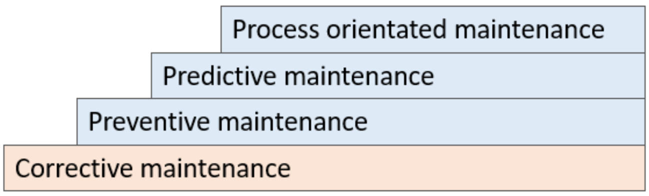


Figure 2.1: Development in maintenance strategies

All these strategies focus on a different aspects of maintenance. In orange, the reactive maintenance type is shown, here something is only repaired when it has broken down. In blue the active maintenance strategies are shown, here it is tried to make sure equipment does not break down [3]. The differences between the strategies will be explained below.

Corrective maintenance

Corrective maintenance is described by Swanson (2001) as a firefighting approach to maintenance [1]. It is the most simple way of performing maintenance. It is an unplanned and run-to-failure based approach. It allows the machine or piece of equipment to run until it fails [10]. When this happens, repairs will be done and the machine can start again, making it a very easy way of performing maintenance [13].

This way of maintenance is very cheap, it minimises maintenance manpower and money to keep the machines running [13]. This strategy does include unpredictable equipment, it is unknown when a machine will break down. When catastrophic failure happens the costs may rise very high and a dangerous situation could arise[1].

Preventive maintenance

From corrective maintenance, the next step is preventive maintenance. Preventive maintenance, or time based maintenance, is a maintenance strategy where maintenance is scheduled based on calendar time or equipment operation time [8]. The scheduled maintenance should take place before failure occurs. The frequency of the scheduled maintenance can be determined by the manufacturer's guidance or from experience [10]. It relies on the estimated probability that the equipment will fail in the specified interval [1].

Preventive maintenance can include lubrication of equipment, part replacement, cleaning and adjustments [33]. There may also be an inspection of the production equipment to look for signs of deterioration during the preventive maintenance stops [1, 13]. This type of maintenance tries to prevent breakdowns from happening but maintenance is performed at set times, even if maintenance is not needed it is performed [9].

Predictive maintenance

Predictive maintenance is based on information about the condition of the equipment [1, 9]. This information is about the deterioration which may result in more energy consumption and/or in failure. Predictive maintenance does not only aim to prevent failure but also for efficient operation [34]. This can lead to improved safety, product quality, reliability, availability and reduction in energy costs [8, 12]. Predictive maintenance is often referred to as condition based maintenance. Diagnostic equipment is used to measure the physical condition of the production equipment [35]. It is like preventive maintenance a type of maintenance that wants to prevent failures from occurring. However, there is an additional benefit which is that maintenance is only done when the need is imminent, and not like with preventive maintenance on a scheduled basis [9].

Process orientated maintenance

Process orientated maintenance goes beyond the effort of avoiding equipment failure. Total productive maintenance is a process orientated maintenance strategy [8]. Improvement of the design of new and existing equipment is key in this strategy [9]. TPM is a philosophy of maintenance management much more than only a strategy. The key is to minimise the six losses in OEE [23]. By doing this the equipment effectiveness is optimised and the breakdowns are eliminated [26]. This method promotes autonomous maintenance by the operators through day-to-day activities involving the total workforce [1, 9].

Proactive maintenance is also a type of process oriented maintenance [36]. It is similar to predictive maintenance as it is also a type of condition based maintenance [33]. Proactive maintenance endeavours to get to the root cause of a potential problem, while predictive maintenance collects relevant data to appropriately schedule routine fixes to ensure equipment is operating effectively [37]. The aim of proactive maintenance is to eliminate the failures of equipment forever [38].

2.2.1 Comparison

To clearly see the differences between the different strategies table 2.2 can be used. Besides the advantages and disadvantages themself, it can also be seen how many advantages vs. disadvantages every strategy has. It can be seen that reactive maintenance has more disadvantages than advantages. For preventive maintenance, this is about 50/50. For predictive maintenance and process oriented maintenance, there are more advantages than disadvantages, but predictive maintenance has more advantages and less disadvantages.

For example, a disadvantage of reactive maintenance is the many unplanned stops. As with reactive maintenance, repairs are only done once a breakdown or stop has occurred, it is always waiting for the next unplanned stop to happen. With preventive maintenance the chances of unplanned stops occurring are much less. With the maintenance interval set based on experience, probability or prescription, the idea is to always perform maintenance before a breakdown happens. However, it is possible that due to some factors a breakdown occurs before the planned maintenance moment. With predictive maintenance it will be known when a breakdown or stop will happen. This way, it is possible to always plan the maintenance actions before the breakdown occurs. With proactive maintenance the operator's involvement with autonomous maintenance is to ensure the state of the equipment is always at its highest, this should eliminate breakdowns.

Table 2.2: Advantages and disadvantages of different maintenance strategies [9]

	Advantages	**Disadvantages**
Reactive	- Easy option - No investment costs	- Unplanned stops - Excessive damage - Spare parts problem - High repair costs - Excessive waiting and maintenance time
Preventive	- Prevents equipment breakdown - Prolong equipment service life - Planned when convenient	- May perform maintenance tasks too often - May replace parts too soon: costly and not sustainable - Still risks of unplanned stops
Predictive	- Only perform maintenance when needed - Only replace parts that need it - Prevents equipment breakdown - Prolong equipment service life - Can be planned when convenient	- High investment costs
Process Oriented	- Operator involvement in maintenance - Optimised equipment effectiveness - Eliminates breakdowns	- High investment costs - High investment in training of staff

For this research the effect of active maintenance on the OEE is experimented with. The two chosen active maintenance strategies to look into are preventive and predictive. It was chosen not to use process oriented maintenance as this is not just a maintenance strategy but incorporates also people.

2.3 Effects of ctive maintenance on OEE value

As mentioned in section 2.1.1, there are six big losses in the Overall Equipment effectiveness. From the information gathered about the OEE and predictive maintenance, it is discussed how PdM affects these losses and the corresponding OEE values.

2.3.1 Availability

As mentioned earlier, the availability rate is calculated with the actual operating time and the planned operating time. The difference between these two is the time spent on stops; unplanned stops, minor stoppages, planned stops and setup and changeover losses. With implementing PdM, maintenance is only performed when the need is imminent and not after the passage of a certain time period [9]. This would lead to the time spent on planned maintenance can be reduced, meaning the planned operating time would reduce, while the actual operating time stays the same. This would lead to a larger percentage of the planned operating time resulting in the actual operating time, thus increasing the availability rate.

With PdM, knowledge about when a part is about to break down or cannot perform standard operations anymore is available. This knowledge can help with planning maintenance in an effective way to maximise the availability of the production line for production itself [35]. With the use of the knowledge about the condition of the production line and its parts comes that no surprise breakdowns should happen any more [10]. This will lead to a reduction in unplanned stops, leading to an increase in the availability rate.

It was found that the implementation of the OEE but also predictive maintenance does not differ very much in different industries. In the dairy industry the above explained way in which predictive maintenance has an effect on the availability rate is no different. If maintenance is only performed on the machines when it is needed, and not routinely every 2 weeks, for example, the time the line can actually be used for production will increase. If the condition of the line is monitored and maintenance is performed on the parts which need it, the chance of them breaking down unexpectedly is reduced. This leads to more actual operating time.

From this decrease in planned downtime and decreases in unplanned maintenance and minor stoppages it can be seen that the planned operating time can decrease while the actual operating time can increase. This would lead to a higher availability rate.

2.3.2 Performance rate

The performance rate is calculated with the theoretical cycle time, actual outputs and operating time. The losses contributing to this are the minor stoppages and the reduced speed losses [14, 39].

Reduced speed losses are due to equipment not operating at the designed speed. It can be the case that lubrication needs to take place to make sure the equipment can operate properly [39]. With the use of PdM it could be monitored how the production line and its parts operate and if actions like lubrication, cleaning or replacement of parts is needed [13]. However, in more high end equipment, like used in the dairy industry, it is more likely that speed losses are due to machines which are not designed correctly and not due to wear. The machine will still be able to work at the same speed but will just break down if something is wrong, not slow down. In the case studies into the diary industry it was found that most speed losses occurred due to dirty equipment, sensor blockage and product misfeeds [28, 31]. The solutions for this are mostly linked to the operators, maintenance will not improve the reason behind the speed losses.

The actual output of the production line can be linked to both the reduced speed losses, if the speed is lower than the norm, less units can be produced in a certain time frame. Minor stoppages also have a play in this, if the machine keeps on stopping it will lead to an increase in the operating time but a decrease in the actual outputs.

As discussed above, minor stoppages can decrease with the use of a predictive maintenance strategy. However, not all reasons for speed losses, which are the main contributor to the performance rate, can be helped with predictive maintenance.

2.3.3 Quality rate

The quality rate is calculated with the processed amount and the defect amount. This is connected to the quality defect losses and yield losses [14]. As stated in section **??** PdM can help improve the product quality, however this can be a secondary effect. Quality defects can be due to malfunctioning production equipment [14, 15]. This can take the form of a machine which needs to add a part to something not working correctly and for example not attaching it correctly or strongly enough. This way the product will not have the quality needed for the market. With the use of a predictive maintenance strategy, malfunctioning of production equipment will be reduced or in a perfect scenario, the equipment will not malfunction anymore [8]. This will have the effect that less quality defects occur. However, this problem is also likely to occur due to the fact that the machine is not programmed properly, or the connection between the different machines is not working properly due to malfunctioning sensors [10].

In the case studies performed by Tsarouhas in the dairy industry, it was found that quantity losses occurred due to tolerance adjustment, scrap, in-process damage or incorrect assembly. This was mainly in the time from startup until stable production process was reached [31]. Another reason was in process damage. In the dairy industry the quality rate can decrease due to the fact that the production line has broken down while there is still dairy in the line and packaging material which cannot move any further. If this stop takes too long, the dairy will go bad and cannot be used anymore [6]. Meaning a higher number of products have to be thrown away, quality losses, which lead to a lower quality rate. This is where predictive maintenance can make sure that lines do not break down and have to stand still for too long [34]. However, this is a secondary effect on the availability of the line. Also, quality defects can also be due to, as said in the example above, not closing the packaging correctly. This problem is more likely due to the fact that the equipment is not programmed properly or because there is a deviation, much more than maintenance needed on the equipment of the line.

2.4 Effects of PM on the OEE

Where the effects of preventive maintenance on the OEE can be noticed do not differ very much from the effects noticed with predictive maintenance. In the comparison table it could already be seen that the advantages of preventive and predictive maintenance overlap quite a lot. Meaning that the effects of fewer breakdowns and thus more available time still stands. However, it could be that a lot of time is spent on maintenance as it is performed very often. This would then have a negative effect on the availability of the production line. How much these two weigh up to each other depends on the number of unplanned stops occurring and the time spend on maintenance.

In the performance rate and quality rate the same secondary effects can be seen as with predictive maintenance. This would primarily be a secondary effect in the dairy industry. As fewer unplanned stops lead to less products being thrown away due to them perishing, leading to a better quality rate. With the performance rate, preventive actions like lubricating timely could lead to well performing equipment, leading to an improvement in the performance rate.

2.5 Conclusion

The effect of preventive and predictive maintenance on the Overall Equipment Effectiveness can primarily be seen in the availability rate of the OEE, which can then have a secondary effect on the performance rate and the quality rate of the production line. These effects are found to be positive, meaning that the rates, and thus the OEE, will likely increase with the use of a predictive maintenance strategy. To conclude, the effect of a preventive or predictive maintenance strategy on the OEE in a dairy production line is a positive effect.

3 Survey on modelling in practice

For this project, two models will be built. The first is a simulation model and the second is a predictive maintenance model. To get an understanding of how to build these models, a literature survey has been done. In this chapter the following will be discussed:

- Simulation techniques
- Predictive maintenance modelling
  - Data acquisition and processing
  - Fault detection
  - Prognosis
  - Decision making
- Verification, validation and sensitivity analysis

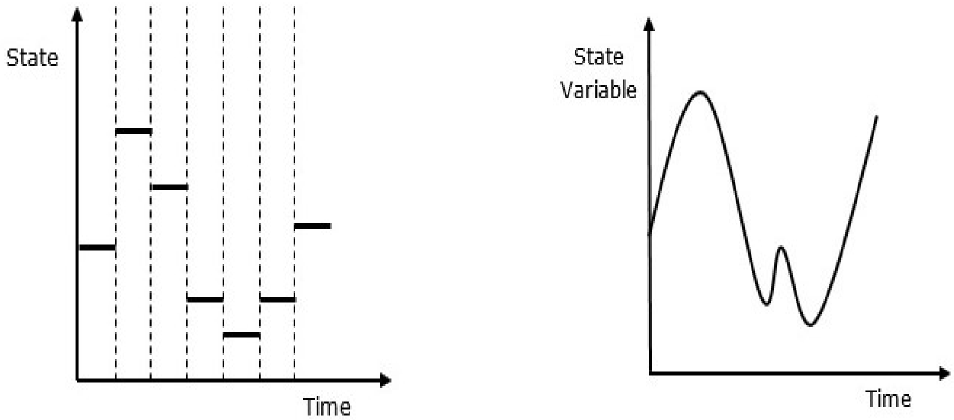
3.1 Simulation Technique

To get a quantified answer about the effect of active maintenance on the OEE, the predictive maintenance model that will be built has to be implemented on something. Implementing this model on a simulation of a diary cup line is a great way to experiment with the model and gain answers for different scenarios. Simulations are generally seen as cheaper, faster, safer and tests/experiments can be replicated multiple times [40].

There are different simulation techniques which can be used for different types of simulations [41]. The first division is between stochastic and deterministic simulations. Stochastic simulations are simulations that have random variables as input, and thus also generate random outputs [40]. A stochastic model can handle uncertainties in the inputs applied [41]. Deterministic simulations are simulations that has an entirely predictable behaviour, meaning, given a set of inputs the model will result in a unique set of outputs [40]. A deterministic model can calculate a future event exactly, without the involvement of randomness [41].

The next division is between static and dynamic simulations. Static simulation models represent the system at a particular point in time, while dynamic simulations represent systems as they evolve [40].

The last division is between discrete and continuous simulations, these are both types of dynamic simulations. In figure 3.1a it is visualised how a discrete time simulation works. Here the changes in the system state are discontinuous and each change in the state of the system is called an event [42]. In figure 3.1b it is visualised how a continuous-time simulation works. Here the state variables change continuously with respect to time [42].



(a) Discrete time (b) Continuous time

Figure 3.1: Visualisation of discrete and continuous time simulation [42]

3.1.1 Simulation model

Building a simulation model, implementing it as a computer model and proving it, works in a cycle. In figure 3.2 this cycle can be seen as defined by [43] and [44].

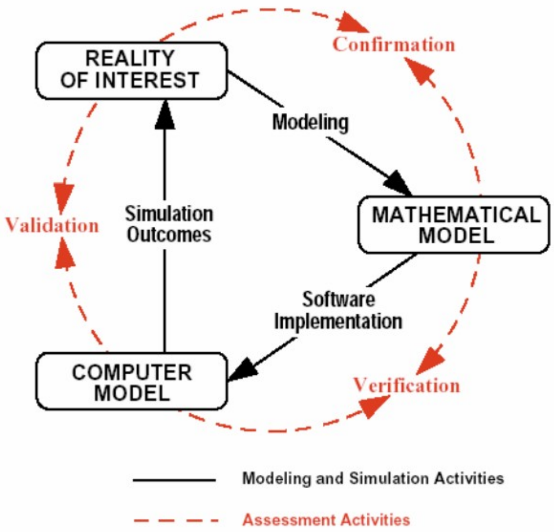


Figure 3.2: Simplified view of the modelling process [43, 44]

The computer model represents the implementation of the mathematical model, usually, in the form of numerical discretisation, solution algorithms, miscellaneous parameters associated with the numerical approximation and convergence criteria [43].

From the 'reality of interest,' the output for the model is chosen. The different inputs are chosen to create this output. With these inputs, a mathematical model is built that gives the wanted output. This model is defined by one of the simulation techniques described above. This mathematical model is implemented into a computer model, or code and can be run to generate the output.

3.2 Predictive maintenance modelling in practice

Predictive maintenance has become a promising approach to decrease the downtime of machines and increase the reliability of systems [1, 10].

In predictive maintenance the following steps are taken [10–12]:

1. Determining vital components to be monitored
2. Determining parameters that indicate deterioration
3. Setting critical thresholds for each variable
4. Data acquisition
5. Data processing
6. Fault detection
7. Prognosis
8. Maintenance decision making

According to [10] steps 1 to 3 are the following actions. Determining vital components to be monitored is investigating which component is most suited for predictive maintenance and will have the largest effect. Determining the parameters that indicate deterioration is finding the parameters for the chosen component that indicates the state of that component. Setting critical thresholds for each variable is to use in the fault detection step. According to [12] steps 4 to 8 are the following actions. Data acquisition provides the access to the installed sensors and collects data. Data processing performs single and or multi channel signal transformations and applies specialised feature extraction algorithms to the collected data. Fault detection conducts condition monitoring by comparing features against expected values or operational limits and returning conditions indicators and/or alarms, it determines whether the system is suffering degradation. Prognosis projects the current health state of the system into the future by considering an estimation of future usage profiles. Maintenance decision making provides recommendations related to maintenance activities and modification of the system configuration.

Steps 1, 2 and 3 will be discussed in chapter 4, but do not need to be modelled. Steps 4 to 8 are the steps in PdM that need to be modelled. This will be discussed in this chapter. The actual modelling for this specific research project will be explained in chapter 6.

3.2.1 Data acquisition and processing

When the vital components and the corresponding parameters are determined, the data from these components need to be gathered. Data acquisition is the process of collecting analogue data from a sensor and converting it to a digital signal that a computer can process [45]. A data acquisition system is composed of sensors, data transmission devices and data storage devices [46]. Common ways of monitoring data are listed below [10, 13, 35]:

- Vibration monitoring
- Lubricant/fluid analysis
- Process parameter monitoring
- Thermography
- Acoustic ultrasonic analysis
- Visual inspection

According to [45] data that is collected can be classified into two categories. The first one is event data. This includes data that concerns the information about what happened and what was done to repair. For example, breakdowns, what caused them and how it was repaired. The second category is condition monitoring data. These are the measurements of the parameters related to the health conditions of the physical asset, for example, pressure, temperature etc. This collected data is transmitted into a PC or portable device through a data transmitting device and then stored in a memory location for further analysis [46].

According to [47], data processing includes two main steps. The first step is data cleaning. Data cleaning is responsible for removing errors and noise from the retrieved data, this is especially important since data always contains errors. There is not one way for data cleaning, sometimes it requires manual examination of data, sometimes prescribed methods are available, this depends very much on the data.

The second step is data analysis. This step involves methods such as time domain analysis, frequency domain analysis and event data analysis. Data analysis for event data is well known as reliability analysis, this fits the event data to time between events probability distribution and uses the fitted distribution for further analysis. Condition monitoring data can fall into the flowing three categories:

- Value type: data collected at a specific time epoch for a condition monitoring variable are a single value.
- Waveform type: Data collected at a specific time epoch for a condition monitoring variable are a time series.
- Multidimensional type: Data collected at a specific time epoch for a condition monitoring variable are multidimensional, like x-ray images, thermographs etc.

Again the type of data generated as condition monitoring data highly influences the method to use for the data analysis [47].

3.2.2 Fault detection

Fault detection is the process of determining if there is a fault in the system or not. Any deviation from a standard behaviour can be categorised as a failure[48]. Depending on the data and the requirements for the system, the methods used can differ. Three methods were classified by [45], these methods are:

- (Physical) model-based
- Knowledge-based
- Data-driven

Within these methods, there can be subsystems. In figure 3.3 these can be seen, in the paragraphs below these methods will be explained.

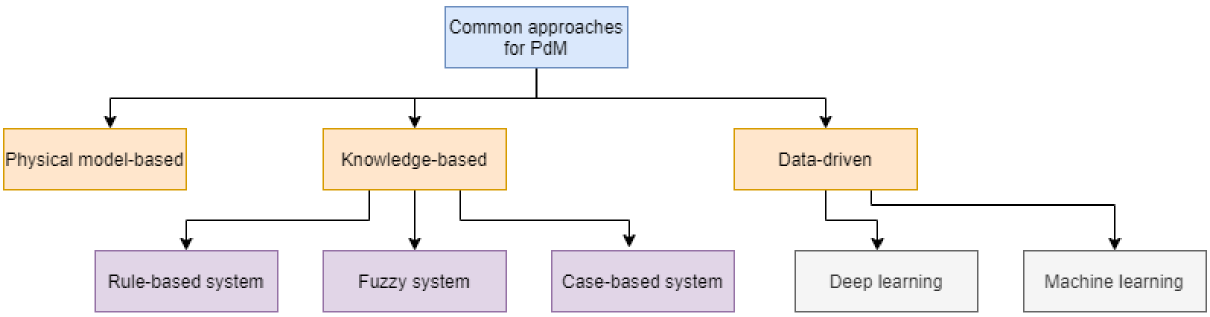


Figure 3.3: Classification for commonly used PdM methods [49]

Physical model-based

Physical models quantitatively characterise the behaviour of a failure mode using physical laws [50]. It normally uses a mathematical representation of the physical behaviour of a machine. The mathematical representation reflects how the monitored system responds to stress from both macroscopic and microscopic levels. To obtain an accurate description of the system, it is important to identify one or several system diagnostic parameters that are specific to the predictive maintenance task [49].

Once the physical model is available, sensor measurements from the actual process are compared against the outputs of the model. Differences between the measured outputs and the outputs of the model are called residuals [50]. Large residuals are assumed to indicate a fault, whole small residuals occur under normal conditions due to, for example, noise or modelling errors [50].

Because physical models require the behaviour of a system to be derivable from first principles, it may bring obstacles to its implementation [49, 50]. When the understanding of failure mechanisms can only be partially obtained this can bring difficulties. Because of this, physical model-based approaches are more likely to be used in isolated cases where failure/fault mechanisms are well understood and predictive maintenance systems are well-developed [49].

Knowledge-based

A knowledge based system contains a knowledge base that stores the symbols of a computational model in the form of statements about the domain and performs reasoning by manipulating these symbols [49]. Knowledge based systems can be further classified into expert systems and fuzzy systems. Expert systems can be rule-based systems or case-based systems. An expert system simulates the performance of human experts in a particular field, it generally consists of a knowledge-base containing accumulated experience from subject matter experts and rule or case base for applying that knowledge to particular problems [50]. From [49] and [50] the following information on case-based, rule-based and fuzzy systems is gathered.

Case based reasoning is one of the emerging paradigms for designing intelligent systems [51]. It solves new problems by adapting previously successful solutions to similar problems. According to [51] it has the following advantages: Commonly each case comprises two parts. The first part is the problem or situation: a description of the state of the world when the case happened. The second part is the solution: the derived solution or answer to the corresponding problem. There are two main steps to case-based reasoning: case retrieval and case adaptation. With case retrieval, the case base is searched for matches between individual cases and the pattern that serves to index the cases. Case adaptation is to find old cases that are most similar to the target case. Against these existing cases, it can be checked whether a fault is detected.

Rule-based reasoning normally encodes problem-solving knowledge of the domain experts in terms of a set of situation actions, IF-THEN rules. These rules are written in the following format:

if A and B, then C
If C or D, then E

Here the *if* portion is called the antecedent and the *then* portion is called the consequent [52]. The rules are often based on heuristic facts acquired by one or more experts. To be useful, a knowledge base must be as complete and exact as possible, meaning each set of inputs must provide only one output and output must be provided for any possible combination of input values [50]. The drawn-up rules can be checked against the output of the physical system and can give the condition of the current state, fault or no-fault.

Fuzzy systems are often used when a real-world situation requires flexible decision making. In a classic predicate logic that is used by classic knowledge-based systems, a statement is either true or false, meaning, a data entity can only belong to one set and be excluded from the remaining sets. However, it is not always feasible to follow this principle when real-world situations involve 'vague' knowledge for decision making. To overcome this challenge, fuzzy set theory is used [49]. A fuzzy system is comprised of a knowledge base, fuzzy rule base and algorithms for applying the fuzzy logic. Data is received and after pre-processing, converted into fuzzy representations that can be compared against the fuzzy rule sets, this process is called fuzzification. It involves using membership functions to define how input data is mapped to particular fuzzy variables. After processing by the fuzzy logic, the resulting data needs to be defuzzified into numerically precise outputs [50]. This output can indicate whether a fault is detected or not.

Data-driven

Because of the exponential growth of data volume and the rapid development of data acquisition technologies, data-driven methods have attracted wide attention and are developing fast in predictive maintenance [49]. Data-driven methods are based on large amounts of data from systems where data analytics is applied, for example, statistics-based, artificial intelligence (AI) or machine learning algorithms [34]. According to [11] these techniques can discover patterns and relationships in data sets which in turn can indicate faults or no faults. An advantage is that no prior knowledge of faults has to be known, the model will recognise this from the patterns. The downside is that incorrect conclusions can be drawn. [49] and [11] have divided the methods for data-driven approaches into machine learning and deep learning methods. In figure 3.4 the difference between these two methods can be seen.

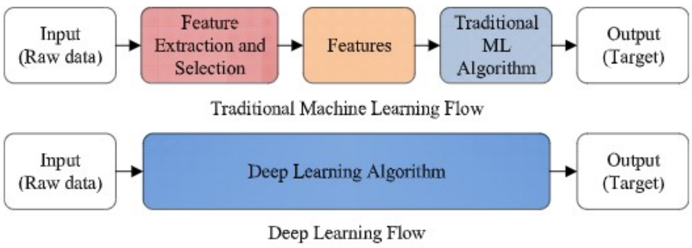


Figure 3.4: Flow of machine learning and deep learning [11]

According to [11] the biggest difference between machine learning and deep learning methods is the complexity. Machine learning generally requires collecting large amounts of data from health conditions and various failure status scenarios for model training. Next, feature engineering is conducted from time, frequency and time-frequency domain. The representation learning of the equipment health is performed using extracted features. Deep learning methods avoid feature engineering and can be learned using an end-to-end learning manner, which is implemented by adding deep layers between the raw data and the prediction results. The deep models can be deemed as a 'black box', which outputs the prediction result from the input directly.

3.2.3 Prognosis

The next step in predictive maintenance is the prognosis. When a fault is detected, the prognosis process will be started. Prognosis is the process of projecting the current health state of the system into the future by considering an estimation of future usage profiles [12]. The main approach widely used in prognosis is concerned with the estimation of the remaining useful life (RUL). RUL approaches also be classified into the above-named model-based, knowledge-based and data-driven methods [45]. As the working of these methods is explained in more detail above, a short explanation of the methods regarding prognosis will be given according to [45].

Physical models provide an assessment of the RUL, based on a mathematical representation of the physical behaviour of the degradation. Case-based reasoning will retrieve a case similar to the degraded state, adapt this to the current situation and based on this give an estimation of the RUL. Rule-based reasoning will use the setup rules with the input of the current situation. The *if* will be the situation and the *then* will be the prognosis of how the system will behave, giving a prognosis on the future states, or RUL. Fuzzy systems will use fuzzy rules which indicate the RUL. With the input of the system fuzzified and compared against these fuzzy rules, the defuzziefied output will give an estimation of the RUL. Data-driven methods will use machine learning or deep learning to create patterns which can indicate the RUL. The input data will be processed by these algorithms, as shown in figure 3.4, and the output will be the RUL.

The prognosis of the RUL will be used in the maintenance decision making.

3.2.4 Maintenance Decision

Decision making is the process which is triggered by the RUL in order to generate proactive recommendations about maintenance actions and plans that eliminate or mitigate the impact of the predicted failure [53]. In a literature review conducted by [53], 5 areas of decision making were determined.

- **Maintenance planning and scheduling**: Algorithms that can recommend the most appropriate maintenance actions according to the company's policies and the estimations regarding the potential impacts and risks of the candidate actions.
- **Reliability- and Degradation- based decision making**: Algorithms incorporating the degradation rates to minimise long-term costs and thus enable the scheduling of mitigating maintenance actions.
- **Joint optimisation**: Algorithms aiming to optimise the maintenance operations, taking also into account production and supply chain-related objectives.
- **Multi-state and multi-component systems optimisation**: Algorithms that allow the identification of intermediate stages of their health state. On this basis, optimisation models lead to intermediate decision making.
- **Maintenance cost and risk estimation and optimisation**: Algorithms dealing with cost and risk estimation aspects capable of facilitating the decision making for optimal maintenance actions.

It is said that the stochastic nature of the degradation process makes decision making for predictive maintenance higly uncertain and complex. Due to this, a large amount of existing decision making algorithms utilise simulation models or iterative solution procedures. It is also said that several decision making algorithms are based upon model-based prognostic algorithms instead of data-driven ones. This leads to the decision making methods and algorithms to be mainly knowledge-based due to the lack of data analytics capabilities. The decision for which maintenance actions and when to perform is then based upon which area is determined most important and to be optimised in combination with the predicted remaining useful life of the component.

3.3 Verification, Validation, Sensitivity Analysis

When a model is built it has to be verified, validated and a sensitivity analysis has to be conducted. [43] has defined verification and validation of a model as the following:

- Verification is the process of determining that a model implantation accurately represents the developer's conceptual description of the model and the solution to the model.
- Validation is the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model.

In short, verification deals with the mathematics associated with the model whereas validation deals with the physics associated with the model.

Sensitivity analyses are conducted to investigate the relations between parameters and outputs of a model. Sensitivity analysis (SA) can be thought of as examining the shape of the response surface of each output to the input parameters [54].

3.3.1 Verification

Verification is concerned with identifying and removing errors in the model by comparing numerical solutions to analytical or highly accurate benchmark solutions [43]. There are two basic approaches for verification, static and dynamic. In static testing the computer program is analysed to determine if it is correct by using such techniques as structured walk-troughs, correctness proofs and examining the structural properties of the program, while in dynamic testing the computer is executed under different conditions and the values obtained are used to determine if the computer program implementations are correct [55]. It also encompasses checking the implementation of the numerical algorithms used in the code [43]. This can be done by running 'test problems' with known solutions, like output will increase or decrease, and comparing it to the solutions obtained by the simulation [43].

3.3.2 Validation

Validation is concerned with quantifying the accuracy of the model by comparing numerical solutions to experimental data [43].

According to [55], for validation of the simulation model, there are different ways to compare the output behaviours. This can be the comparison of the output of the simulation model to either the system or another, already validated, model. An objective and subjective validation can be done. Objective validation would be graphical comparisons of data. Here three types of graphs, histograms, box plots and behaviour graphs using scatter plots, are used to compare the model output and the system output. To make an objective decision on the validity of the model it is said that either using the confidence interval or hypothesis test are best. For the confidence interval method a confidence interval is chosen and for the hypothesis test method, an acceptable range of accuracy is chosen. The confidence interval method checks if the system output fits within the confidence interval created when running the simulation n times. The hypothesis tests compare the means, variances, distributions and time series of the output variables of the model and the system for each set of experimental conditions to determine if the simulation model's output behaviour is acceptable.

To validate the simulation model the confidence interval validation method is used. This method is a type of dynamic validation, this means that the simulation model has to be run to validate it [55]. The confidence interval validation method compares the given or observed value for the behaviour or performance of the simuland to a confidence interval for that value calculated from data obtained by executing the model [56]. According to [56] this method consists of the steps that can be seen in figure 3.5.

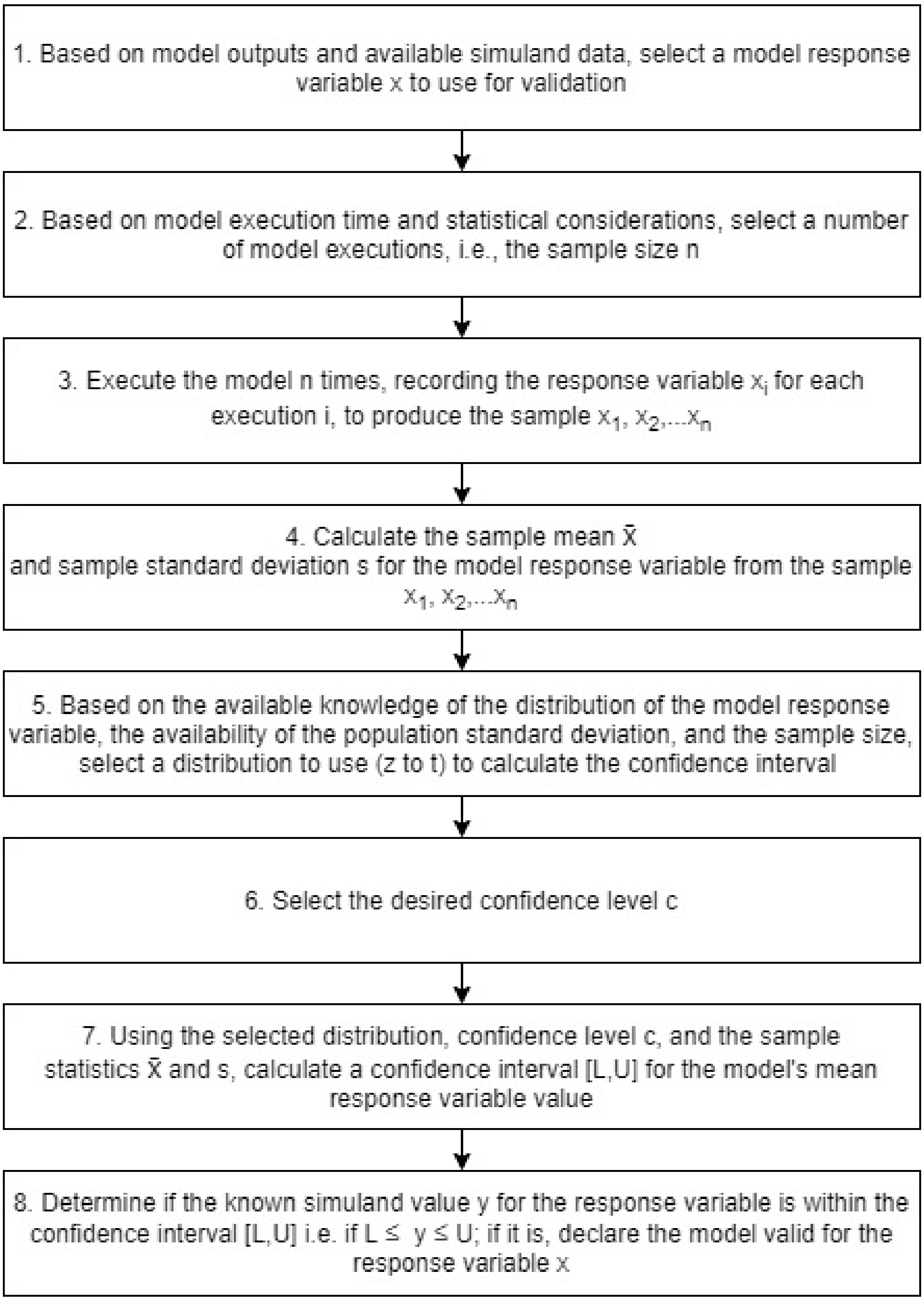


Figure 3.5: Steps for confidence interval validation method according to [56]

3.3.3 Sensitivity Analysis

According to [54], sensitivity analysis gives insight and answers to the following questions:

- For each output, in what order of importance do the parameters influence it?
- Are there parameters which affect the outputs so little that the model should be rewritten without them?
- How well can the combined effect of a collection of parameters be found by summing their individual effects?
- Conversely, what are the significant interactions between parameters in their effect on an

outcome?
- How closely is an output change proportional to the change in parameter value which causes it?
- More broadly, how does the effect of a given change in a parameter value vary with that value?

[54] defined four methods for the sensitivity analysis, listed from simplest to the most complex.
- One-at-a-time perturbations
- Algebraic 'no box' SA
- No-box SA of a dynamical model: influence equations
- Sampling based SA

For the one-at-a-time perturbations, the idea is to change one parameter at a time and see how much the output changes. For the algebraic 'no box' SA, the idea is that the model is not seen as a black box, but the equations and principles are known and can be analysed. The no-box SA of a dynamical model goes one step further, the model has a memory which depends on previous inputs. It is also likely that, in this case, the entire behaviour of the outputs as time goes on is of interest. The last method is sampling-based SA, here it is wanted to explore sensitivity over the whole range of credible model parameters with an acceptable computational load.

3.4 Conclusion

The simulation model that will be used to simulate the production flow, stops occurring, routine stops and maintenance moments will be a mix of a continuous and discrete time simulation. As the production flow is a continuous flow but the occurrence of stops are discrete events.

The predictive maintenance model will have a fault detection part, where it is found if faults and degradation occur, a prognosis part, predicting how much remaining useful life is left, and a decision making part. This model is based on a predictive maintenance strategy.

With the building of models, verification, validation and sensitivity analysis are important to conduct. With verification, it is checked if the model implementation generates outcomes that are as expected. Validation is to see if the output of the model is representative of the real-world system on which it is based. It is not always possible to validate a model, for example, if no real-life system or similar models are available. With sensitivity analysis, it can be analysed which input parameters have the biggest influence on the model and what their interactions might be.

4 Dairy cup line at FrieslandCampina

In chapter 2 information about the use of the OEE and active maintenance is provided. For this case study, the link between these two will be studied at FrieslandCampina Maasdam. The plant of FrieslandCampina Maasdam has 12 working production lines. One of the newest production lines is line 14, it was installed at the beginning of 2021. FrieslandCampina Maasdam has been encountering problems with the production line since the beginning. While most of the problems are now solved, the line still does not perform at the wanted standard. The plant is often overthrown by failures or breakdowns of the production line, as there is no indicator for this. The failures just happen.

FrieslandCampina Maasdam wants to improve the productivity of the production line. One way of doing this is for them to be able to 'see' failures and breakdowns coming. A good way of doing this is by using an active maintenance strategy. Implementing an active maintenance strategy, like predictive maintenance, can be costly and should have a good enough return in the increase in productivity. At FrieslandCampina Maasdam, the OEE is used to monitor the productivity of the production line. To be able to see how large the effect is on the OEE when using an active maintenance strategy to prevent failures and breakdowns from happening, the dairy cup line and the active maintenance strategies will be simulated. For the building of the models needed for the simulation, the following about the production line has to be known:

- The working of the production line
- Current situation of production line regarding OEE and performed maintenance
- Critical part in production line which can be improved with maintenance

In this chapter these points will be discussed. The result will be the build-up of the production line model which can be simulated.

4.1 Production line working

Production line 14 is what is called a Flex line. This means that the production line can be used to produce different types of products. The production line can produce cups of two base sizes, 112mm and 95mm. Cups of different heights are also possible. Different types of dairy products can be handled by the line, these products are porridge, yoghurt and quark. These products can either be plain or mixed with flavouring, like vanilla, or fruits. All cups are sealed, some with Polyethylene Terephthalate (PET) seals and some with aluminium seals. It is also possible to put lids on the cups, however, not all products are provided with a lid.

In figure 4.1 a flow diagram of the production line can be seen. The production line consists of 6 different machines. Within the filling machine, there are multiple sections, these sections all consist of different pieces of equipment and will be viewed as individual machines which all have a direct effect on the whole machine and production line.

In the figure, the filling machine is presented in blue. Inside the filling machine, the cups are transported by means of a chain with holes in it. The yellow blocks are external in-feeds, these are either pipelines or chutes going down into the machine. In red are the conveyors which are used to transport the trays. The green blocks are other machines. The tray folder provides the trays to the packer station. The palletizer stacks the trays on pallets. The pallet wrapper wraps the pallet in foil and sends it to the distribution centre, the pallet moves through a cooling tunnel to get there.

The filling machine, in blue, works in series. Meaning all the steps are done after one another. The trays are produced parallel to the flow of the dairy product. When there are no

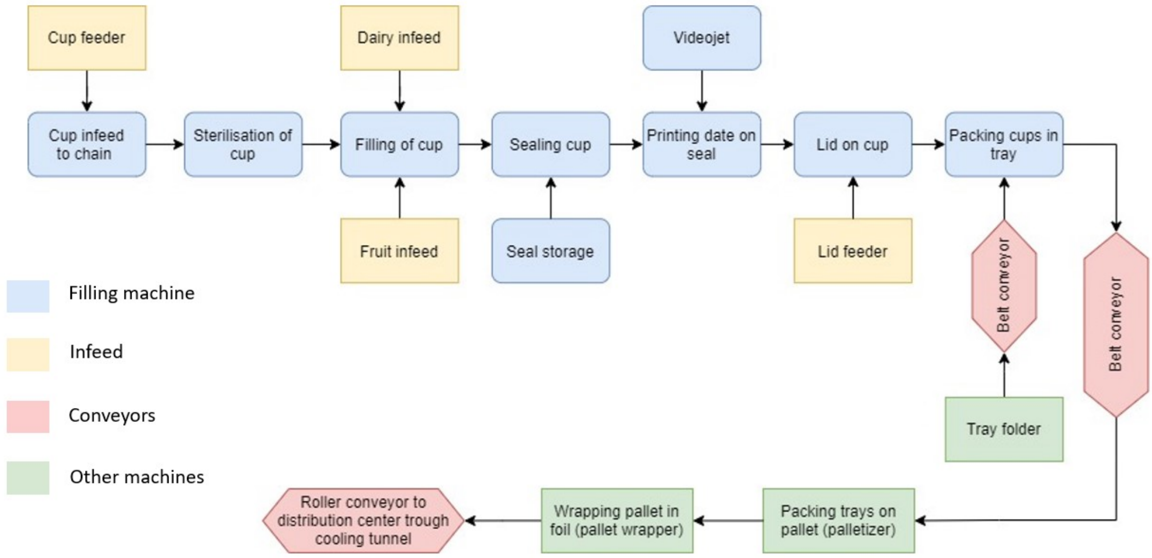


Figure 4.1: Flow diagram of production line 14 with different in- and out-feeds and components

trays at the packer station, the whole production line will stop, as the packer inside the filling machine cannot move the cups out of the chain. This means the chain will have to stop, stopping the whole filling machine. The other way around works a little different. If the filling machine has stopped, the tray folder will keep working until the conveyor is full.

The palletizer can operate on its own. If the filling machine has stopped but there are still trays left on the belt conveyor, it will finish stacking those until there are no more trays to stack. The pallet wrapper will also wrap as long as there is a pallet to wrap. If the palletizer or pallet wrapper malfunction and stop, the filling machine will continue to produce cups until the outfeed belt conveyor is full.

Filling machine

The filling machine is the most complex machine in the production line. The machine consists of different sections, which can all be viewed as different machines. These sections are all dependent on each other. Meaning, that if something goes wrong in one of the stations, the whole filling machine will stop. For example, if there are no seals extracted from the seal storage, the cups will not be sealed and this will give an error. The cups will not be moved forward and the whole machine will stop, meaning all the other stations will stop as well. This is due to the fact that the cups are transported through the filling machine by means of a board chain with cup holes in it, see figure 4.2, see number one for the holes. This means that if there is a stop at one section in the filling machine, the chain will stop moving, resulting in the whole filling machine stopping.

Figure 4.2: Chain with cup holes for transportation

Besides the named sections, the machine also has some general systems which work over the whole machine. In figure 4.3 the different sections and systems in the filling machine can be seen. These stations are:

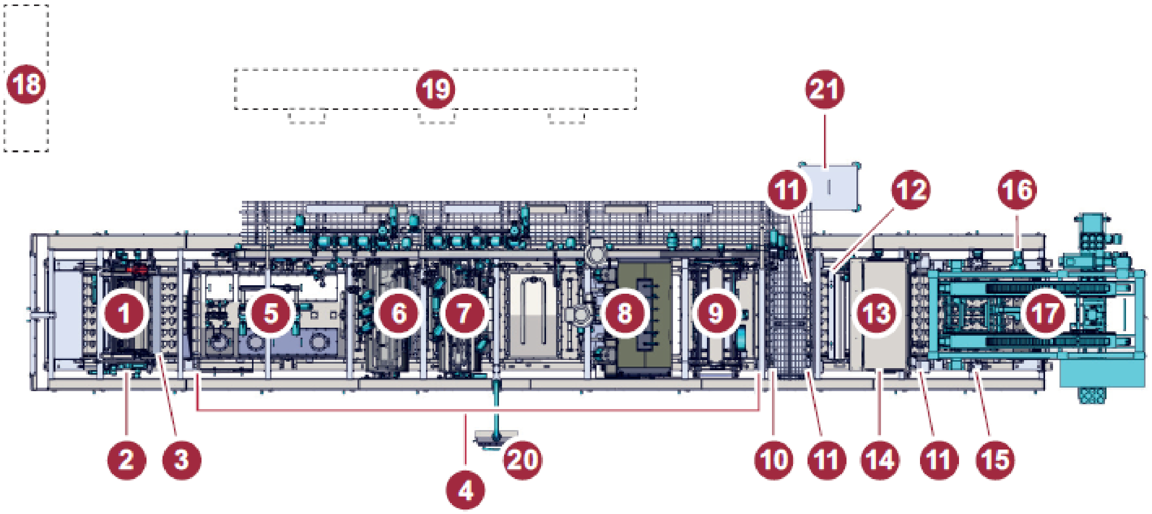


Figure 4.3: Filling machine

1. Cup feeder
2. Cup station
3. Cup check
4. Sterile tunnel
5. Cup sterilization station
6. Dosing station unit 1
7. Dosing station unit 2
8. Seal station - seal applier
9. Seal station - sealing unit
10. Leak detection station
11. Printing station
12. Re-aligning chain holes
13. Lid feeder
14. Lid station
15. Packer station - cup lifter
16. Drive unit
17. Packer station - out-feed conveyor
18. Sterile air unit
19. Control cabinet
20. Main control panel
21. CIP return tub

In 1. cup feeder, the cups are transported from the cup storage into the filling machine. In 2. cup station, the cups are extracted from the cup feeder by means of vacuum cups and placed in the chain. In 3. cup check, a check is done using light and pressure sensors to check if there is a cup in the chain. 4. is the sterile tunnel, this is the part of the machine where the product is in contact with the 'open air'. In 5. cup sterilisation station, the cups are sprayed with H2O2 to sterilise them. 6 and 7 are dosing units, here the product is dosed before filling. These units can work simultaneously but also separately, depending on the product. In 8. seal station - seal applier the seals are extracted from the seal storage and placed on the cups. In 9. seal station - sealing uni, the seals are 'melted' on top of the cups with hot sealing heads. In 10. leak detection station, the cups are checked on leaking seals. In 11. printing station, the best before data and other information is printed on the seals. In 12. the chain holes are realigned for the packer, this way the packer can lift 3 rows of cups. In 13. lid feeder, the lids are transported from the lid storage into the filling machine. In 14. lid station, the lids are placed on top of the cups, after which they go through the second printing station. In 15. packer station - cup lifter, the cups are lifted from the chain, this is done with 18 cups at the same time, and are placed into the 3 trays. 16. is the drive unit which drives the chain of the filling machine. In 17. packer station - out-feed conveyor, a small outfeed conveyor moves the trays to the out-feed conveyor which transports the trays to the palletizer. 18. the sterile air unit, provides sterile air to the cup sterilisation, seal sterilisation and to the whole machine during the sterilisation process. 19. is the control cabinet where the electronics and controls can be found. 20. is the main control panel where the operators can change settings, see warnings and stops, and operate the machine. The CIP (Cleaning in Place) return tub, 21., is where the CIP liquids are returned. In appendix C more in-depth information about the filling machine can be found.

4.2 Current situation

At FrieslandCampina the OEE is used as an indicator of productivity and where improvement areas can be found. Doing this is based on the general understanding of the OEE and how it can be used as an improvement tool. The current situation of how the OEE and maintenance are used in line 14 for improvements is discussed.

4.2.1 Line 14

The production line has been producing for the market since April 2021. The plant of Maasdam is normally closed for production during the weekend. However, with the many breakdowns and stops, the production line cannot always meet the demand within the time frame of Monday-Friday. The Overall Equipment Effectiveness is currently used to monitor the production line but also to indicate where improvement areas are. The OEE on average over the months October to February is 24%. In table 4.2 the OEE for these months can be found. Due to the many routine stops this production line has, the OEE target is not set to the world class standard but to 45%.

OEE

The OEE is currently used by the improvement team to see due to which value, availability rate, performance rate or quality rate, the OEE is below target. For all production lines, this is the availability rate. From here, they analyse the different stops contributing to the low availability rate. When the biggest losses have been found, they are tried to be solved. When this is due to stops happening very often due to breakdowns, the preventive maintenance plans will be reviewed. If the stops happen due to minor stoppages due to blockages or other short stops, improvements in the machine might be made to reduce these. If changeover stops contribute to a large part of the loss, there will be looked into how these could be reduced.

At this moment for Line 14, machine improvements to reduce minor stoppages have been carried out and are still being carried out. For example, there were problems with the placements of the lids, the cups could not be centred correctly under the lids, causing many minor stoppages. An improvement to the cup lifters was made to reduce these stops. In the palletizer sheets of paper have to be placed in between every layer of trays. The suction cups on the palletizer would be completely degraded every 2 weeks and could not pick up the paper sheets anymore. This caused stops due to not being able to stack the layer of trays onto the pallet. Adjusting the maintenance schedule for these cups reduced these stops significantly. Changeover, or routine stops as they are called in Maasdam, contribute to a reduction of 35% in the availability rate. To reduce this percentage Single Minute Exchange of Die is being implemented.

As can be seen, there are many different actions which can increase the OEE of the dairy production line. However, if the actions are for a reduction in minor stops or breakdowns, there is no clear methodology to follow. Simply by looking at what that problem might be different tactics are tried to reduce the stops from happening. Very often a corrective action is taken to reduce the stops but after a few weeks, it might occur again.

Maintenance

The maintenance strategy that was implemented until week 6 of 2022 was purely corrective. Breakdowns would happen unexpectedly and the technicians of the plant would have to repair the damage. With this came the fact that the technicians did not have a lot of knowledge about the production line, resulting in long standstills due to not knowing how to resolve the problem. Currently, preventive maintenance is executed on the filling machine of the production line.

Since week 7 in 2022 preventive maintenance is performed on the filling machine of the production line. The preventive actions are based on a list of tasks provided by the manufacturer of the filling machine. These actions are based on 4, 8, 12, 24 or 48 week cycles. This means that every 4 weeks the production line has to be stopped for 8 hours for preventive maintenance. A lot of the actions for the scheduled preventive maintenance are inspections that have to be done.

The preventive actions are divided into the different sections and systems of the filling machine. These are:

- Vacuum system
- Cup station
- Sterilisation system
- Filling station
- Seal station

- Leak detection station
- Print station
- Lid station
- Packer station
- Chain

However, since this type of maintenance has only started in February, all the data used is based on corrective maintenance. Also, preventive maintenance is only applied to the filling machine, as was discussed above, the production line consists of more machines. On those machines corrective maintenance is still applied.

4.3 Data Analysis

To gather a good insight into where the problems of the production line lie, a thorough analysis of the production line has to be made. To be able to make this analyis, a few steps have to be taken. In figure 4.4 these steps are depicted.

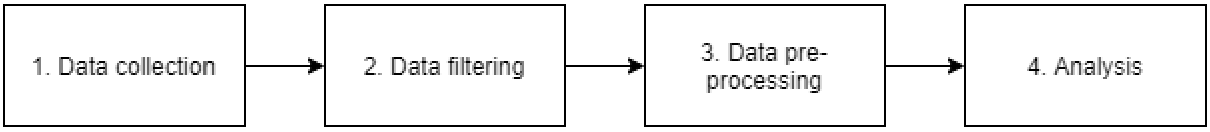


Figure 4.4: Steps in data analysis

For step 1, data is collected from the monitoring system Patch, here everything is stored and data can be extracted. Data from October ’21 until February ’22 was used for the analysis. The data included the following information:

	Information
Machine	Which machine
Machine group	Which machine cluster
Startingtime	Date + time of start of production run or stop
Endtime	Data + time of end of production run or stop
Duration	Duration of stop or production run
Units	Units produced per run
Code	Stop/production code group
Stop code explanation	Stop code explanation
OEE category	6 big losses
OEE subcategory	Further division in big losses
Operator note	Note added by operator on stop
Norm [units/h]	Set norm for production speed
Average production [units/h]	Average production speed per run
Order	Order number
Product	Product number
Product group	Product group
Product description	Product description
Number of units	Number of units produced
Scrap	Number of products scrapped
Original stop code	Original stop code
Shift	Monring, afternoon, night
Year	Year
Month	Month number
Week	Week number
Day	Number of the day into the year

Depending on the use of the data, the data was filtered into only the needed entries, this is step 2. Step 3 is data pre-processing. Here the filtered data is processed into usable data. This can be splitting a data entry into different categories or ordering the data. In step 4 the filtered and pre-processed data is used to make the needed analysis. In this chapter, this will be an analysis of the OEE and the failures that occur. In the following sections, it will first be explained how the data was filtered and processed and then how it was used for the analysis.

4.3.1 OEE

It was known that the data was needed for the calculation of the OEE of the production line. The OEE is calculated with the availability rate, performance rate and quality rate. In table 4.1 the first column shows what is actually needed to calculate these rates. In column two it can be seen in which data entry from the collected data is needed for the corresponding needed data. The third column shows what information is extracted from each entry after processing the data. With the processed data the OEE analysis can be made.

Table 4.1: Information needed for OEE calculation, collected data and data after processing

Needed for OEE	Collected Data	Processed Data
Operating time	Duration + code	Duration of production runs
Stop time	Duration + code	Duration of unplanned stops
Planned downtime	Duration + code	Duration of planned stops
Units produced	Units	Units produced per run
Ideal Cycle time	Norm	Norm set for speed [units\h]
Defective units produced	Scrap	Scrap units per run

The availability rate is calculated with the operating time and the planned operating time. The planned operating time is the total time minus the planned downtime, like planned maintenance or planned breaks. The performance rate is calculated with the parts produced, the ideal cycle time and the operating time. The quality rate is calculated with the units produced and the defective units produced. The Overall Equipment Effectiveness can then be calculated by multiplying the availability rate, performance rate and quality rate. In table 4.2 the availability rate, performance rate, quality rate and OEE can be seen for the production line and what the World Class standard is for these values.

In Appendix B the data used for the calculation of the availability rate, performance rate and quality rate can be found.

Table 4.2: OEE values for production line 14, October - February vs. World Class values

	Availability rate	Performance rate	Quality rate	OEE
Oct ’21	23.3%	95.94%	99.12%	22.15%
Nov ’21	22.6%	99.74%	99.05%	22.32%
Dec ’21	25.96%	99.22%	98.91%	25.12%
Jan ’22	24.7%	99.75%	99.16%	24.43%
Feb ’22	26.8%	96.43%	99.20%	25.63%
Average	**24.6%**	**98.22%**	**99.09%**	**23.94%**
World Class	90%	95%	99%	85%
Difference	- 65.4%	+ 3.22%	+ 0.09%	- 61.06%

From this table, it is very clear that the availability rate is way below the World Class standard. The performance rate and quality rate are actually both above the World Class standard, meaning that when the production line operates it does perform well and without many rejects. Because the availability is so low, the OEE, in the end, is also much below the World Class standard. It is very clear that the problem with the production line is with the availability. From the literature found and the conclusion drawn in chapter 2, an active maintenance strategy will have the biggest impact on the availability rate. An active maintenance strategy looks promising so far to improve the OEE.

Within the availability rate, there are different types of losses which contribute to the actual operating time. These losses are the breakdown losses, minor stoppages and setup and changeover losses. To get an understanding of how these losses proportionate to each other charts are made. In figure 4.5 the number of occurred losses for every category can be seen. In figure 4.6 the time spend (hour:min:sec) on the occurred losses for every category can be seen.

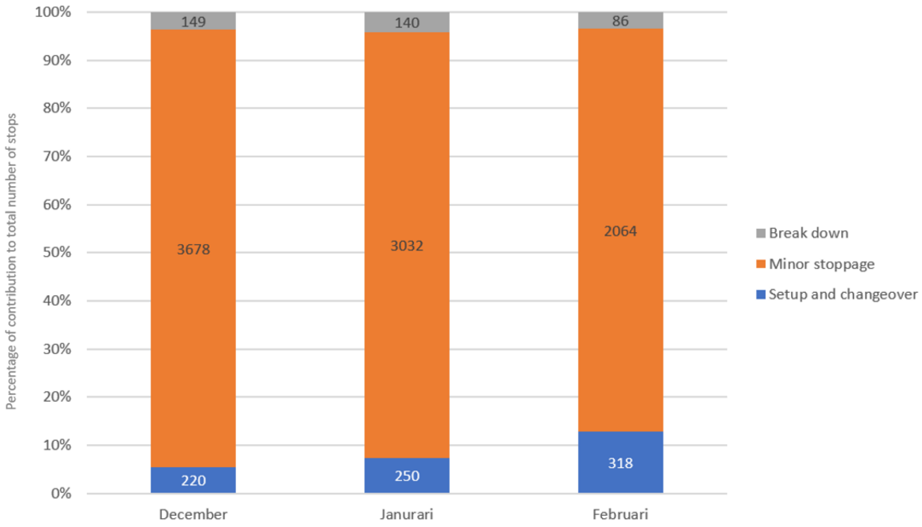


Figure 4.5: Stacked chart showing the number of occurred losses per category

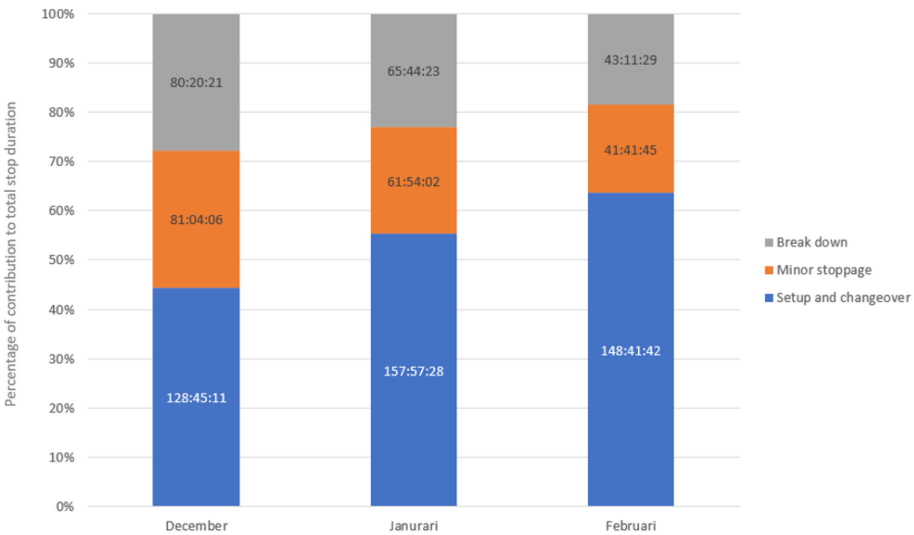


Figure 4.6: Stacked chart showing the time spend on the occurred losses per category

In figure 4.5 it can clearly be seen that the minor stops contribute the most to the number of stops. However, in figure 4.6 it is seen that between 15-25% of the time is spent on those losses. With the breakdown losses being the least number to contribute, the contribution in time is still between 20% and 28%. This shows that the time spend on a breakdown on average is much larger than that spent on a minor stop. The setup and changeover losses contribute to a large percentage of the availability rate losses in time, between 45% and 65%. However, these losses will not be reduced with the use of an active maintenance strategy, as they are not failures but losses due to the result of the many varieties of products and packaging.

Within these breakdowns and minor stops, an analysis of the cause can be made for further understanding of the losses and pointing to critical equipment or parts in the production line.

4.3.2 Failure analysis

To be able to find a piece of equipment which has the biggest impact on the production line's availability, an analysis of the breakdowns and the breakdown causes has to be made. The breakdowns have been monitored in the time span of October to February. All the figures created are based on this time frame. From the available data mentioned in section 4.3, the following information is needed for the failure analysis:

Table 4.3: Information needed for failure analysis, collected data and data after processing

Needed for failure analysis	Collected Data	Processed Data
Failures	Stop code explanation	Different failures
Stop time failure	Duration	Duration of failures
Failures per section	Stop code explanation	Stop codes per section divided

The processed data mentioned in table 4.3 will be different data entries for every section. In these entries the duration of every failure in that section is shown, in short this can look like the table below:

Cup Feeder

Failure code	**Duration [h:m:s]**
Cup Feeder not ready	0:40:21
Cup Feeder jam	0:32:19

Above two occurrences of failures for the cup feeder are shown. The occurred failures, the cup feeder not being ready and the cup feeder jam, are shown in the Failure code column. For both failures, the time spent on the failure is noted in the column duration.

The cause of the breakdowns was later determined by inspection, interviews with the operators and technicians or analysis of the generated data of the equipment. The breakdowns can happen in different sections of the production line, these sections have been divided into:

- Cup feeder
- Cup station
- H2O2 station
- Sealing station
- Leak detection station
- Printing station
- Lid feeder
- Lid station
- Packer station
- Chain
- Tray folder
- Tray conveyor
- Out-feed conveyor
- Palletizer
- Pallet wrapper
- Cooling tunnel
- Software
- External

By adding the duration of every failure in a section, the total failure time per section is calculated. By counting the number of failures that occurred in a section, the total number of failures per section is calculated.
In figure 4.7 the amount of breakdowns for every section can be seen. In figure 4.8 the time spend on breakdowns for every section can be seen.

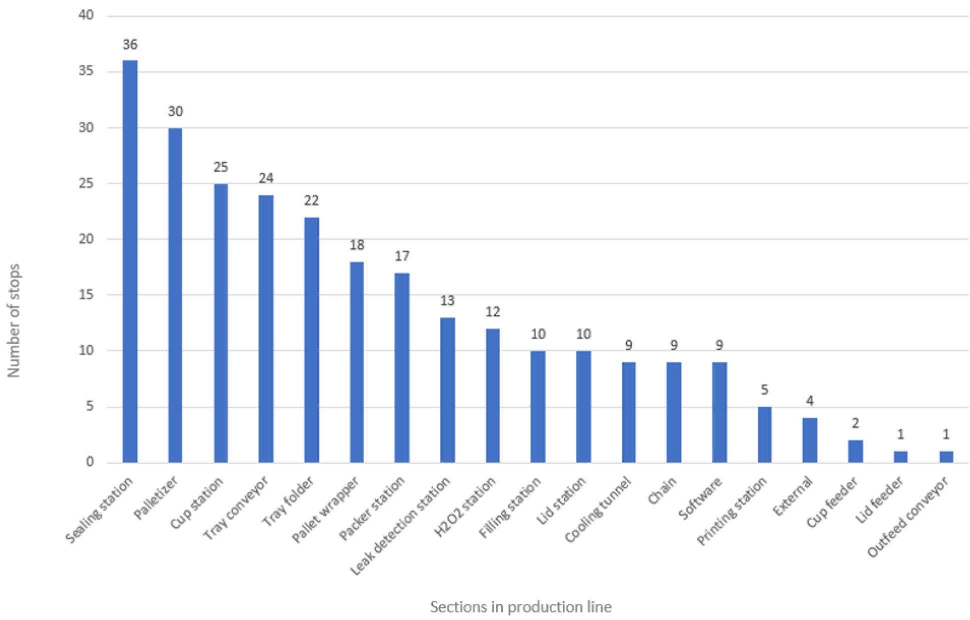


Figure 4.7: Total number of breakdowns in each section

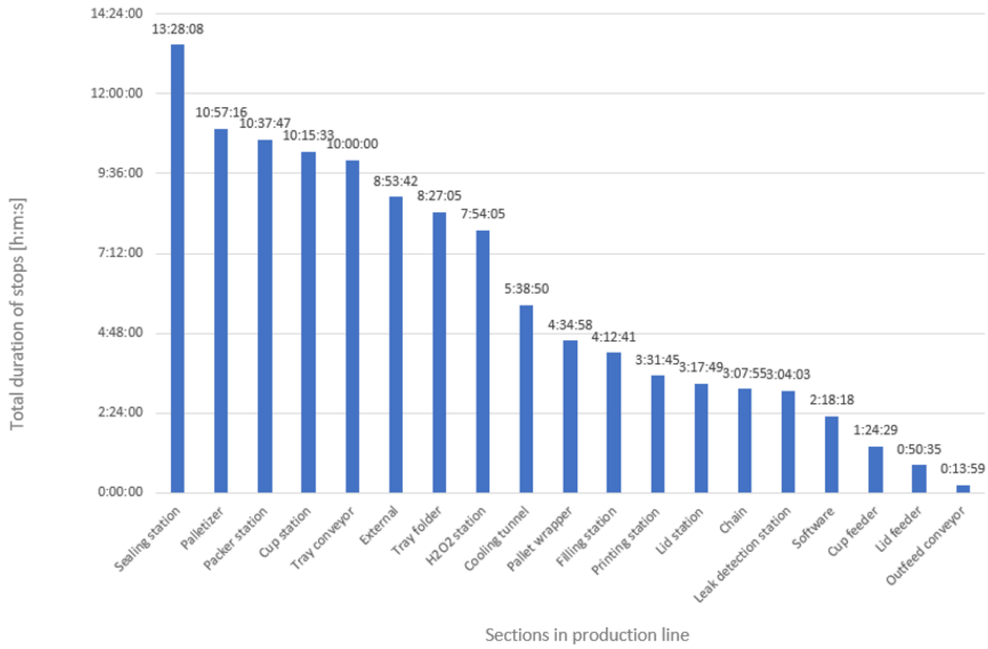


Figure 4.8: Total time spend on each section caused by breakdowns

It can be seen that the sealing station and the palletizer have the highest number of breakdowns and also the longest standstill time due to breakdowns. The breakdowns in the palletizer are very often due to mishandling and not due to broken or deteriorated parts.

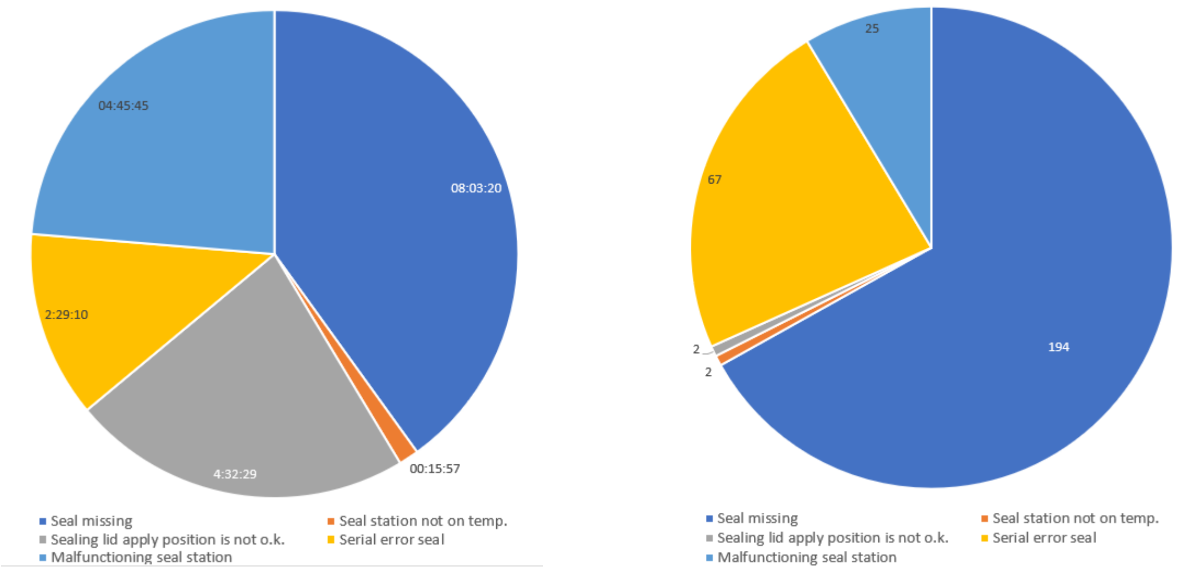
Seal section

The seal station is the biggest problem contributing to the breakdowns. There are several reasons for the seal station to stop. Within the seal section, different error messages occur that indicate breakdowns or minor stoppages. These can be generated due to different reasons. The error messages have the following meaning and possible causes, see table 4.4:

Table 4.4: Failures contributing to the seal station with the meaning and the possibles causes

Failure code	Meaning	Cause
Seal missing	Seal not detected on suction cup	- Seal jammed in storage - Not enough vacuum - Seal is broken
Sealing lid apply position not OK	Seal storage not in position	- Movement curve of storage is wrong - Storage does not move into position
Serial error seal station	On 3 consecutive cups no seal detected	- Not enough vacuum - Seal was misplaced on the cup - Seal is broken
Seal station not on temp.	Temperature seal sterilisation not OK	- Steam not in the correct temperature range of 120-130 - Condensejar clogged - Heating elements not working correctly
Malfunctioning seal station	Unplanned stops	- Repairing parts - Leaking seals - Cleaning sealing heads - All other reasons for stopping

In figure 4.9b the ratio between the different error messages can be seen in a number of messages and in figure 4.9a in time spend on the errors.



(a) Total time [h:m:s] spend on error messages per type of seal station error message

(b) Number of error messages per type of seal station error message

Figure 4.9: Error messages seal station

From these graphs, it becomes clear that the most time lost and the most frequently occurring failure is 'seals are missing'. From interviews with the maintenance department and the mechanics, it became clear that this was due to 3 out of the 6 suction cups being deteriorated. In figure 4.10 it is visible where one of the suction cups was torn, see inside blue circle. Due to

Figure 4.10: Suction cup with tear

this, air could enter the vacuum area and the amount of vacuum needed to extract a seal could not be reached. To check if this component is suitable for monitoring and predictive maintenance it had to be checked whether the stops are really due to deterioration and if maintenance actions make a difference in stop reduction. In figure 4.11 the number of stops due to seals missing and serial error seal are shown for 12 weeks.

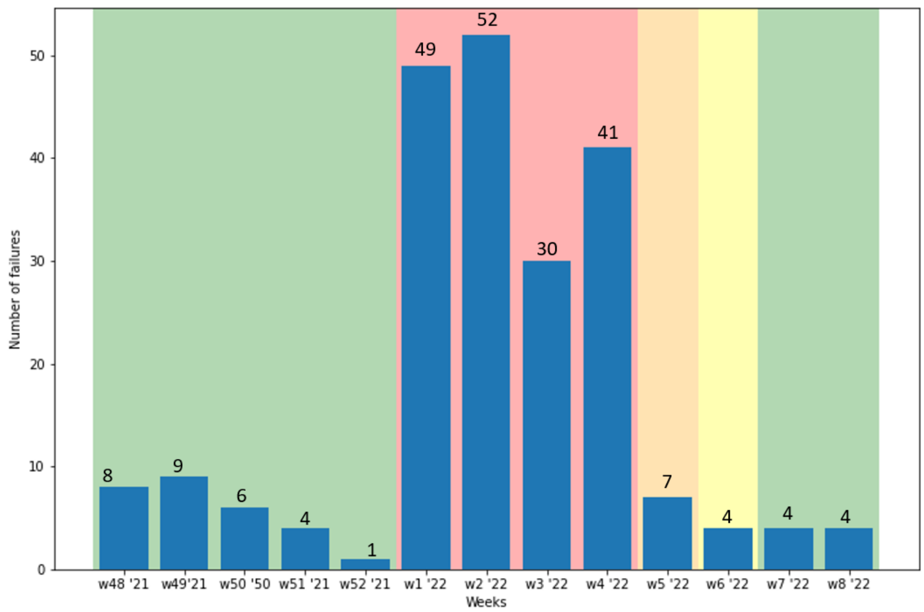


Figure 4.11: Development of number of failures due to seals missing due to deteriorated suction cups

Week 52 is visible in the figure but is not representative. This week was the week between Christmas and new year, the production line had less production time in this week. The green area is where there is no problem with the suction cups, they are not torn or deteriorated around the edges. The red area is when there was a tear forming in the suction cup, due to this it could not build up enough vacuum to extract the seal, resulting in seals missing. The orange area is when a 'quick' fix was put in place. The vacuum was set stronger, meaning that even with a torn suction cup enough suction could be built up to extract a seal. In week 6 maintenance was performed and the torn suction cup was replaced, and the vacuum setting was set back to normal. In weeks 7 and 8, after the maintenance actions were taken, the number of failures due to seals missing was back to before production with a broken seal. This concludes that maintenance actions are effective in the reduction of stops for this component of the production line, making it suitable for active maintenance.

4.3.3 Suction Cups

The suction cups mentioned in the section above cannot only be found in the seal section but also in the cup and lid section. From historic events and information gathered from the manufacturer of the filling machine, the inspection intervals and replacement intervals are gathered. By the manufacturer, these times are given in operating hours. The maintenance department has translated this to intervals in weeks based on the average hours the machine runs in one week. In table 4.5 these can be seen for the different sections with suction cups. The difference in replacement interval can be explained by the fact that the suction cups handle different types of materials which make them deteriorate faster or slower. The cups are either made out of PET or paper, the seals are made out of PET or aluminium and the lids are only made out of PET. However, not all cups require a lid, so the lid section is not always used, meaning the suction cups are not always used. The average of usage in a production week was used to determine the replacement interval.

Table 4.5: Inspection and replacement intervals determined by filling machine manufacturer for suction cups in cup, seal and lid section

	Inspection Interval	Replacement Interval
Cup Section	4 weeks	16 weeks
Seal Section	4 weeks	12 weeks
Lid Section	4 weeks	20 weeks

As discussed in chapter 2, now that the vital components to monitor are determined, the next steps are to determine the parameter which indicates deterioration. The suction cups are connected to three separate vacuum systems, see appendix C for more information on the vacuum system, The pumps in these systems always produce a vacuum of Xbar, due to confidentiality the real number cannot be used, instead, the setting for the vacuum pump used will be at -1bar. By the means of valves and tubes the vacuum is directed over the suction cups. From historic events regarding degradation, it was found that when the suction cups have tears or are deteriorated around the edges, the vacuum needed for operations cannot be achieved anymore, resulting in stops due to missing cups, seals or lids. The vacuum achieved, is also a fictive number due to confidentiality and will be used throughout the whole report, for every row of suction cups is analogy visible inside the machine in the corresponding sections. The vacuum updates every 0.5seconds to the at that moment achieved value. This will look something like the following:

0 sec	0 bar
0.5 sec	0 bar
1 sec	-0.72 bar
1.5 sec	-0.76 bar
2 sec	-0.75 bar

Meaning, at 0 and 0.5 seconds no vacuum is created, as no cup, seal or lid is placed upon the suction cups. At 1, 1.5 and 2 seconds vacuum is created, as there is a cup, seal or lid placed upon the suction cups.

If the suction cups have deteriorated around the edges or have tears in them, air can get into the space where vacuum should be created. If this happens, the values of the created vacuum will become closer to 0 bar.

Based on this information it was decided that the parameter to indicate degradation is the achieved vacuum of the suction cup rows. The threshold for this variable is determined from the minimal vacuum under which the suction cups can still operate. The desired achieved vacuum is -0.75bar, when the achieved vacuum reaches -0.65bar, there is not enough vacuum for cups, seals or lids to be extracted and the machine stops. This leads to the threshold for operation of -0.65bar.

To show where and how the suction cups are used for the extraction of the cups, seals and lids, the different sections where they occur are explained below. Due to confidentiality, the machines in these sections are not displayed in great detail.

Cup section

The filling machine starts with the cup section. In this section, the cups are placed from the cup storage into the chain which moves through the whole machine. With suction cups, the cups are retracted from the storage and placed into the chain. The chain has 6 cups in each row.

The level of the cups in the storage is checked, if this level is low a warning will be sent and if it is almost empty the machine will stop. The cup storage has to be filled by hand. When the cups are placed into the chain, a check is done to see if in all the cup holes are filled. If cups are missing the machine stops and cups can be placed in the holes by hand. If double cups are detected the machine stops and the extra cups have to be taken out. The cup station, see

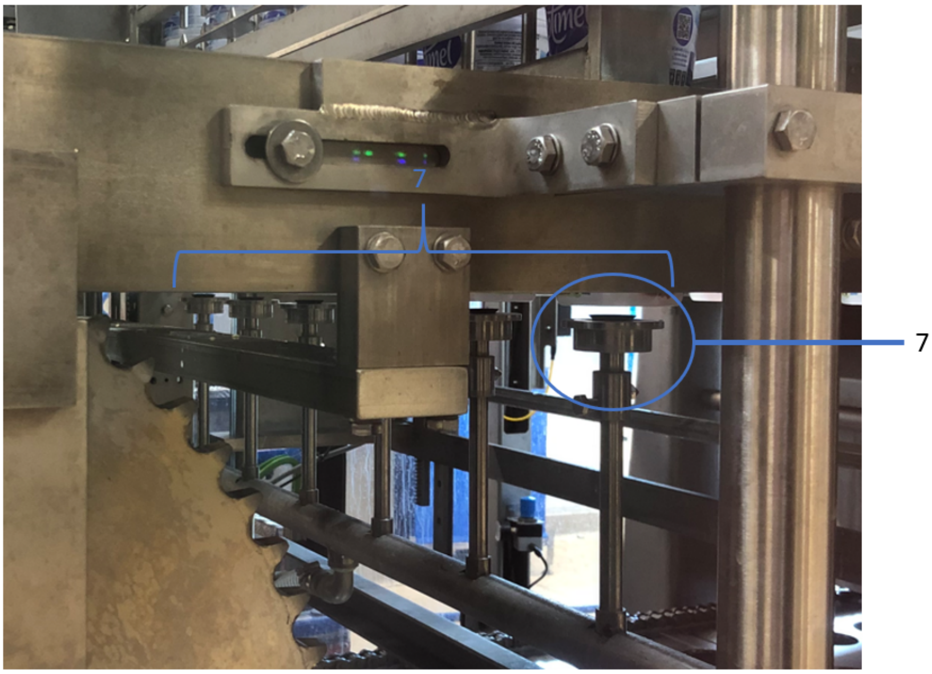


Figure 4.12: Cup station

figure 4.12 consists of the following parts:

1. Cup storage - 6 lanes
2. Light sensor - level of cups in cup storage
3. Servo motor - lifting movement forced unstacking
4. Servo motor - holding strips open/close
5. Cup break (pneumatic driven)
6. blocking and holding strips
7. Cup check
8. Suction Cups
9. Servo motor - forced unstacking open/close
10. Servo motor and adjustment belt - hight setting cup unstacker

In figure 4.12 number 8 shows the suction cups. As can be seen, the cups enter from above and the suction cups are pulled down. There are 6 stamps which have a suction cup, one for every cup in a row. These suction cups need to be able to create vacuum on plastic and paper cups. From here the cups move to the sterilisation and filling sections.

Seal section

After the cups are filled they will be sealed. The sealing can be done with an aluminium or a PET seal. The seals get extracted from the seal storage by suction cups on a rotatory arm. The seals get sprayed with H2O2 and dried with hot air. The arm rotates until the seals are placed above the cups and are placed on top of the cups. With heated sealing heads, the seals are melted on top of the cups. This station consists of the seal applier and the sealing unit.

In figure 4.13 the seal applier can be seen. Here the seals are extracted from the seal holder and placed on the cups. The seal applier consists of the following parts:

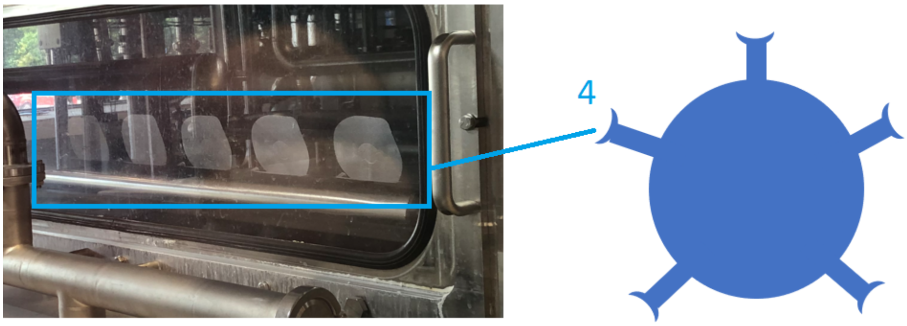


Figure 4.13: Seal applier in seal station

1. Servo drive with rack and pinion
2. Chutes for suction strips
3. Drum drive
4. Suction strips
5. Drums
6. Suction connection drum
7. Approach switch to detect drum position
8. Ejector
9. Suction cups

Part 4, the suction strips, are strips which contain 6 suction cups on them. In this section, there are 5 suction strips. The drum rotates the suction strips, this way the suction strips are placed below the seal holder and three beats later the suction strip is placed above a cup. As soon as the suction strip is placed under the seal holder and a seal touches the suction cups, vacuum is created. When the strip is placed above the cups, this vacuum is switched off and with the ejector the seal is placed on the cup. Next, the seal will be melted on top of the cup and the best before date and other information is printed on the seal.

Lid section

From the printing station, the cups are transported to the lid section. Not all products require lids. If they do not require a lid, this section is just passed through without anything happening to the cups. If lids are required the following steps happen in this section. The chain moves the cups over the cup lifters. The cup lifters are moved upwards by a servomotor, this way the cups are lifted slightly out of the holes. The lids are extracted from the lid storage by a row of suction cups. They take the lids and with a rotary movement of 180 degrees, the lids are placed on top of the cups. The lids are then pressed on the cups to snap on. The cup lifters lower the cups again into the holes. The cups now rest on the rims of the lids in the chain holes and are positioned slightly higher. This is also the test to see if the lid has been applied correctly. If the lid has not been applied (correctly), the cup will be positioned higher, leaving a small area underneath the cup. With a 'light curtain,' it is checked if a light is visible underneath the lid, if this is the case the lid is applied correctly. If there is no light visible, the lid has not been placed correctly, the machine will stop and give the error that a lid is missing. Double lids are detected the same way but with a light sensor above the chain. After the lids have been placed the cups are transported to another printing station which works the same way as explained above.

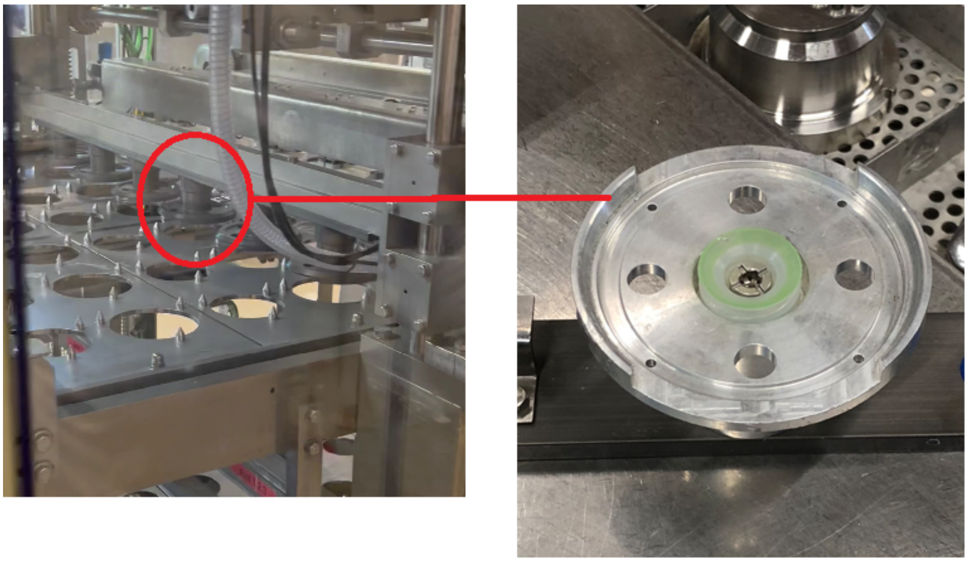


Figure 4.14: Lid applier in lid station

The lid applier, see figure 4.14, consists of the following parts:

1. Cam disk
2. Suction bridge
3. Suction cups
4. Guide roller
5. Gear wheel rotary direction
6. Servo drive suction bridge
7. Rack and pinion

In figure 4.14 the suction bridge can be seen on the left, the circled part is one of the suction cups. The suction bridge is an interchangeable part. For the 95mm cups and the 112mm cups, there is a different suction bridge with different size lid holders. This bridge has 6 suction cups attached, these suction cups create a vacuum on the lids and extract them from the lid holders. The bridge is rotated 180 degrees and press the lids on the cups. The vacuum is switched off and the lids as released.

The suction cups in all these three sections are difficult to reach for inspection. If an inspection has to take place the whole filling machine has to be shut down. Because the sterile tunnel is opened, see figure 4.3 number 4, the tunnel has to be sterilised again after the inspection has taken place. This whole process can take up to three hours. in figure 4.11 it can also be seen that the effect of the degradation can happen very abruptly. This can mean that even with inspection, no deterioration could be visible but in fact, there are already problems.

4.4 Conclusion

The dairy cup line at FrieslandCampina Maasdam has an OEE that is beneath the world standard determined by Nakajima. This is due to the large number of stops and time spent on those stops. One of the reasons for so many stops to happen is due to the fact that the maintenance strategy applied was corrective maintenance, if something breaks down, you fix it. When looking into the different sections of the production line and which causes the most stops and longest total duration in the analysed time frame, the seal section comes forward. After further analysis, it is found that the suction cups in this section are the part that causes the most problems due to not being maintained properly. These suction cups are also found in the cup section and lid section. The parameter defining the rate of deterioration for these suction cups is the vacuum achieved by them.

5 Dairy cup line simulation model

To be able to experiment with the different active maintenance strategies, a simulation model of the production line will be made. The simulation model of Line 14 will have to show the flow of the products through the production line. This included the stops that happen due to breakdowns, minor stoppages, routine stops and the planned maintenance. This chapter will give an understanding of the model of L14. The following will be discussed:

- General working of simulation model
- The output generated by the simulation model
- Mathematical expressions used for the simulation model
- Distributions used to simulate the stop occurrences and duration
- Verification, validation and sensitivity testing of model

5.1 Simulation Model Line 14

The filling machine is the main component in the production line. All sections in the filling machine are dependent on each other. If one section malfunctions and stops, the whole filling machine stops. This is due to the fact that the cups move trough the filling machine by means of chain with holes in it, as explained in section 4.1 in figure 4.2. If one section stops, the chain stops and all previous or next sections will not get new cups to process. This way all sections are dependent on each other in the filling machine.

It was found that the most critical component in the filling machine are the sections which work with suction cups. The suction cups being are sensitive to degradation and difficult to inspect. These suction cups occur in the filling machine in three sections, the cup section, seal section and lid section.

For the model some sections have been grouped, as the individual sections do not contribute any different as to when they are grouped in to one modelled component. The sections that will be modelled are:

1. Cup Feeder
2. Cup Section
3. Section 1
4. Seal Section
5. Section 2
6. Lid Section
7. Packer

In figure 5.1 it can be seen how different sections in the filling machine are grouped into one. The sections which are the same colour are grouped into one. For example, the H2O2 section and filling section, both orange, are grouped into section 1, also orange.

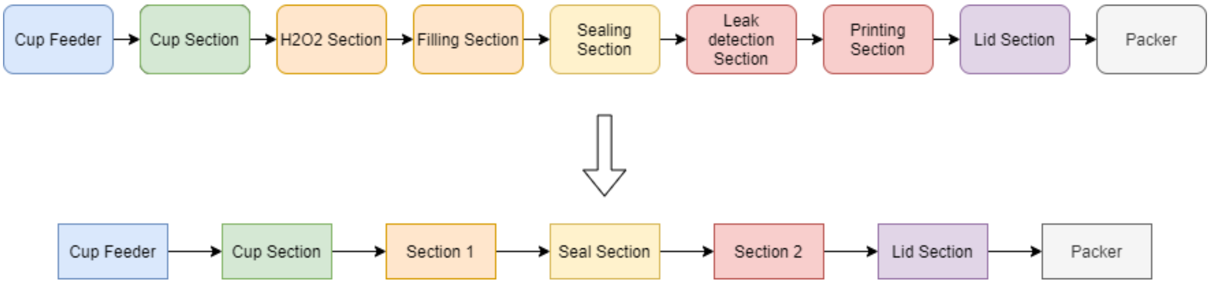


Figure 5.1: Sections in model L14

The model is based on the process a row of cups makes through the filling machine. One row is 6 cups in parallel, meaning that all six cups are processed simultaneously by one section. The row moves trough the filling machine and all the sections process the row in series. When the first row is processed by the cup feeder and moves to the cup section, the next row already enters the cup feeder. Every row in the chain is filled with cups when production is fully started. Every 2 seconds a row leaves the filling machine and a new row enters the filling machine. The whole process takes 16 seconds for one row. Every section has its own process time.

For the simulation model of dairy cup line 14 a mix of discrete and continuous simulation is used, see chapter 3 for information about these methods. The production of the rows is a continuous process, the state variable changes continuously with respect to time. The movement of the chain in which the cups are placed is a continuous movement, making sure there is always a row of cups at every section of the production line. The stops will be simulated as discrete events. Every stop is a change in the system and are discontinuous of each other. Every stop is a different event in the discrete system.

The simulation model works with orders per week. This means that a number of weeks the simulation needs to run can be decided. For every week, the production order expressed in number of rows is chosen. From the demand per week data it is visible that the minimum number of units that need to be produced in a week is 250 900 and the maximum is 307 700. This translates to a minimum of 41817 rows and a maximum of 51283 rows. In the simulation model an uniform distribution between this minimum and maximum is used to generate the demand for every week.

In figure 5.2 the total model of line 14 can be seen.

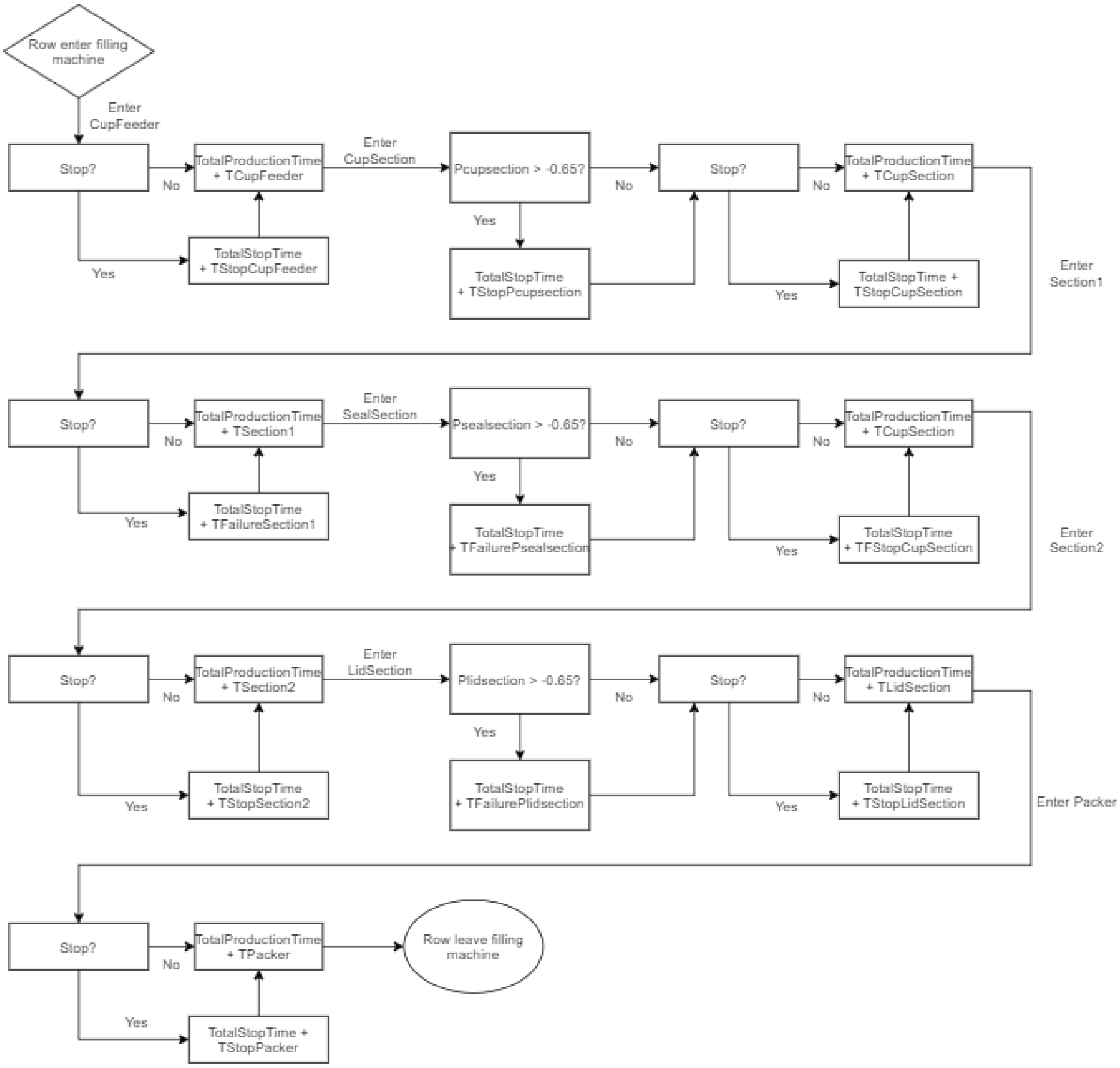


Figure 5.2: Line 14 model

This model follows the complete process a row goes trough in the filling machine, from the cup feeder until the packer. When the process is started, the row first enters the cup feeder. If no stops occurs at the cup feeder, the model will add the process time of that section to the total production time. If a failure occurs at the cup feeder the model will also add the stop time for that section, in that row, in that week, to the total stop time. How the times between stops and the stop times are distributed will be explained in section 5.1.4. There is a distinction between 'normal' sections and sections with the to be monitored parameters for the predictive maintenance model. All normal sections, cup feeder, section 1, section 2 and the packer, are modelled the same. In figure 5.3 it can be seen how a 'normal' section is modelled. In this figure it can be seen that when a row enters a section, it checks if there is a stop. If there is a stop, the stop time is added to the total stop time. Then the production continues, meaning the process time is added to the total production time. If there is no stop, the production continues as normal and the process time of that section is added to the total production time.

All sections with the parameter which needs to be monitored, the cup section, seal section and lid section, are modelled the same. These sections 'generate' the achieved vacuum for

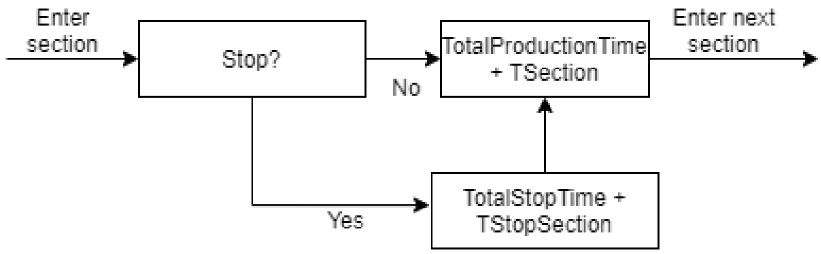


Figure 5.3: Modelling of the cup feeder, section 1, section 2 and packer

every row produced according to a determined change in achieved vacuum. If the vacuum in that section is higher than -0.65bar, a stop will be generated. If not, it checks if there is a stop due to other reasons in that section and continues the flow the same as the other sections. In figure 5.4 it can be seen how the sections with the pressure parameter is modelled.

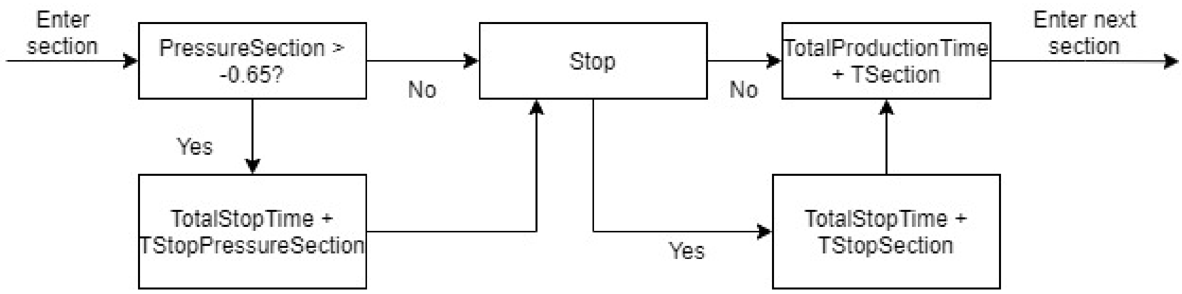


Figure 5.4: Modelling of the cup section, seal section and lid section

Besides stops in the filling machine due to breakdowns or minor stoppages there are also stops due to maintenance and routine stops. Routine stops are losses due to setup and changeover. These stops are performed every time an order is finished. There are five types of routine stops:

- 1x hot water flush
- 2x hot water flush
- 1x hot water flush with sterilisation
- 2x hot water flush with sterilisation
- Cleaning

The routine stops are modelled the following way, see figure 5.5. After a certain amount of rows, in section 5.1.4 it will be explained how this is determined, there will be a routine stop. In figure 5.5 when the production is started, for every row the check whether there is a routine stop is done. If the answer is no, the production continues. If the answer is yes, the production stops for the predetermined time, this time is then added to the total stop time.

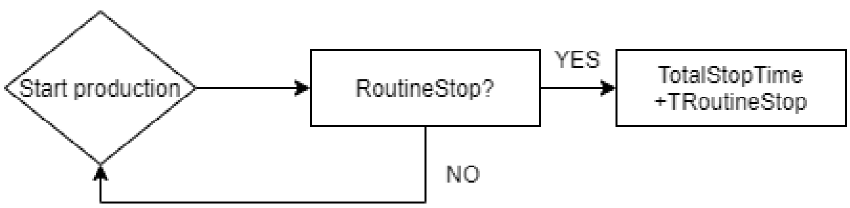


Figure 5.5: Modelling of routine stops

There are also other stops which have an influence on the production line. For the modelling, only the filling machine is modelled, the inflow of product or the out-feed conveyor, palletizer and cooling tunnel are not explicitly modelled, but of-course still contribute the the availability rate of the production line. To still have those parts have an accurate influence on the whole production line OtherStops will be modelled. This will work in exactly the same way as the modelling of the routine stops, if a stop in the production line happens that is not in the filling machine, that stop time will be added to the total stop time.

5.1.1 Maintenance

For predictive maintenance a separate model is build. For preventive maintenance this will not be necessary. The preventive maintenance actions are, as mentioned in chapter 4, planned every 4 weeks. In table 5.1, the planned maintenance moments for the suction cups can be seen.

Table 5.1: Replacement frequency and maintenance time per section

	Frequency	Maintenance time
Cup section	16, 32, 48 weeks	2 hours
Seal section	12, 24, 36, 48 weeks	2 hours
Lid section	20, 40 weeks	2 hours

Depending on which preventive actions need to be taken, the production line stops anywhere between 6 and 8 hours. In the weeks that the suction cups are prescribed to be changed, the maintenance actions can take more than 8 hours. This time is during the available production time, meaning that the time spend on maintenance will be time that cannot be spend on production. There are two ways to model the maintenance. The first is to adjust the order in a week where maintenance is performed. The number of rows which could be produced during the maintenance time will be deducted from the order of that week, this is how it works in practice. Another way is to model the production as a normal week, as explained above, and to deduct the maintenance time from the total production time of that week. The second options is not 100% accurate, as during the 'production' the model will also model failures, which could not have occurred if the production line stood still. Because of this the stop for maintenance will be modelled as the amount of rows produced less in that specific week. This is illustrated in figure 5.6.

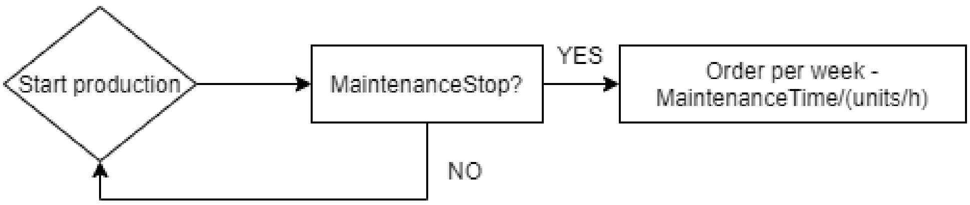


Figure 5.6: Modelling of maintenance stops

For the preventive maintenance actions for the suction cups the predetermined weeks will be used. After the replacement of the suction cups, the achieved vacuum will start from the base of -0.75bar again and slowly increase until the next maintenance moment. This will repeat for the duration of the simulation. The weeks before and after this, a buffer will be created to still meet the orders. In these weeks, more rows will be produced.

5.1.2 Output

In the end the output of the Line 14 model is the Availability rate. This rate can be determined for a momentum but also an average of a whole year. In figure 5.7 it is shown which inputs for the availability rate are needed. These inputs come from the other different modelled sections, routine stops and stops from other parts of the production line that have an influence or from things like utilities.

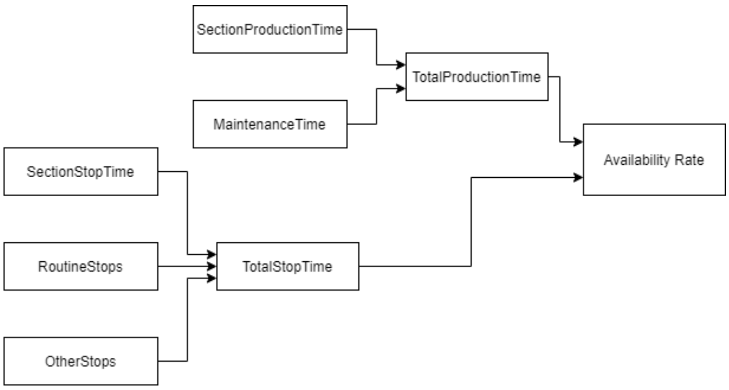


Figure 5.7: Modelling of availability rate

The simulation model that will have a few outputs which will be used as inputs in the predictive maintenance model as well. In figure 5.8 these outputs can be seen. In return, the predictive maintenance model will give a few inputs back into the line 14 model with which the availability rate can again be calculated.

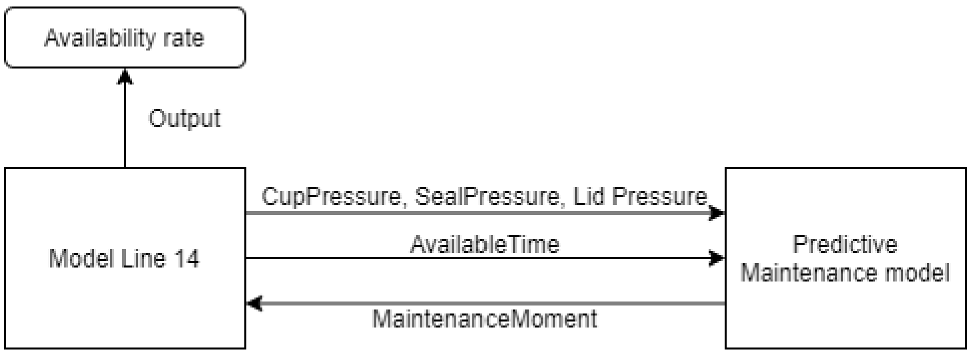


Figure 5.8: Interaction between Model Line 14 and Predictive Maintenance Model

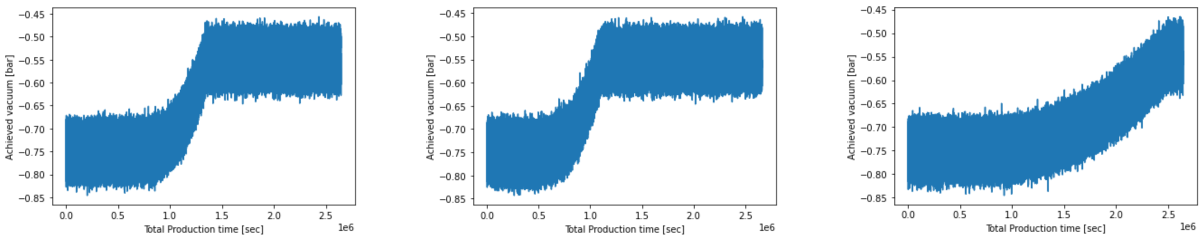
Model Line 14 will give as outputs the CupPressure, SealPressure, LidPressure, AvailableTime and the Availability rate. The CupPressure, SealPressure and LidPressure are used in the fault detection part of the predictive maintenance model. From historical data, talking to the manufacturer of the filling machine and talking to operators, the way the vacuum changes with time and degradation is reconstructed. It is known that the achieved vacuum has a standard deviation of 0.02bar and the desired value is at -0.75bar. In figure 5.9, the reconstructed change in achieved vacuum can be seen for the cup, seal and lid section, which will be similar for the cup and lid section. This reconstruction is made from linking the amount of stops due to deteriorated suctions cups at a specific moment in production time. If the stops are more frequent, the achieved vacuum is nearing the -0.65bar, the operational threshold. It was found that the deterioration makes for the change in achieved vacuum to follow a third order polynomial for the cup and seal section and for the lid section quadratic. The deterioration is only set in after a certain amount of production time. For a normal scenario for the seal section this is after 10 weeks, for the cup section after 12 weeks and for the lid section after 16 weeks. The following formulas for the deterioration have been drawn up according to this reconstruction.

$$deterioration_{cup} = 0.5 * 10^{-18} * x^3 - 0.75 \tag{5.1}$$

$$deterioration_{seal} = 0.6 * 10^{-18} * x^3 - 0.75 \tag{5.2}$$

$$deterioration_{lid} = 0.7 * 10^{-13} * x^2 - 0.75 \tag{5.3}$$

These formulas set in after the set number of weeks where deterioration has not yet set in, here the achieved vacuum is set at a constant of -0.75bar. To this complete reconstruction the noise of 0.2bar is added, the outcomes of this can be seen in figure 5.9.



(a) Reconstructed change in vacuum for cup station

(b) Reconstructed change in vacuum for seal station

(c) Reconstructed change in vacuum for lid station

Figure 5.9: Reconstructed change in achieved vacuum for the three sections

As mentioned, if the achieved vacuum is -0.65bar or higher, that section will stop and thus resulting in a production line stop. As mentioned, the values the achieved vacuum takes will thus not only be used as an input for the predictive maintenance model but also to generate stops in the simulation model.

The AvailableTime is used in the decision part of the predictive maintenance model. The predictive maintenance model, in the decision part, decides on when it is best to perform maintenance on which section of the machine. This moment is returned to Model Line 14, and will be integrated into the MaintenanceTime section. From here, the new availability rate will be calculated.

5.1.3 Mathematical model

As shown in chapter 3, a mathematical model will have to be made based on the system of interest. From the information gathered in chapter 4 and the above explained general working of the production line, the following mathematical model is set up.

To start with the different sets are defined. 5.4 is the set of the number of weeks the simulation will need to run for. 5.5 is the set of the number of rows that will be produced in a week k, this is based on the order. As mentioned, on average the orders are between 41817 and 51283 rows in a week. An uniform distribution will be used to simulate the order for every week. 5.6 is a set of the sections in the filling machine.

$$K : \text{number of weeks} \tag{5.4}$$

$$I_k : \text{number of rows in week k} \tag{5.5}$$

$$J : \text{number of sections} \tag{5.6}$$

The different parameters and variables are defined as follow:

Table 5.2: Parameters and variables for simulation model

pt_j	Time to process a row in section j
p_{kij}	Production in week k of i number of rows in section j
mr_k	Rows not produced due to maintenance in week k
b_k	Buffer rows produced before and after maintenance in week k
c bw_k	Weeks k in which buffer is created
m_k	Maintenance in week k
st	Setup Time after maintenance
PPT	Planned Process Time
TPT	Total Production Time
rst_{ki}	Time spend on routine stops in week k after i rows
rs_{ki}	Routine stop in week k after i rows
sr_{kij}	Stop in week k in row i in section j
ttr_{kij}	Time to restart in week k during row i for section j
TST	Total Stop Time

Parameter m_k,bw_k, rs_{ki} and sr_{kij} are binary. For m_k the parameter equals 1 if there is maintenance, this is every 4 weeks. The parameter equals 0 if there is no maintenance, this is in all the other weeks.

$$m_k : \begin{cases} 1 & : \quad \text{maintenance performed in week k,} \\ 0 & : \quad \text{no maintenance performed in week k} \end{cases} \tag{5.7}$$

For bw_k the parameter equals 1 if buffer has to be created in week k, and equals 0 if no buffer has to be created:

$$bw_k : \begin{cases} 1 & : \quad \text{Buffer created in week k,} \\ 0 & : \quad \text{no buffer created in week k} \end{cases} \tag{5.8}$$

For rs_{ki}, the parameter equals 1 if a routine stop occurs and equals 0 if no routine stop occurs:

$$rs_{ki} = \begin{cases} 1 & : \quad \text{routine stop in week k after i rows,} \\ 0 & : \quad \text{no routine stop in week k after i rows} \end{cases} \tag{5.9}$$

For sr_{kij}, the parameter equals 1 if a stop, due to failure or minor stoppage, occurs and equals 0 if no stop occurs:

$$sr_{kij} = \begin{cases} 1 & : \quad \text{in week k, row i has a stop in section j,} \\ 0 & : \quad \text{in week k, row i does not have a stop in section j} \end{cases} \tag{5.10}$$

With the above mentioned parameters the total Planned Process Time (PPT) can be calculated, which is needed as an input into the availability rate. The PPT is the time planned for production plus time planned for maintenance plus the setup time. With equation 5.11, the PPT can be calculated. The first part calculates the planned time for production. The production (p_{kij}) is multiplied by the process time (pt_j), this gives the time spend on production for a week k with i rows for a section j. By summing this over k, i and j, the total time spend on production is calculated. The second part of equation 5.11 calculates the planned time for maintenance. The binary parameter m_k is multiplied by the maintenance rows (mr_k), by doing this only the weeks in which maintenance is performed are left over with a value of the 'rows' spend on maintenance. The binary parameter bw_k is multiplied by the buffer rows (b_k), by doing this only the weeks in which buffer needs to be created are lef over with a value. This is added to the 'rows' spend on maintenance. This is then multiplied by the sum over j of the process time (pt_j), to give the actual time spend on maintenance for every week and the time spend on buffer production. This is summed over k, giving the total time spend on maintenance and the corresponding buffer production. With every maintenance moment a setup time (st) is also needed, as after every maintenance moment the machine needs to be cleaned again. The third part of the equation calculates the setup time. It multiplies the weeks in which maintenance is performed with the setup time, which is a constant, and sums this over k, giving the total setup time. In total this gives the following equation:

$$PPT = \sum_k \sum_i \sum_j (p_{kij} * pt_j) + \sum_k (m_k * mr_k + bw_k * b_k) * \sum_j pt_j + \sum_k (m_k * st) \tag{5.11}$$

To calculate the Total Production Time (TPT), equation 5.12 can be used. This is the same as the first section in equation 5.11, minus the second- tweaked part of the equation. Here the buffer is not added but subtracted from the rows for maintenance. This way when subtracting that part, the buffer rows are added to the production.

$$TPT = \sum_k \sum_i \sum_j (p_{kij} * pt_j) - \sum_k (m_k * mr_k - bw_k * b_k) * \sum_j pt_j \tag{5.12}$$

To calculate the availability rate the total stop time (TST) is also needed. Contributing to this is the stop time and routine stops. To then calculate the total stop time equation 5.13 can be used. The first part of the equation is for the stops due to failure or minor stoppages. The total time to restart (ttr_{kij}) is multiplied by the stop rows (sr_{kij}). This gives the time spend on a stop in a certain week k during production of a row i in a section j, so only when a stop occurs are the times given. Summing this over k, i and j gives the total time spend on these stops. The second part of the equation is for the routine stops. Here the routine stop time (rst_{ki}) is multiplied by the routine stops (rs_{ki}). The routine stops define in which week, after which row a routine stop occurs and the routine stop time defines how long this then takes. This results in the time spend on routine stops for certain weeks k after i rows. Summing this over k and i gives the total time spend on routine stops. Together these two parts give the Total Stop Time (TST).

$$TST = \sum_k \sum_i \sum_j (ttr_{kij} * sr_{kij}) + \sum_k \sum_i (rst_{ki} * rs_{ki}) \tag{5.13}$$

With the outcomes of equation 5.11, 5.12 and 5.13, the availability rate (AR) can be calculated with the use of equation 5.14.

$$AR = \frac{TPT}{PPT + TST} * 100\% \tag{5.14}$$

Besides the availability rate, the available time left for every week is also calculated. Equation 5.15 shows per week how much time is left over after production, stops and maintenance. Where the TotalShiftTime is the number of shifts times the duration of a shift. This equals 14 shift of 8 hours per week. For example, if in a week no maintenance is performed, small orders are produced, and relatively little time is spend on routine stops, the available time left that week will be more than in a week where maintenance is performed, the orders are larger and there are more routine stops.

$$AvailableTime_k = TotalShift_k - TST_k - PPT_k \tag{5.15}$$

5.1.4 Distributions

The parameters ProcessTime, TimeToRestart and StopRow have to be determined for every section separately. To do this an analysis of the historical stops has to be made. For every section in the production line the Mean Rows Between Stops (MRBS) and Mean Time To Restart (MTTR) are determined. The MRBS is the mean number of rows between stops, stops in this case is breakdowns and minorstoppages. The MRBS is determined for every section separately. The MTTR is the mean time determined from the stop of production until the first products are produced again. The MTTR is also determined for every section separately.

It was chosen to work with rows between stops and not time between stops because the production line works in means of units produced and not on a time basis.

The MRBS and the MTTR for the different sections is determined from the historical data over a period of 3 and a half months. During those three months, the number of breakdowns and minor stoppages was constant, with exception for degraded parts which were replaced during the three months.

In section 4.3 it is explained what types of data were available. This data was filtered and pre-processed before an analysis of the MRBS and MTTR could be made. In table 5.3 it can be seen what data was needed for the analysis, what data was available to do this and how it had to be pre-processed to get the correct data.

Table 5.3: Information needed for stops analysis, collected data and data after processing

Needed for stops analysis	Collected Data	Processed Data
Operating time	Duration + code	Duration of production runs per section
Stop time	Duration + code	Duration of unplanned stops per section
Units produced	Units	Units produced per run per section

With this processed data an analysis on how the stops behave per sections can be made. For this, the sections used for the model are the sections for the stops analysis. This means that the sections cup detection and cup filling will be viewed as one section, taking all their stops into account together, and the same for the leak detection and printing sections. With this data the Mean Rows Between stops, Number of stops, Mean Time To Restart, Minimal time spend on a stop and the maximum time spend on a stop can be determined. In table 5.4 this information can be seen.

Table 5.4: MRBS, Number of stops, MTTR, min time spent on stop and max time spent on stop for every simulated section

	Mean Rows Between Stops	Number of stops	Mean Time To Restart	Min time spent on stop	Max time spent on stop
Cup Feeder	5209	116	00:03:12	0:00:12	00:53:09
Cup Section	1757	429	00:02:03	00:00:16	4:35:59
Section 1	565	1072	00:02:07	00:00:06	3:25:00
Seal Section	1852	531	00:04:00	0:00:09	2:23:59
Section 2	973	621	00:01:56	0:00:05	2:00:14
Lid Section	3003	201	00:04:03	00:00:07	1:38:54
Packer	1795	360	00:06:44	00:00:05	6:32:04
Other Stops	82	7431	00:02:17	00:00:05	9:45:28

With the information in table 5.4 the inputs for the parameters of the simulation model can be generated. In table 5.5, the different parameters with the needed distribution input are given.

Table 5.5: Parameter input for simulation model

Parameter	**Distribution**	**Needed input**
pt_j	Constant	Production time
p_{kij}	Uniform	Order per week
mr_k	Uniform	Maintenance time
b_k	Uniform	Buffer needed
st	Constant	Setup time
sr_{kij}	Chance	Number of stop & total events
ttr_{kij}	Exponential	Lambda

The production time for every section can be found in table 5.6. The uniform distribution for order per weeks, is as said before, a distribution between 41817 and 51283 rows: [41817,51283]. Maintenance rows is the rows that could have been produced during maintenance, these will be subtracted from the actual production planned. mr_k is a uniform distribution between [5000, 6000] rows. b_k is a uniform distribution between [2500, 3000] rows.

With the number of stops, as can be found in table 5.4, the chance of a stop occurring in a section can be calculated. By calculating the chance of a stop happening in the total number of rows produced, the chance of a stop happening is found. This was done with equation 5.16, with total events being total rows produced + stops in that section. In table 5.6 the chance of a stop happening for all the sections is stated. sr_{kij} will be generated by the chance of either a 1 occurring, this is equal to a stop occurring, or a 0 occurring, this equals to no stop.

$$P(stop) = \frac{\#Stop}{TotalEvents} \tag{5.16}$$

For ttr_{kij} an exponential distribution is needed, this was determined from the historical data about the stops that occurred. In figure 5.10 the different duration's of stops for every section can be seen. From the historical data it became clear that the time to restart for every section is an exponential distribution.

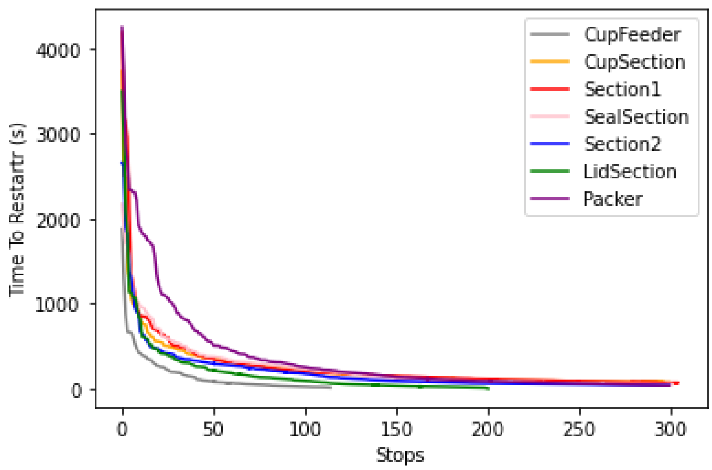


Figure 5.10: Duration's of stops for every section

To be able to generate stops for a longer period of time in the simulation, for example 1 year, new data will have to be generated. To do this, exponential variates will have to be generated.

To do this, equation 5.17 can be used. TTR (Time To Repair) is the generated exponential variate, U is an uniform distribution between 1 and 0 and lambda is the shape factor.

$$ttr = \frac{-ln(U)}{\lambda} \tag{5.17}$$

Lambda was determined from the distributions of the Time To Restart of the historical data. In table 5.6 these values can be seen for the different sections.

Table 5.6: Parameters for process time, lambda, chance of stop for different sections

	Process time [sec]	Lambda	Chance of stop
Cup Feeder	2	0.0052	0.000192
Cup Section	2	0.0081	0.000569
Section 1	4	0.0079	0.001771
Seal Section	2	0.0042	0.00054
Section 2	2	0.0086	0.001027
Lid Section	2	0.0041	0.000333
Packer	2	0.0025	0.00557
Other Stops	0	0.0073	0.0121

Routine stops

Routine stops are predetermined in duration. As mentioned there are different types of routine stops. In table 5.7 the different types of routine stops, how long they take and on average how often they occur in one week is shown. With this information the values for the RoutineStopTime and RoutineStop parameters can be determined.

Table 5.7: Routine stop duration and average occurrence per week

Routine stop type	Duration	Occurrence per week on average
1x flush	45 min	8x
2x flush	90 min	6x
2x flush + sterilisation	140 min	2x
Cleaning	240 min	2x

Depending on the size of the order in a certain week more or less routine stops will be planned. The cleaning and 2x flush + sterilisation always take place 2 times per week. The other flushes will depend on a busy or not so busy week.

5.2 Verification, Validation and Sensitivity testing

Once the simulation model is completely finished it is time to verify and validate the model. Verification is the process of evaluating the model to find out whether it meets the specified requirements or not [57]. So, does it generate a logical outcome or not. Validation is the process in which the model is evaluated to found out if the model meets the expectations and requirements [57]. So, does it generate the expected outcome. A sensitivity test will also be performed. This will show how the model reacts to disturbances and if this is within reasonable limits.

5.2.1 Verification

For the verification of the simulation model a few tests have been drawn up. If all these tests are passed the model is verified. In chapter 6 the idea behind verification and how to do it is explained. In table 5.8 the different tests, expected outcomes, actual outcomes and whether the test is passed or not can be seen. In the end, all the tests were passed.

Table 5.8: Verification tests and outcomes

	Expected Outcome	Model Outcome test 1	Model Outcome test 2	Passed?
Rows Between Stops x 100	Availability rate increases as less stops occur	34.12%	38.91%	Yes
Rows Between Stops /100	Availability rate decreases as more stops occur	1.07%	1.07%	Yes
Time To Restart x 100	Availability rate decrease as more time is spend on stops	0.69%	0.77%	Yes
Time To Restart /100	Availability rate increase as less time is spend on stops	37.70%	39.15%	Yes
Rows Between Routine Stop x100	Availability rate increases as less routine stops occur	40.45%	40.55%	Yes
Rows Between Routine Stop /100	Availability rate decreases as more routine stops occur	0.62%	0.62%	Yes
Duration of Routine Stop x100	Availability rate decreases as more time is spend on routine stops	0.62%	0.59%	Yes
Duration of Routine Stop /100	Availability rate increases as less time is spend on routine stops	40.01%	40.05%	Yes
No stops at all	Availability rate is 100%, as there is only production time	100%	100%	Yes
Always a stop	Availability rate is almost 0%, as production time is very small compared to stop time	0.04%	0.05%	Yes

As can be seen, all the test that were conducted to see if the implementation is correct are passed. This means that the working of the simulation model is verified and the model generates a logical outcome based on the inputs.

5.2.2 Validation

To validate the simulation model it has to be tested against the real line 14 to see if the generated outcome, the availability rate, is in line with the actual availability rate. The steps mentioned in chapter 3 have been followed and lead to the following:

1. Model response variable x:	availability rate
2. Sample size n:	11
3. Response variable x_i:	$x_1 = 25.9\%$, $x_2 = 23.9\%$, $x_3 = 25.1\%$, $x_4 = 23.8\%$, $x_5 = 24.4\%$, $x_6 = 24.6\%$, $x_7 = 24.6\%$, $x_8 = 25.7\%$, $x_9 = 25.4\%$, $x_{10} = 25.1\%$, $x_{11} = 25.3\%$
4. Sample mean x̄:	24.9%
5. Distribution for calculation:	$[\bar{x} - t_c\frac{s}{\sqrt{n}}, \bar{x} + t_c\frac{s}{\sqrt{n}}]$ $t_c = 2.228 \quad s = 0.69$
6. Confidence level c:	95%
7. Confidence interval [U,L]:	[24.4%, 25.4%]
8. Known simuland mean value y:	24.6%
9. Validated?	Yes

It was chosen to use a confidence level of 95% as this is most widely used [56]. The simuland mean value was determined from the data gathered from October 2021 until February 2022, as can be seen in chapter 4 table 4.2. Because this value is within the calculated confidence interval, the model can be regarded as a valid representation of the actual system.

5.2.3 Sensitivity analysis

Lastly a sensitivity analysis is performed. Sensitivity analysis investigates the relations between parameters and outputs of a simulation model [54]. In chapter 6 different methods for sensitivity analysis are briefly explained. For this analysis the *one-at-a-time perturbations* method is used. To make this analysis the parameters and values assessed can be seen in table 5.9.

Table 5.9: Parameters for sensitivity analysis

#	Parameter	Base case	Lower value	Higher value
1	Order size per week in rows	[41817 , 51283]	[20909 , 25642]	[83634 , 102566]
2	Time for maintenance	[6h , 7h]	[3h , 3.5h]	[12h , 14h]
3	Mean time to restart	see table 5.6	base case x 0.5	base case x 2
4	Chance of stop	see table 5.4	base case x 0.5	base case x 2
5	Simulation time	52 weeks	26 weeks	104 weeks

In figure 5.11, the results from these tests can be seen. Here the difference between the base value for the availability rate and the availability rate when the lower value or higher value is used for the different parameters can be seen.

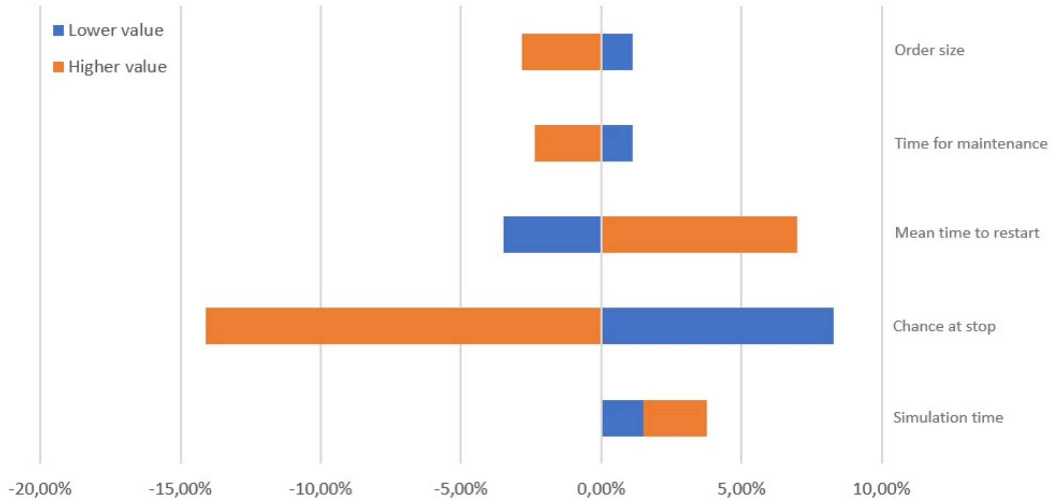


Figure 5.11: Results from sensitivity analysis on availability rate

The biggest differences can be seen in the the chance at a stop and the mean time to restart. These are both distributions related to the stops that occur at the production line. The chance at a stop indicates how often a stop occurs and the mean time to restart is how long the stop takes. The order size, time for maintenance and simulation time have far less effect on the availability rate when slightly changed. With the order size and simulation time the chance of a failure and the amount of products produced, or the production time, change pretty proportionally. The time for maintenance takes up on average roughly 2% of the time, when changing the time spend on maintenance it makes sense that it will change accordingly with the 2% time spend on the base value.

5.3 Conclusion

A simulation model is made of the whole production line, as all the sections contribute to stops occurring which effect the availability rate of the production line. The cup, seal and lid section are simulated in a way that not only the stops and production are simulated but also the achieved vacuum. This achieved vacuum can indicate if a stop happens but also if deterioration has set in and at what rate. This is one of the outputs the simulation model will give as an input to the predictive maintenance model. With the simulation model, the availability rate can be calculated but also the available time per week. This will also be an input for the predictive maintenance model. So, the simulation model of the production line will be able to calculate the availability rate and give different inputs needed for the predictive maintenance model. In return, it will receive the advised maintenance moment which will then influence the availability rate again.

6 Predictive maintenance modelling

The predictive maintenance model that will be used with the simulation model of dairy cup line 14 will have to use the available outputs for the decision making. For the different techniques found in literature for decision making in the different parts of a predictive maintenance strategy, techniques to be used in this model need to be chosen. There will also be an explanation of how it is modelled and the interaction between the different parts. This chapter will discuss the following:

- Modelling of predictive maintenance to implement on the build simulation model
  - Data acquisition and processing
  - Fault detection modelling
  - Prognosis modelling
  - Decision making
- Verification, validation and sensitivity testing of model

6.1 Modelling

A predictive maintenance model is made to implement on the simulation of line 14. As explained in chapter 3, the predictive maintenance model consists of a few parts, each needing their input. This model will have as input the vacuum in bar of the cup, seal and lid sections of the filling machine. This is the parameter which indicates the condition of the suction cups, with this parameter it can be checked if a fault occurred and what the RUL is of the suction cups for the different sections. The available time per week and when planned maintenance is performed will also be used as inputs for the model, this information can be used in the decision making step. This is visualised in figure 6.1.

In figure 6.1 the working of the model can be seen.

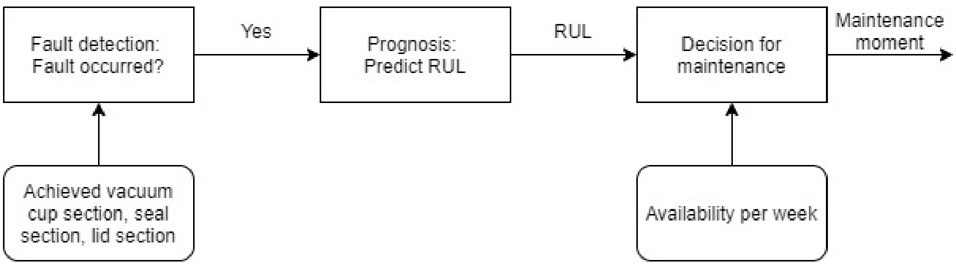


Figure 6.1: Interaction of different parts of maintenance model

In the sections below the modelling of the fault detection, prognosis and decision making is explained.

6.1.1 Data acquisition and processing

As input for the fault detection and prognosis condition monitoring data is needed. Because this model will be implemented on a simulation, the problem of sensor placement and data retrieval is not present. As mentioned in chapter 4 the vital components to be monitored are the suction cups that are present in the cup, seal and lid section. The parameter that indicates deterioration is the achieved vacuum. As shown in chapter 5, one of the outputs of the simulation is this achieved vacuum. The achieved vacuum is set at -0.75 bar with a standard deviation of 0.02 bar. This deviation is also simulated, resulting in output with noise.

This noise will sometimes lead to the case of the vacuum reached being close to the threshold for a stop of -0.65bar. To not mistake these outliers for degradation, it was decided to calculate the moving averages of the vacuum achieved. Moving averages is a calculation to analyse data points by creating a series of averages of different subsets of the full data set. With this, the trend can be determined of the achieved vacuum without the noise present. In figure 6.2 the simulated achieved vacuum, in blue, and the moving averages, in orange, can be seen. The data of the achieved vacuum is the vacuum per second of operations.

The moving averages were calculated using the following formula:

$$MA = \frac{1}{k} \sum_{i=n-k+1}^{n} p_i \tag{6.1}$$

Where k is the window size over which the average is taken, n is the size of the data set and p_i are the data points.

This moving average is then used for fault detection.

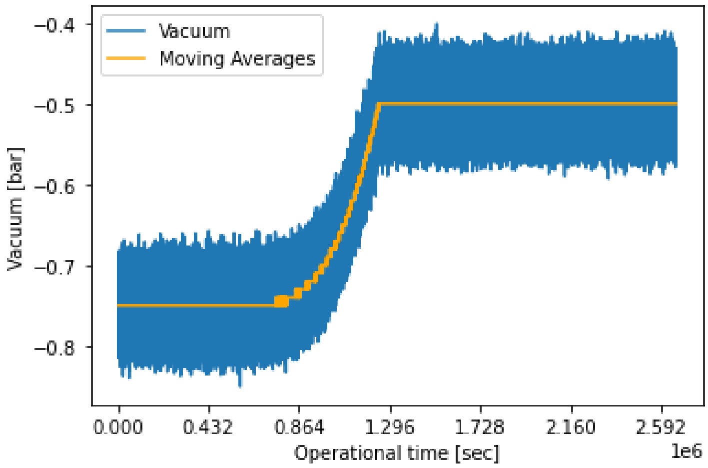


Figure 6.2: Achieved vacuum (blue) with moving averages (orange).

6.1.2 Fault detection

The chosen parameter has a steady value for the whole duration of production if no degradation occurs. This leads to easier fault detection. The change in vacuum achieved can be classified into different stages of degradation. In figure 6.3 the different stages of the effect of the deterioration on the achieved vacuum can be seen. The green stage is when the vacuum is at the desired value. The yellow stage is when the achieved vacuum starts changing and slowly increasing towards 0 bar, here operations can continue as normal and no effect will be noticed. In the orange state, above -0.7 bar, deterioration of the cups is leading to stops in the production line. The red area is when the vacuum is -0.65 bar or higher, here total degradation has occurred and operations are no longer possible with these suction cups.

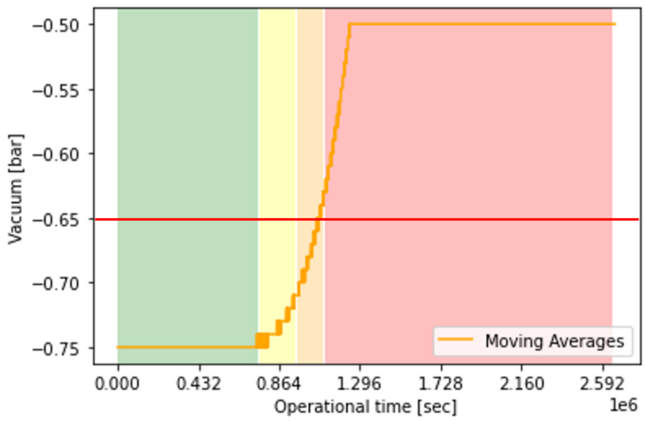


Figure 6.3: Stages of deterioration seen in the changes in the achieved vacuum.

It can be seen that expert knowledge is used to define how the achieved vacuum relates to the degradation of the suction cups. To model fault detection, a knowledge-based method is used, the rule-based approach.

The rules drawn up in this scenario are fairly simple rules, this is because the data input is also simple data and no other aspects, are taken into account at this moment. It was chosen to use the rule-based method as this is very suitable for the following cases [50]:

- Well understood, a stable and narrow problem area
- Human experts are available to develop the knowledge base
- Operating conditions are stable and predictable
- Simple precise queries to define potential faults is possible

All the above are true for this scenario, making rule-based reasoning suitable for fault detection. It was chosen not to use case-based reasoning as not sufficiently enough cases are known and building these cases would not add enough compared to drawing up rules for the rule-based reasoning.

To double check, if the achieved vacuum has started to deviate from the set -0.75 bar, the delta of the vacuum was computed. Calculating delta is normally done using equation 6.2.

$$Delta = \frac{y_2 - y_1}{x_2 - x_1} \tag{6.2}$$

Where y_1 and x_1 correspond to the data point closest to the origin and y_2 and x_2 furthest away. If delta is 0, no change in the values between y_1 and y_2 has occurred. If delta is not 0, it means there is a difference between the values of y_1 and y_2.

The calculation of delta, is done as follows:

$$Delta = \frac{1}{i}(MA_i - MA_0) \tag{6.3}$$

Where MA is moving averages. Equation 6.3 calculates the delta between every new point in the MA set and the first point in the MA set. This produces the delta between the first data point and every other data point, resulting in figure 6.4.

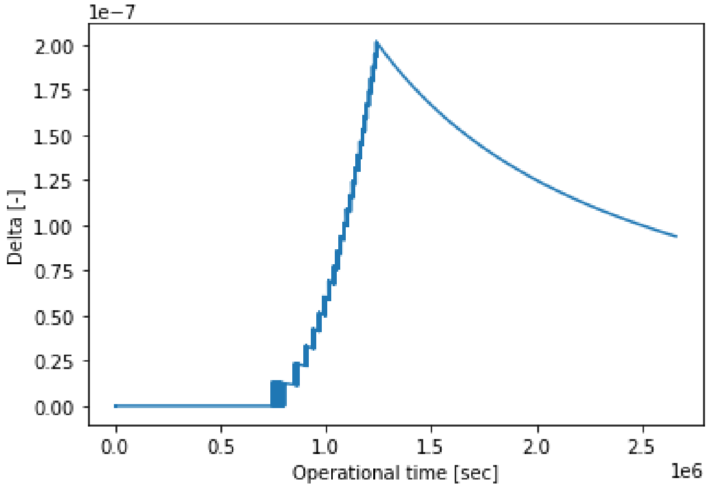


Figure 6.4: Computed delta of the moving averages of the achieved vacuum

As long as delta is 0, there is no change in the achieved vacuum, as soon as delta is no longer 0, there is a change in the achieved vacuum.

With this information, the rules are drawn up. The following symbols are used for these rules:

j:	Sections: cup section, seal section, lid section
k:	Weeks
$P_{k,j}$:	Vacuum achieved for section j in bar in week k
$ma_{k,j}$	Moving averages of achieved vacuum in bar for section j in week k
$Delta_{k,j}$:	Delta determined for the section j in week k

Mode	Rule	Meaning
Cup section	$P_{k,1} \geq -0.65$	Stop due to lack of vacuum in cup section
	$ma_{k,1} > -0.75$	Deterioration of suction cups in cup section started
	$Delta_{k,1} \neq 0$	Deterioration of suction cups in cup section started
Seal section	$P_{k,2} \geq -0.65$	Stop due to lack of vacuum in seal section
	$ma_{k,2} > -0.75$	Deterioration of suction cups in seal section started
	$Delta_{k,2} \neq 0$	Deterioration of suction cups in seal section started
Lid section	$P_{k,3} \geq -0.65$	Stop due to lack of vacuum in lid section
	$ma_{k,3} > -0.75$	Deterioration of suction cups in lid section started
	$Delta_{k,3} \neq 0$	Deterioration of suction cups in lid section started

If one of the rules is true, a fault is detected or deterioration has started. It can then be determined in which week this occurred and this information can be used for the prognosis and decision making.

6.1.3 Prognosis

For the prognosis process, data-based reasoning is used. The remaining useful life has an easy correlation with the vacuum achieved. With the prognosis the load is also taken into account, as this is the same for every row of production, the load does not make a difference in the prognosis of the RUL. This leaves the achieved vacuum parameter as an indicator for the remaining useful life.

Within the data-based reasoning, there are multiple methods, because this is a simple correlation between two variables it was chosen to use a regression analysis using Neural Networks. Neural Networks (NN) are Artificial Intelligence tools which can learn and generalise from examples and experience to produce meaningful solutions to problems [58]. NNs have an input layer, output layer and hidden layer [59]. According to [58] the functions of the input, hidden and output layer are as follow, the connection between these layers can be seen in figure 6.5.

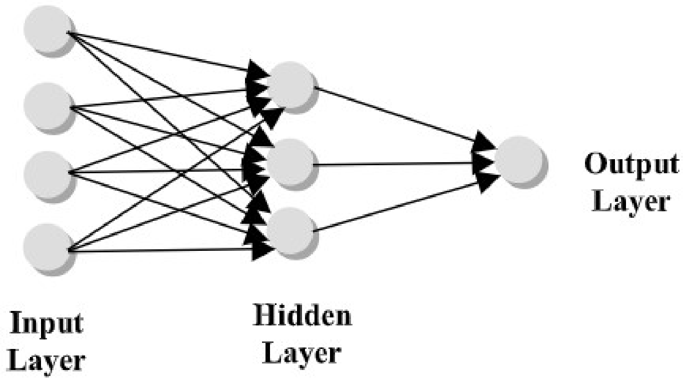


Figure 6.5: Nueral Network model [58]

The input layer is to receive input from the outside world. The output layer is to output the result of the NN prediction to the outside world. The hidden layer links the input layer to the output layer, its function is to extract and remember useful features and sub-features from the input patterns to predict the outcome of the network. The input data is broken down into different features.

The hidden layer consists of neurons that 'work' together to perform calculations and produce the output. Each neuron takes a set of input values, each is associated with a weight and a numerical value known as bias[60]. The output of each neuron is a function of the output of the weighted sum of each input plus the bias. The weight for each neuron is a numerical value that can be derived using either supervised or unsupervised training. The network chooses from the answer produced by the neuron based on the weight and bias [61].

Regression analysis is mainly used to determine the quantitative relationship between variables, which can be used to model the data relationship between different sampling points [59]. Since there is only one input, the achieved vacuum, and one output, the RUL, a very simple neural network was built using an available library to perform the regression analysis and give the corresponding prediction of the RUL with the given achieved vacuum as input.

The neural network needs to be trained to form the hidden layer, the data used for this is called training data. The training data does not need to be the same as the data input for the input layer but the same relations between the input and output layer need to be made. As training data, the achieved vacuum over 3 months is used with the corresponding RUL that was determined from the number of stops due to the deterioration. If the number of stops increases, the RUL decreases and this can be set out against the achieved vacuum at that moment. In figure **??** the determined RUL and the predicted RUL with the corresponding vacuum can be seen.

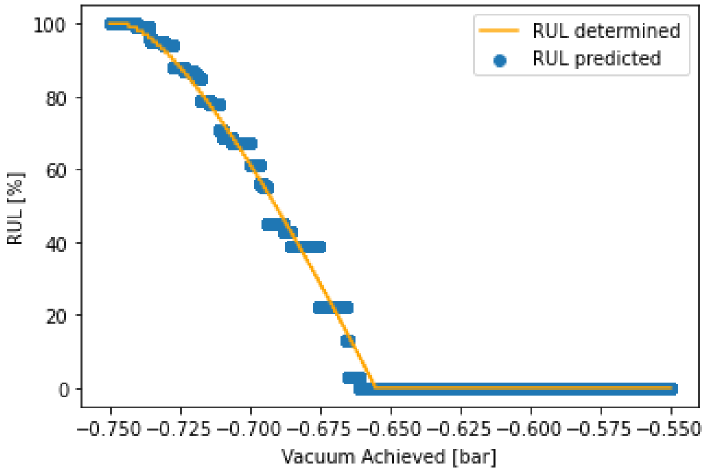


Figure 6.6: Determined and predicted RUL

In this figure, it can be seen that the overlap between the determined and the predicted RUL very good is. This indicates that the regression analysis with neural networks is sufficiently trained and that it can be used for the prognosis of the RUL. With the predicted RUL a maintenance decision can be made.

6.1.4 Maintenance Decision

For the decision making one of the 5 areas for decision making mentioned in section 3.2.4 is used. It was chosen to use maintenance planning and scheduling to decide whether and when maintenance should be performed. This is due to the fact that this area is based on recommending the most appropriate maintenance actions based on the company's policies. It was chosen not to minimise on the cost or other aspects as this is not within the scope of the project. In this project, the scope is to see the effect on the OEE or the availability rate. That would mean optimisation of the availability, which goes hand in hand with maximising the available time. To make this decision a few variables, parameters and optimisation equations are used. As input, the RUL, available time, planned maintenance moments and duration of maintenance actions are taken. The following maximisation equation and constraints are used to generate the advised maintenance moment for the different suction cups. The following indices are used:

k:	Weeks
i:	Rows
j:	Sections
l:	Maintenance time frame

The following parameters and variables are used:

$S_{k,j}$	Decision variable: stop in week k for section j
AT_k	time available in week k
$RUL_{k,i,j}$	Remaining useful life in week k during production of row i in section j
MT_j	Time spend on maintenance for section j
SW_k	Stop weeks k in which maintenance is performed
ST	Setup time for production after maintenance
TS_k	Total number of stops in week k

To determine in which time frame maintenance should be performed for which section the RUL is used. If the RUL for a section is lower than 60%, it is known that maintenance should be performed within the maintenance time frame l. The time frame l is the time between 60% and 40% RUL, this differs for every section.

Section j	**Maintenance time frame l**	**Time 100% to 60% RUL**
Cup section	$\pm$ 2 weeks	$\pm$ 3 weeks
Seal section	$\pm$ 2 weeks	$\pm$ 3 weeks
Lid section	$\pm$ 4 weeks	$\pm$ 4 weeks

The 40% was determined in such a way that a little buffer was still available in case the maintenance action has to be postponed due to unforeseen reasons. The maintenance action, in this case, will always be the replacement of the suction cups in the corresponding section. To determine when the maintenance time frame will start, the first week k in which the RUL is 60% or lower is determined. This can easily be determined as the RUL is expressed for every week, row and section.

The maximisation equation with which the available time is maximised is determined to be the following:

$$Max : \sum_k AT_k - \sum_k \sum_j (S_{k,j} * MT_j) - \sum_k (SW_k * ST) \tag{6.4}$$

The AT_k is determined as in equation 5.15 in section 5.1.3. $S_{k,j}$ is the decision variable which can either take 1 or 0 as a value:

$$S_{k,j} = \begin{cases} 1 & : \quad \text{Stop for maintenance of section j in week k,} \\ 0 & : \quad \text{no stop} \end{cases} \tag{6.5}$$

MT_j is the time it takes to replace the suction cups in one of the section (j) if this action is performed by one person.

Besides the maintenance time, there is also a setup time, ST, which plays a part. After maintenance is performed, the machine needs to be cleaned again. If multiple maintenance actions are performed in the same stop, the times for all these actions are added but there is only one time the setup time. If all the actions are performed at different times, every stop will have a separate ST. This could make it more favourable to perform maintenance at the same time, or as the advice would be, in the same week. This is defined by SW_k, the weeks in which a stop occurs due to maintenance, multiplied by the ST. This results in an array of k weeks long, with the setup time in the weeks where a stop occurs, when this is summed over k, the total setup time is calculated.

With the following constraints, the decision on when to stop can be made. This constraint says that for every section maintenance must be performed at least once in the maintenance time frame.

$$\sum_l S_{l,j} \geq 1 \tag{6.6}$$

For the stop weeks, SW_k, the sum of the stops in each week has to be taken:

$$TS_k = \sum_j S_{k,j} \tag{6.7}$$

And then the following will apply: If $TS_k \geq 1; SW_k = 1$.

This will give the weeks in which maintenance is performed, not taking into account the number of maintenance actions.

With these equations, the advised week in which to perform maintenance is determined for every section.

6.2 Verification, Validation and Sensitivity analysis

Verification, validation and sensitivity testing are also performed for the predictive maintenance model. In chapter 3 the reason for verifying, validating and analysing the sensitivity of the model is explained. In short, to make sure the model does as expected and generates a realistic outcome these tests have to be performed.

6.2.1 Verification

Verification is the process of checking if the model does as expected. Different tests can be set up to check this. Just like the simulation model, the predictive maintenance model will be verified dynamically, meaning that the model will be run to verify its working. The relation of the input-output of the model is assessed with these tests. So, if the input is changed in a certain way, what is expected to happen in the model and what is the expected corresponding output, this will then be tested and checked if the model generates this expected output. This is done to check if the model is error-free. These checks will be performed on the whole model, but the expected outcomes will not only be the final output of the model but also the outputs of the different parts of the model. All the tests are conducted with a simulation run time of 52 weeks. In table 6.1 the different tests conducted can be seen.

Table 6.1: Verification tests predictive maintenance model

	Test	Expected outcome	Model outcome	Passed?
1.	Vacuum cup section constant for 12 weeks	- Fault detection after 12 weeks - Advised maintenance moment after 12 weeks	- Week 15 - Week 20	YES YES
	Vacuum seal section constant for 8 weeks	- Fault detection after 8 weeks - Advised maintenance moment after 8 weeks	- Week 10 - Week 16	YES
	Vacuum lid section constant for 16 weeks	- Fault detection after 16 weeks - Advised maintenance moment after 16 weeks	- Week 19 - Week 24	YES
2.	Vacuum constant at -0.75bar for duration of 10 weeks for all sections	- Fault detection for all sections after 10 weeks - Advised maintenance moment for all sections after 10 weeks	- Week 12, 12 and 13 - Week 20, 20, 20	YES
3.	Vacuum constant at -0.75bar for duration of 52 weeks for all sections	- No fault detected for all sections - No advised maintenance moment	- No faults detected - No advised maintenance moment	YES
4.	Vacuum above -0.65bar at 0 weeks for all sections	- Fault detection at week 0 - Advised maintenance moment week 0	- Week 0, 0, 0 - Week 0, 0, 0	YES
5.	No available time for maintenance	- No advised maintenance moment found	No optimum found	YES

6.2.2 Validation

Validation is the check to see if the model represents the real-world problem sufficiently. To do this, data on the real-life system or similar models are checked against the build model [55]. However, these are both not options for the particular research into the predictive maintenance strategy applied to a dairy cup production line. This means that the complete model cannot be validated.

6.2.3 Sensitivity analysis

For the sensitivity analysis conducted on the predictive maintenance model, a few parameters have been chosen to change. As there are only two direct input parameters in the predictive maintenance model, the achieved vacuum and the availability, the parameters which can affect the availability will also be used. In table 6.2 these parameters can be seen and also how they have been adjusted.

Table 6.2: Parameters used in sensitivity analysis of predictive maintenance model

#	Parameter	Base case	Lower value	Higher value
1	Achieved vacuum cup section	constant 12 weeks	constant 10 weeks	constant 14 week
2	Achieved vacuum seal section	constant 10 weeks	constant 8 weeks	constant 12 weeks
3	Achieved vacuum lid section	constant 16 weeks	constant 14 weeks	constant 18 weeks
4	Maintenance time	2 hours	1 hour	4 hours
5	Available time	Simulation output	base x 0.5	base x 2

The results will be the output of the maintenance model: the advised maintenance moments.

Table 6.3: Results sensitivity analysis predictive maintenance model

#	Parameter	Base case	Lower value	Higher value
1	Achieved vacuum cup section	weeks 20, 40	weeks 16, 32, 48	weeks 20, 40
2	Achieved vacuum seal section	weeks 16, 32, 48	weeks 15, 30, 45	weeks 19, 38
3	Achieved vacuum lid section	weeks 24, 48	weeks 24, 48	weeks 28
4	Maintenance time	Cup section: weeks 20, 40 Seal section: weeks 16, 32, 44 Cup section: weeks 24, 48	Cup section: weeks 20, 40 Seal section: weeks 16, 32, 44 Cup section: weeks 24, 48	Cup section: weeks 20, 38 Seal section: weeks 16, 32, 44 Lid section: weeks 24, 50
5	Available time	Cup section: weeks 20, 40 Seal section: weeks 16, 32, 44 Lid section: weeks 24, 48	Cup section: weeks 20, 38 Seal section: weeks 16, 32, 44 Lid section: weeks 24, 50	Cup section: weeks 20, 40 Seal section: weeks 16, 32, 44 Lid section: weeks 24, 48

From the results of the sensitivity analysis, it can be seen that for the cup section there is a bigger influence from the lower value than from the higher value. This can be explained by the fact that when normal operations decrease in time, maintenance has to be performed sooner and in this case thus more often. For the higher value, the advised maintenance moments were at the start of the maintenance interval but were chosen as the optimum since they correspond to the already planned maintenance moments.

For the seal section, the effects of the lower value and higher value are roughly the same. However, for the higher value, only two maintenance moments are needed.

For the lid section, it can be seen that there is a larger time frame to conduct maintenance. With the lower value, the maintenance moments remain the same, with the higher value it is more suitable to pick a later moment, needing only one in the year.

The maintenance time only influences the advised maintenance moments with the higher value. This is because, with a longer time taken for maintenance, it might not fit in the available time to conduct the maintenance at the same time as the already planned maintenance. The lower value does not affect the advised maintenance value.

The available time only influences the outcome when it is halved. It does not influence all moments but only the weeks in which the available time is not enough to perform the maintenance together with the already planned maintenance. It is interesting to see that the same moments are advised as when doubling the maintenance time. When doubling the available time it does not change the optimisation and the maintenance can be performed in the same weeks as the base.

6.3 Conclusion

With the outputs generated by the simulation model, the achieved vacuum at the cup, seal and lid station and the availability per week, the predictive maintenance model can advise as to in which week to perform maintenance. With the achieved vacuum as input for the fault detection and the prognosis, it is decided when the threshold for normal operations is crossed and in which time frame maintenance should be performed. This output, the advised maintenance week, can then be used as an input for the simulation model. The simulation model calculates the availability rate based on the advised maintenance moment, thus including time spend on maintenance but also the change in achieved vacuum back to standard when maintenance is performed. This will give an output of the availability rate in a percentage, making it possible to quantify the effect the predictive maintenance strategy has on the availability rate.

7 Experiments and Results

With the simulation model and the predictive maintenance model, some experiments will be conducted. The simulation of dairy cup line 14 with the use of preventive or predictive maintenance, can show the availability rate for different scenarios. This will be done to see what the effect of implementing an active maintenance strategy is. In this chapter the following will be discussed:

- Experiments conducted
- Results of experiments
- Discussion of results and the meaning of them for FrieslandCampina Maasdam
- Limitations

7.1 Experimental setup

To be able to answer the question what the quantified effect of predictive maintenance on the availability rate and thus the OEE, a few experiments will be conducted. Firstly the base has to be set, this is an experiment without the use of predictive maintenance. This will give the availability rate for the situation as is for the production line, this is by using corrective maintenance. Experiments concerning the different sections and the effect of predictive maintenance when this is applied to them or not. Experiments regarding the deterioration time and time before deterioration is noticeable will also be conducted to see, if extreme cases occur, what will be the result in those cases.

For all experiments the following setup is used:

- **Total simulation time**: 52 weeks
- **Orders per week**: Uniform distribution [41817,51283]
- **Stops**: As mentioned in chapter 5
- **Number of runs**: 10

The stops occurrence and time distributions are as explained in chapter 5. This includes the stops for planned maintenance every four weeks and their reduction in rows produced per week and the extra buffer that needs to be created the week before and after maintenance. The order per week will be adjusted based on the maintenance moments of the different sections and their maintenance time.

The results gathered from the experiments will be:

- Availability rate of total simulation
- Maintenance moments determined by maintenance model per section

Experiment 1: Corrective maintenance

In the historic data used for the simulation model, the advised replacement moments are not used for the suction cups in the production line. Instead, when more stops occur due to the deterioration of the suction cups it is decided to replace them. This leads to fewer maintenance moments but more stops. To give a basis for how the maintenance was performed during the period of October '21 until February '22, this base experiment is conducted. Against this corrective strategy, preventive maintenance and predictive maintenance will be compared.

	Frequency	Duration
General maintenance	4 weeks	6-7 hours
Cup section	When effect is noticed in operations	2 hours
Seal section	When effect is noticed in operations	2 hours
Lid section	When effect is noticed in operations	2 hours
Setup time	Every maintenance moment	1 hour

Experiment 2: Comparison PM and PdM

To compare the difference between the two active maintenance strategies, PM and PdM, both strategies will be simulated.

Preventive maintenance is the newly applied maintenance strategy on the production line, but no information about how this strategy affects the OEE is gathered yet. To determine how the production line would perform with the prescribed replacement intervals from the manufacturer, the simulation is run with these given maintenance intervals.

The predictive maintenance model will be implemented on the model of dairy cup line 14. This will generate the advised maintenance moments based on the monitored value of the parameter achieved vacuum. For PdM, the simulation will be run with these given maintenance moments.

For both strategies, different scenarios will be simulated to see how the OEE is influenced. First, the duration of normal operations is used, meaning that deterioration sets in after 12, 10 and 16 weeks for the cup, seal and lid section respectfully. Next, the deterioration of the suction cups in all sections is simulated to start after 10, 20 and 30 weeks of operations. Lastly, the worst-case scenario is run, here deterioration sets in immediately after the replacement of the suction cups. The following setup is used:

	Duration normal operation
Cup, seal, lid section	12, 10 and 16 weeks
All sections	10 weeks
All sections	20 weeks
All sections	30 weeks
All sections	Immediate deterioration

For preventive maintenance the following frequency of maintenance and maintenance time is used:

	Normal operations	Frequency	Duration
General maintenance	-	4 weeks	6-7 hours
Cup section	12 weeks	16 weeks	2 hours
Seal section	10 weeks	12 weeks	2 hours
Lid section	16 weeks	20 weeks	2 hours
Setup time	-	Every maintenance moment	1 hour

For predictive maintenance the following frequency of maintenance and maintenance time is used:

	Normal operations	Frequency	Duration
General maintenance	-	4 weeks	6-7 hours
Cup section	12 weeks	Determined by maintenance model	2 hours
Seal section	10 weeks	Determined by maintenance model	2 hours
Lid section	16 weeks	Determined by maintenance model	2 hours
Setup time	-	Every maintenance moment	1 hour

Experiment 3: Section comparison

In the fourth experiment, predictive maintenance is only applied to the cup, seal or lid section. This will show the effect of the change in the type of maintenance for the different sections. This will also give an insight into if one or more sections are beneficial and where the biggest effect can be seen. For example, the seal section has a replacement interval of 12 weeks and the lid section only 20 weeks. The effect these maintenance actions have is different on the availability rate. Within this experiment the following three setups are used:

Experiment 3.1

	Frequency	Duration
General maintenance	4 weeks	6-7 hours
Cup section	Determined by maintenance model	2 hours
Seal section	12 weeks	2 hours
Lid section	20 weeks	2 hours
Setup time	Every maintenance moment	1 hour

Experiment 3.2

	Frequency	Duration
General maintenance	4 weeks	6-7 hours
Cup section	16 weeks	2 hours
Seal section	Determined by maintenance model	2 hours
Lid section	20 weeks	2 hours
Setup time	Every maintenance moment	1 hour

Experiment 3.3

	Frequency	Duration
General maintenance	4 weeks	6-7 hours
Cup section	16 weeks	2 hours
Seal section	12 weeks	2 hours
Lid section	Determined by maintenance model	2 hours
Setup time	Every maintenance moment	1 hour

7.2 Results

The results of the experiments are stated below. The graphs which represent the change in achieved vacuum corresponding to the different situations experimented with can be found in appendix D. All experiments have been run 10 times, from those the average availability rate and the standard deviation are calculated. It was chosen to run the experiments 10 times, this was due to the computational time. It was also found that the standard deviation did not change as much after 8 experiments as before, it converged to 0.56, see appendix D for the deviations of experiment 1. The advised maintenance moment did not differ for the different simulation runs. In appendix D the results from all the experiments can be found.

Experiment 1: Corrective maintenance

Table 7.1: Results Experiment 1: Corrective maintenance

	Result
Availability rate 52 weeks	24.80 % $\pm$ 0.59
Maintenance moment cup section	week 22, 44
Maintenance moment seal section	week 20, 40
Maintenance moment lid section	week 34

Experiment 2: Comparison PM and PdM

Table 7.2: Results experiment 2.1: Normal operations

	Results PdM	Result PM
Availability rate 52 weeks	28.65% $\pm$ 0.64	28.27 % $\pm$ 0.57
Maintenance moment cup section	week 20, 40	week 16, 32, 48
Maintenance moment seal section	week 16, 32, 48	week 12, 24, 36, 48
Maintenance moment lid section	week 24, 48	week 20, 40

Table 7.3: Experiment 2.2: Deterioration after 10 weeks

	Result PdM	Results PM
Availability rate 52 weeks	28.63 % $\pm$ 0.62	28.21% $\pm$ 0.54
Maintenance moment cup section	week 16, 32, 48	week 16, 32, 48
Maintenance moment seal section	week 16, 32, 48	week 12, 24, 36, 48
Maintenance moment lid section	week 20 , 40	week 20, 40

Table 7.4: Experiment 2.3: Deterioration after 20 weeks

	Result PdM	Results PM
Availability rate 52 weeks	28.68 % $\pm$ 0.63	28.24 $\pm$ 0.46
Maintenance moment cup section	week 26, 52	week 16, 32, 48
Maintenance moment seal section	week 26, 52	week 12, 24, 36, 48
Maintenance moment lid section	week 32	week 20, 40

Table 7.5: Experiment 2.4: Deterioration after 30 weeks

	Result PdM	Results PM
Availability rate 52 weeks	28.73% ± 0.22	28.23 ± 0.48
Maintenance moment cup section	week 36	week 16, 32, 48
Maintenance moment seal section	Week 36	week 12, 24, 36, 48
Maintenance moment lid section	Week 40	week 20, 40

Table 7.6: Experiment 2.5: Immediate deterioration

	Result PdM	Results PM
Availability rate 52 weeks	28.05% ± 0.49	2.61 ± 0.52
Maintenance moment cup section	week 7, 14, 21, 28, 35, 42, 49	week 16, 32, 48
Maintenance moment seal section	Week 7, 14, 21, 28, 35, 42, 49	week 12, 24, 36, 48
Maintenance moment lid section	Week 12, 24, 36, 48	week 20, 40

Experiment 3: Section comparison

Table 7.7: Experiment 3.1: PdM on cup section

	Result
Availability rate 52 weeks	28.37% ± 0.64
Maintenance moment cup section	Week 20, 40
Maintenance moment seal section	Week 12, 24, 36, 48
Maintenance moment lid section	Week 20, 40

Table 7.8: Experiment 3.2: PdM on seal section

	Result
Availability rate 52 weeks	28.29 % ± 0.64
Maintenance moment cup section	Week 16, 32, 48
Maintenance moment seal section	Week 16, 32, 48
Maintenance moment lid section	Week 20, 40

Table 7.9: Experiment 3.3: PdM on lid section

	Result
Availability rate 52 weeks	28.33% ± 0.63
Maintenance moment cup section	Week 16, 32, 48
Maintenance moment seal section	Week 12, 24, 36, 48
Maintenance moment lid section	Week 24, 48

7.3 Discussion

In the base situation determined the results presented in table 7.1 show an availability rate of 24.80% with a deviation of 0.19, this equals an OEE of 24.14%. The maintenance moments, in this case, are determined from the moment the achieved vacuum is substantially low and hindering production.

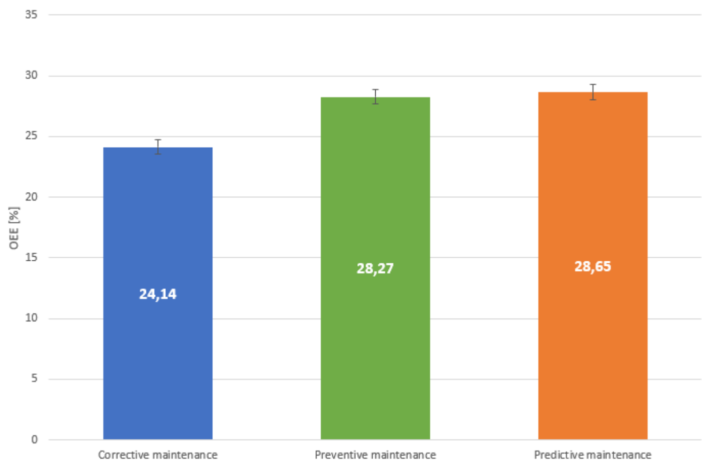


Figure 7.1: OEE for corrective, preventive and predictive maintenance

In figure 7.1 the OEE values for corrective, preventive and predictive maintenance for normal deterioration of the suction cups is shown. When comparing the results of corrective maintenance to the results of preventive maintenance it can be seen that the OEE increases. Even though with preventive maintenance there are more maintenance moments, 5 moments for corrective vs. 9 for preventive maintenance, the OEE increases. This is because fewer stops occur due to the suction cups that have deteriorated too far. If maintenance is only performed when the problems are noticeable, the problems will also affect the availability rate. And this is visible, with an average increase of 3.37% in OEE.

When comparing corrective maintenance and predictive maintenance, it can be seen that the OEE has increased on average by 3.74%. This increase is even though there are 2 more maintenance moments used. This means that with the implementation of predictive maintenance, maintenance is performed before the effect of the deterioration of the suction cups is noticeable in the availability of the production line.

Comparison of PdM and PM

In table 7.10 the results of the experiments conducted in experiment 2, the comparison of PM and PdM, are summarised.

Table 7.10: OEE result for comparison of PdM and PM with different deterioration rates

	Normal deterioration	**10 weeks**	**20 weeks**	**30 weeks**	**Worst case**
Preventive Maintenance	27.51%	27.46%	27.48%	27.48%	2.54%
Predictive Maintenance	27.88%	27.86%	27.91%	27.96%	27.30%

When comparing the results of PM and PdM for the normal deterioration, it can be seen that there is only a slight difference between the availability rates, on average only 0.68%, which means an increase of 0.37% in OEE. This could mean that the change in maintenance strategy has the biggest effect on the reduction in stops due to deteriorated cups and not so much on the reduction in maintenance moments. Preventive maintenance has 9 advised maintenance moments while predictive maintenance has 7, which is 2 less, which in total is 4 hours over the whole year. However, when using the advised moment for maintenance determined by the predictive maintenance model the most optimal moments are chosen.

With preventive maintenance, maintenance is still performed in periodic intervals, meaning that for example when the deterioration sets in after 20 weeks, the deterioration of the cup and seal suction cups only starts after the replacement moment. This results in replacing parts when nothing is wrong with them.

Experiment 2.3, see table 7.3 and table 7.10, shows that when deterioration sets in after 10 weeks for all sections there are 8 advised maintenance moments determined by predictive maintenance, resulting in an average availability rate of 28.84%, and OEE of 27.86%. With preventive maintenance the maintenance moments are always the same, resulting in an average availability rate of 28.31% and OEE of 27.48%. This difference is most likely because one more maintenance moment is used. The maintenance moments for the seal and lid section are determined to be the same with PdM and PM. This shows that when deterioration is set on earlier than usual, the advised moments are the same as the predetermined moments with PM, meaning that the predetermined moments might be too early.

Experiment 2.3, see table 7.4 and table 7.10, shows when deterioration sets in after 20 weeks for all sections. With PdM, there are in total 5 advised maintenance moments while with PM there are still 9 maintenance moments. This also shows in the availability rate of the two strategies. With PM there are 8 hours more time spend on maintenance. Because the replacements take place before the suction cups deteriorate, there won't be any stops due to the achieved vacuum being too high. With PdM, it is still possible that a few stops due to this occur.

Experiment 2.4, see table 7.5 and table 7.10, shows what happens when deterioration sets in after 30 weeks for all sections. With PdM, this results in only one advised maintenance moment for every section, while PM still has all 9 maintenance moments. Just like with experiment 2.3, replacements will be made before deterioration has set in with preventive maintenance. With 12 hours less spent on maintenance when using PdM there is a small difference in the availability rate and OEE.

It can be seen that the differences between the OEE with PdM and PM are very small in experiments 2.1, 2.2, 2.3 and 2.4, not even a 0.5% increase. This can be because the time spent on the maintenance actions is very small. Within one year spending on average 112 hours on maintenance, the change from 112 to 100 will not be very big on the bigger picture including the other stop occurring. This difference between the OEE when using PM or PdM is very small and it can be argued that it is insignificant. By using a t-test, it is determined if this difference is statistically significant or not. To also illustrate the difference between the obtained results of PM and PdM, figure 7.2 was made. Here the average OEE with the corresponding 95% confidence interval is shown for the different scenarios.

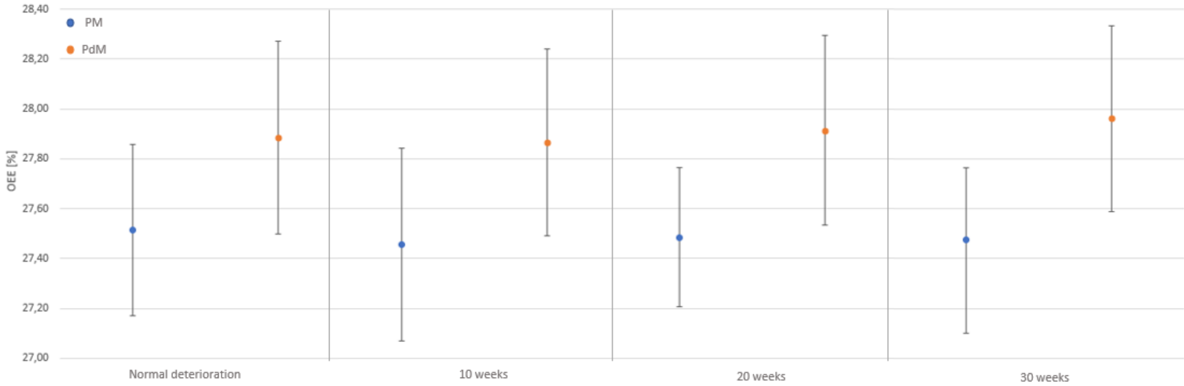


Figure 7.2: Average OEE with the 95% confidence interval for the different scenarios

Here it can be seen that the confidence intervals overlap. For the normal deterioration and the 10 weeks, the averages even lie within the interval of the other strategy. This would mean that the resulted averages of the one strategy could also occur in the interval of the other strategy. This would lead to believe that the difference is not significant, with the t-test this can be validated.

With the t-test, the determined t value is compared to the t value corresponding to a 95% interval in the t-table. If the found t value is equal to or smaller than the value found in the table corresponding to the 95% value, or alpha of 0.05, the difference is insignificant. In appendix D the t-table can be found. For the t-test, the following is needed [62]:

n_1	Number of samples sample 1
n_2	Number of samples sample 2
s_1	Standard deviation sample 1
s_2	Standard deviation sample 2
$\bar{x}_1$	Mean of sample 1
$\bar{x}_2$	Mean of sample 2

t is calculated using formula 7.1.

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{(\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2})}} \tag{7.1}$$

Where s_p^2 is calculated using formula 7.2.

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} \tag{7.2}$$

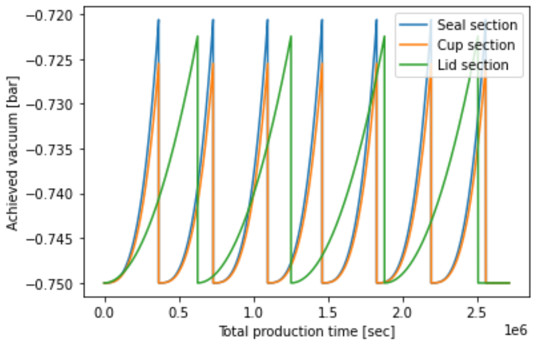
This results in the following values for t for the different scenarios and the differences between the PM and PdM OEE:

	Normal deterioration	10 weeks	20 weeks	30 weeks
t	1.402	1.491	1.784	1.394

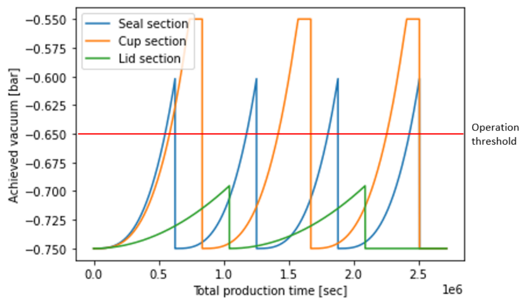
The value corresponding to 18 degrees of freedom, $n_1 + n_2 - 2$, for the 95% confidence interval is 1.734. This shows that for the normal, 10 weeks and 30 weeks the difference is insignificant. For the 20 weeks, the difference is statistically seen as significant, but for the company, a difference of 0.49% is insignificant compared to the costs of implementing PdM vs. PM.

The results of the worst-case scenario do show a very significant difference between PM and PdM. In experiment 2.5, see table 7.6 and table 7.10, the 'worst case scenario' can be seen. Here deterioration sets in immediately after the replacement of the suction cups. With the PM strategy, it can be seen that maintenance is performed too late, and the availability rate has decreased significantly, to an average OEE of 2.54%.

To illustrate how the OEE can differ so much for the worst-case scenario the achieved vacuum is set out against the operating time. Here the replacement moments are taken into account, from there the achieved vacuum will go back to the desired -0.75bar and deterioration will set in immediately again. This can be seen in figures 7.3a and 7.3b. In figure 7.3b the threshold for normal operation is also indicated. When the achieved vacuum is equal to or above this value, the suction cups do not create enough vacuum and no cup, seal or lid is extracted, this will have to be done manually.



(a) Result exp 2.5 PdM



(b) Results exp 2.5 PM

Figure 7.3: Results experiment 2.5 illustrated in achieved vacuum

In figure 7.3a it can be seen that the replacement if performed too late, the achieved vacuum is above -0.65bar for quite some time, meaning normal operation is not possible. Of course, this would not happen in practice, if it was found that deterioration has impacted the production line the suction cups will be replaced. This would be a corrective action and thus corrective maintenance. As this maintenance strategy had an average availability rate of 24.80%, or an OEE of 24.13%, this could be assumed to be roughly the case. While with the PdM strategy applied, the availability rate remains on average 28.05%, and OEE of 27.30%, even though there are more maintenance moments needed. This can be seen in figure 7.3a, there are a lot of replacement moments used, this is illustrated as the achieved vacuum dropping back to the wanted achieved vacuum of -0.75bar. The achieved vacuum stays under the -0.72bar with PdM which is sufficient for normal operation.

From the comparison of PdM and PM for different scenarios, it becomes clear that there is no significant difference between the two strategies in almost all scenarios except for the worst case. This is because with both strategies the number of stops is reduced. The difference between the two is the number of maintenance moments needed, but it seems that this does not make a significant difference in the OEE. With the worst-case scenario This again indicates that the number of maintenance moments needed has little effect on the availability rate but the reduction in stops occurring in the sections has a very big effect.

Section comparison

Table 7.11: OEE result for comparison of sections

	Preventive maintenance	PdM cup section	PdM seal section	PdM lid section
OEE	27.51%	27.61%	27.53%	27.57%

In experiments 3.1, 3.2 and 3.3 it is tested how much the individual sections contribute to the availability rate when changing the maintenance strategy from preventive to predictive maintenance. These found availability rates will be compared against the found availability rate when PM is implemented, see table 7.11.

In experiment 3.1, see table 7.7, PdM has been implemented on the cup section. This increases by 0.1%. This only difference is the reduction of maintenance time by 2 hours. In experiment 3.2, see table 7.8, PdM has been implemented on the seal section. This results in an average increase of 0.02%. Again, the only difference is the reduction of the maintenance time by 2 hours. In experiment 3.3, see table 7.9, PdM has been implemented on the lid section. This results in an average increase of 0.6%. In all these experiments, the replacement of the suction cups with PM was also done in time. To show that this means that there is no significant increase in stops in these sections, the OEE averages and their 95% confidence intervals are plotted for these experiments, see figure 7.4.

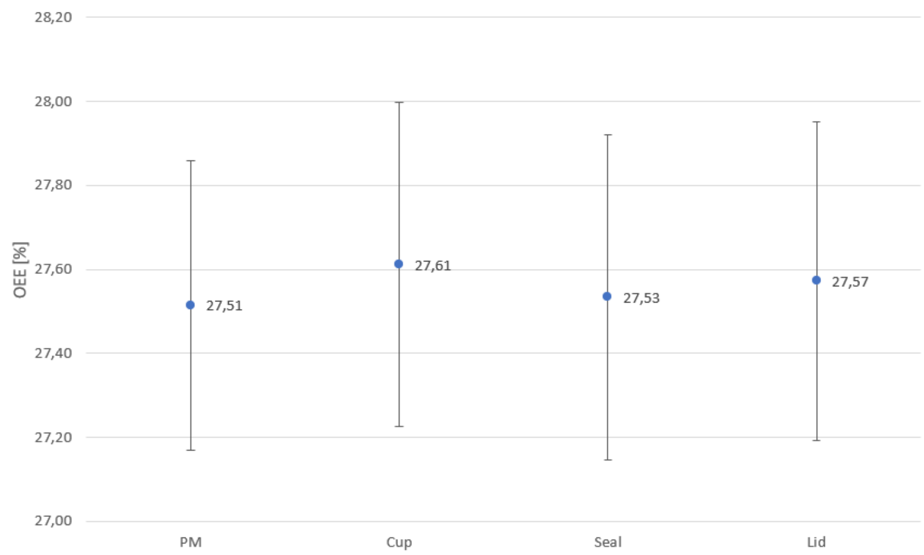


Figure 7.4: OEE averages and 95% confidence interval for PM and experiment 3

It can be seen that all the average OEEs lie well within the confidence interval of the preventive maintenance case, this shows that there is no significant difference between the contribution of the sections when implementing predictive maintenance.

7.3.1 Savings for FrieslandCampina Maasdam

With this increase in OEE, savings can be made. These can be savings regarding money due to less production time needed or more income because more can be produced at the same time. Savings can also be in man-hours needed or in parts needed.

When looking at what the OEE increase means for production time, the comparison between corrective, preventive and predictive is made. This will be done based on a simulation time of 1 year. In table 7.12 the increase in production time is shown.

Table 7.12: Difference in production time from corrective to active maintenance

	OEE	Production time	Difference from corrective
Corrective maintenance	24.14%	1173:24:22	-
Preventive maintenance	27.51%	1337:12:59	163:48:37
Predictive maintenance	27.88%	1355:12:06	181:47:43

An increase of 163 hours for preventive maintenance production is roughly the same as the current time spend on one-month production. In table 7.13, it can be seen how many more units per year can be produced with the increase in production time. When more can be produced at the same time, it means the production costs per unit go down. This results in a saving in costs, this is also shown in the table.

Table 7.13: Difference in units produced and savings due to this

	Units	Difference in units	Savings
Corrective maintenance	12.668.400	-	-
Preventive maintenance	14.439.600	1.771.200	€4090
Predictive maintenance	14.634.000	1.965.600	€4964

This table shows that yearly savings of up to almost 5000 euro's can be made. The difference between PM and PdM is roughly 900 euros, this is not enough to cover the investment cost of predictive maintenance, also not over 5 years.

Besides savings in costs, savings can also be made in man-hours and parts needed. Because the dairy cup line had trouble meeting the demand it is unlikely that with the increase in units the machine will not operate as often, this means no savings in operator man-hours will be made. However, savings in mechanic man-hours can be realised. Also, the number of parts needed can differ when different maintenance intervals are used. In table 7.14, the man-hours needed by a mechanic and the parts needed for a whole year are shown for the different strategies.

Table 7.14: Maintenance man-hours needed and parts needed

	Maintenance man-hours	Difference in hours	Parts needed	Difference in parts needed
Corrective maintenance	10	-	30	-
Preventive maintenance	18	+8	54	+24
Predictive maintenance	14	+4	42	+12

This shows that with preventive and predictive maintenance more maintenance man-hours and parts will be needed. For the company, it is to look into if the costs of these man-hours and extra parts are less than the possible savings. If this is the case, the active maintenance strategies, with the higher OEE, lead to savings in costs but not in mechanic man-hours or parts needed.

7.4 Limitations

In this research there are a few limitations that come forward, these can be due to the chosen scope or other reasons.

Firstly, the predictive maintenance model is designed to advise on the maintenance of the suction cups. This means that it is built in such a way that it can translate the input of the achieved vacuum into an advised maintenance moment. The way the predictive maintenance model works at this moment, other parts of the production line and their input cannot be used as input for the predictive maintenance model. To do this, the fault detection would have to be changed to the corresponding faults and the prognosis would have to be trained again with the input parameters and their RUL.

Another limitation is the fact that the predictive maintenance model now only takes one input regarding the condition of the monitored part. If a part were to have multiple parameters indicating the condition, this would not be possible at the moment. This would have to be changed in the fault detection and prognosis part. More rules would have to be set up for fault detection and the prognosis algorithm would have to be trained with multiple inputs.

Lastly, another limitation has to do with the fact that on only one part of the production line predictive maintenance is applied. This way, the results only give insight into how predictive maintenance affects the OEE if it is applied to that specific part. It does not say anything about how it might affect the OEE if it is implemented on other parts of the production line. It also does not indicate if this was the best part to implement predictive maintenance on.

7.5 Conclusion

From the results and the discussion of the results, it became clear that the implementation of predictive maintenance can have a large effect on the OEE when going from a corrective maintenance strategy to a predictive maintenance strategy. The difference in OEE when implementing a preventive maintenance strategy or a predictive maintenance strategy is minimal. This can be explained by the fact that the predictive maintenance and preventive maintenance strategy both reduce the stops significantly compared to a corrective maintenance strategy. The reduction in stops is what makes the increase in OEE for this specific case. The reduction in time spent on maintenance does not contribute very much compared to the reduction in time spend on stops. The limitations encountered in this research can also be the reasons for these results. The results might differ if, for example, a part was chosen with a longer time spent on maintenance.

8 Conclusion

This thesis project is conducted to show the effect of implementing an active maintenance strategy, like preventive and predictive maintenance, on the OEE of a dairy cup line.

With the use of a simulation model of the dairy cup line at FrieslandCampina Maasdam and a predictive maintenance model, this research was conducted. The main research question: *To what extent can an active maintenance strategy improve the Overall Equipment Effectiveness of a dairy cup line?* was tried to be answered.

It was chosen to look at preventive and predictive maintenance as the active maintenance strategies. Preventive maintenance is a strategy that focuses on performing maintenance at a set interval. Predictive maintenance is a strategy that focuses on only performing maintenance when it is needed. It was found in literature that the effect of active maintenance on the Overall Equipment Effectiveness is primarily due to the improvement in the availability rate. This means that if the biggest improvement area of a production line is the availability rate, especially the breakdown losses, implementing predictive maintenance can lead to improvements.

From the analysis of the production line it was found that with a difference of 65.4% from the world class standard, the availability rate is the component of the OEE that needs the most improvement. The breakdown losses contributing to the availability rate can be split into the different sections in the production line. The sections which contribute the most to this are the sections with suction cups. These suction cups are used to extract cups, seals and lids from the holders and place them in the designated place. With this critical component, the achieved vacuum was found to be the parameter to indicate deterioration.

With the use of the simulation model of the dairy cup line with the ability to 'plan maintenance' and the predictive maintenance model it is possible to simulate different scenarios of deterioration and how preventive maintenance or predictive maintenance reacts to this. The simulation model generates the availability rate, the biggest influenced factor of the OEE by predictive maintenance.

Different experiments have been conducted to see what the quantified effect of preventive and predictive maintenance is on the OEE of the dairy cup line, this research gives a limited answer as only one part of the production line was used. First, the base was determined, this was based on the historic data used to make the simulation model, this was during the period of corrective maintenance, leading to an average OEE of 24.14%. In the second experiment, the difference in OEE between preventive and predictive maintenance was determined. It was found that, for normal operations, the OEE increases both for preventive and predictive maintenance compared to corrective maintenance.

In the experiments with different deterioration rates, it was also found that the difference between preventive and predictive maintenance was statistically insignificant, except for the worst case scenario. It was found that for the chosen critical component the reduction in maintenance moments, with more stops needed for preventive maintenance than for predictive maintenance, does not make a difference in the increase in OEE. This leads to the conclusion that for the chosen critical components and its maintenance duration, the increase in OEE is mainly due to the reduction in stops.

With the worst case scenario, there is a big difference visible in the availability rates of the preventive and predictive maintenance cases. It is visible that predictive maintenance can indicate when maintenance is needed and preventive maintenance does not take into account worst case scenarios. In the worst case scenario the preventive maintenance is not sufficient enough and in the real world corrective maintenance would be applied.

So, in a normal operating scenario, the difference between a preventive and predictive maintenance strategy applied to the suction cups on OEE is statistically insignificant. But, when a worst case scenario presents, the predictive maintenance strategy is much better suited to reduce the number of stops due to the suction cups not achieving the vacuum.

To conclude, with the chosen part of the production line, the suction cups, the implementation of active maintenance can lead to an increase of more than 3% in the OEE when coming from corrective maintenance. The difference between preventive and predictive maintenance is for the chosen component insignificant. This is because for the chosen part the maintenance time is short, meaning that a reduction in stops for maintenance will not lead to a large increase in the OEE. This increase is realised due to a reduction in unplanned stops, something both active strategies realise. So, active maintenance is suited to reduce the number of stops due to the deterioration of the chosen component and increase the OEE.

Using a simulation model to simulate how the OEE is affected by preventive maintenance or predictive maintenance was found to be a suitable method for finding the effect of changing maintenance strategies on the OEE. It gave a clear view of how the strategies would react in different scenarios and showed the quantified increase in OEE, which can be used to determine if a strategy is worth implementing. This is also found to be something valuable by the company, as they would like to simulate this for more components and production lines. This would give them the best suited maintenance strategy for every piece of equipment.

8.1 Recommendations

There are a few recommendations that can be made for the academic world and a few for the company.

The predictive maintenance model is now only applied to one component of the production line, which occurs in multiple places. It could be further researched how the OEE would change if the simulation model would also simulate the deterioration and degradation of other parts in the production line. This could show on which parts the implementation of predictive maintenance can be interesting but also how the connection between the different sections would be. Also, the chosen part of the production line has a short maintenance time, it could be investigated what happens when a part is chosen which has a high maintenance time and how this difference translates into the change in availability rate.

The validation of the predictive maintenance model could not be done due to a lack of a representation of the model as a real life system or an already validated model. It would be recommended to do either of those and to be able to validate the predictive maintenance model, making its use and outcome of it even more reliable. This could be done by a case study to analyse the implementation of predictive maintenance.

The predictive maintenance model now only takes one input to detect deterioration and predict the RUL, it could be further researched if the accuracy of the model would increase if more input parameters are chosen. This could also lead to different outputs besides if there is deterioration detected or a 'normal' stop and the RUL, like what kind of stop occurs.

Besides the recommended research there are also a few steps FrieslandCampina can take related to the simulation model and predictive maintenance model. It can be interesting to check the cost reduction of maintenance when applying predictive maintenance vs. preventive maintenance. It is found that in the OEE there is not a significant difference between predictive and preventive maintenance, but the reduction in the number of maintenance actions can lead to a reduction in maintenance costs, which might also be interesting for the decision making in applying predictive maintenance or not. It was found that the man hours and parts needed do increase when going from reactive to active maintenance, but there is a difference between preventive and predictive maintenance here. It is advised to look into the costs this brings against the savings that can be made.

For now, the final recommendation for FrieslandCampina Maasdam is: focus on preventive maintenance, as this is easier and cheaper in implementation but gives the same result in OEE increase for the suction cups.

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A Scientific paper

The quantified effect of an active maintenance strategy on the Overall Equipment Effectiveness in dairy production lines

a case study at FrieslandCampina Maasdam

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Abstract

This paper researches the effect of active maintenance on the Overall Equipment Effectiveness (OEE) in dairy cup lines. Finding a suitable maintenance strategy to improve the OEE can be difficult and the implementation of active maintenance can be a timely and costly one. To be able to determine the effect before implementation of the maintenance strategy can be very valuable. By developing a method and testing this at a case study performed at FrieslandCampina Maasdam on a dairy cup line this effect can be found. A simulation model and a predictive maintenance model were build, the interaction between these models can show how predictive maintenance effects the OEE. How preventive maintenance effects the OEE can be tested with solely the simulation model. It was found that the implementation of active maintenance results in an increase in the OEE, of roughly 3%. It was found that for the component of the dairy cup line on which active maintenance was implemented, the increase was mostly due to the reduction in stops and not due to the reduction in time spend on maintenance.

1 Introduction

In the production industry a lot of companies strive towards the zero state [1]. The zero state means zero waste, zero accidents, zero rejects, zero failure and zero stock. Implementing an effective maintenance strategy is for a lot of companies a way of achieving this zero state [2]. Effective maintenance can extend equipment life, improve equipment availability and retain equipment in the proper condition, while poorly maintained equipment may result in breakdowns, malfunctioning and slower production [3]. Active maintenance is a way to do this, preventive and predictive maintenance are both active maintenance strategies while corrective maintenance is a reactive maintenance strategy [4].

Another way companies use to achieve this zero state is with Total Productive Maintenance (TPM), defined by Nakajima in 1988 [5]. Together with TPM, Nakajima defined a quantitative metric , called the Overall Equipment Effectiveness (OEE). The OEE is now widely used by companies as an indicator of productivity and how well equipment operates as well as a tool which can be used to direct in improvement areas [6, 7].

In the dairy industry this zero state is of great importance, as dairy is a perishable product [8]. FrieslandCampina is a Dutch dairy production company which has factories and sales world wide. For them this zero state is very important. Achieving this can sometimes still be a difficulty as it is not always known what might be an effective strategy for improving on this.

Active maintenance and the OEE have been used together in the production industry for quite some time, sometimes even without a conscious decision to use them together. The connection between active maintenance and the OEE has been researched before. However, there is a lack of quantitative knowledge about this effect in the dairy industry.

Research Field

This research has been conducted at one of the factories of FrieslandCampina. Maasdam is the production plant of FrieslandCampina which makes the fresh dairy products for the Netherlands, Belgium and some for France.

This plant handles 260 million kgs of raw milk, which is processed into 4 million units every week, providing for a very big market. Due to this large demand of products every week, the productivity of the production lines is very important. The OEE is used to track the productivity of the production lines at the plant. Every production line has a target OEE, this is based on the planned production time and planned stops.

One of their production lines is a dairy cup line, called line 14, this line in particular has problems with it's productivity. With an average of 24% OEE it does not meet the set target of 45% by far. It is known that an advanced maintenance strategy could improve the OEE, however, for the company it is always a battle between the efforts and the gains in the end. Finding whether implementing PdM would be a suitable strategy to improve the OEE of this production line would be very valuable.

Research Problem & Question

The scientific problem consists of the gap between knowledge about the effect of active maintenance on the OEE in the dairy industry. It is known that in general, the OEE will increase if active maintenance is implemented, but there is no quantified effect in the dairy industry known. Also, there is no tool or model to easily test this. The implementation of predictive maintenance, for example, can be a difficult, timely and costly process [2]. It would be very interesting to be able to see what the effect in OEE is when implementing predictive or preventive maintenance for companies in the dairy industry, as this could help them in the decision making of implementing this strategy or not. This has lead to the following research question: *To what extend can an active maintenance strategy improve the Overall Equipment Effectiveness of a dairy cup line?*

Outline

To be able to answer the research question, first some literature background on the connection between OEE and active maintenance will be discussed. Based on the information found here, two models will be developed. The first model being a simulation model of the production line in scope, the dairy cup line at FrieslandCampina Maasdam. The second model being a predictive maintenance model. The results of the implementation of the predictive maintenance model on the simulation and the simulation run with preventive maintenance, will be discussed. The outcome of these experiments will be discussed and a conclusion will be drawn.

2 Literature Background

Overall Equipment Effectiveness

The Overall Equipment Effectiveness can measure the gap between the actual productivity and the potential productivity of a manufacturing unit [9]. The OEE value is calculated using three values, the availability rate, performance rate and quality rate [6]:

$$OEE = Availability\% * Performance\% * Quality\%$$

The three values are influenced by what are called the six big losses [10]. In table 1, the OEE values and their corresponding losses can be seen.

Table 1: OEE values and the corresponding losses [11]

Availability rate	**Performance rate**	**Quality rate**
Breakdown losses	Minor stoppages	Quality and rework losses
Set-up and adjustment losses	Reduced speed losses	Yield losses

If these losses decrease, it means an increase in the availability rate, performance rate or quality rate. When these rates increase the OEE also increases.

It is found from reviewing case studies that the use of the OEE can be classified into two ways. The first being as an improvement tool. In studies conducted by [6, 10, 12–14] this can be seen. In these studies the availability rate, performance rate and quality rate were calculated. It was checked which of these rates scored the lowest. Within this lowest scoring rate the losses contributing to that were checked to see which loss had to be improved upon. With improvement initiatives in place, the whole cycle would start over and the new biggest negative influence would be tackled.

The second way of using the OEE was found to be as an indicator of improvement. In studies [15–18] this was the case. With this way of using the OEE, other improvement initiatives, like Total Productive Maintenance (TPM) also from Nakajima and linked with OEE, were used. The studies started off with calculating the current OEE and using that as a base to compare to. Then the improvement initiative would be implemented and the OEE would be monitored to see how much improvement was made. At the end of the track, the starting OEE and final OEE would be compared to see if the initiative was successful.

The use of the OEE in the dairy industry is not really any different from the use in other industries. In the studies conducted by Tsarouhas in the dairy industry they even differ a little between the different case studies. It can be explained that there is no big difference between the use of OEE in the dairy industry and any other industry. The OEE is calculated using a set of equations, which do not change for industry types. And as found, the use of the OEE could be split in either using as improvement tool or as indicator. This also does not change for the different industries. It could however change which improvement initiative is used or on which rate is first being improved, however this is not specifically found.

Active maintenance

Maintenance strategies started out with corrective maintenance, went on to preventive maintenance and are now at predictive maintenance [2].

Preventive maintenance, or time based maintenance, is a maintenance strategy where maintenance is scheduled based on calendar time or equipment operation time [19]. The scheduled maintenance should take place before failure occurs. The frequency of the scheduled maintenance can be determined by the manufacturer's guidance or from experience [4]. It relies on the estimated probability that the equipment will fail in the specified interval [2]. It is a straight forward type of maintenance compared to predictive maintenance. The main goal is to reduce the unplanned stops [20].

Predictive maintenance is based on information about the condition of the equipment [2, 20]. This information is about the deterioration which may result in more energy consumption and/or in failure. Predictive maintenance does not only aim to prevent failure but also for efficient operation [21]. This can lead to improved safety, product quality, reliability, availability and reduction in energy costs [19, 22]. Predictive maintenance is often referred to as condition based maintenance. Diagnostic equipment is used to measure the physical condition of the production equipment [23]. It is like preventive maintenance a type of maintenance that wants to prevent failures from occurring. However, there is an additional benefit which is that maintenance is only done when the need is imminent, and not like with preventive maintenance on a scheduled basis [20].

Within PdM the following steps have to be taken [4]:

1. Determining vital components to be monitored
2. Determining parameters that indicate deterioration
3. Setting critical thresholds for each variable
4. Data acquisition
5. Data processing
6. Fault detection
7. Prognosis
8. Maintenance decision making

Step 1, 2 and 3 can be described as investigating which component is most suited for predictive maintenance and will have the largest effect, determining the corresponding parameter which indicates deterioration and setting the thresholds for normal operation [4]. Steps 4 to 8 are the process of providing access and collecting data, performing single and/or multi channel signal transformations to this data, monitoring the parameter against the expected value, projecting the current health state of the system into the future and based on this making a decision on maintenance [22].

Steps 6, 7 and 8 can be modelled using three different methods:

- (Physical) model-based
- Knowledge based
- Data - driven

Within these methods there is a further division of methods, see figure 1.

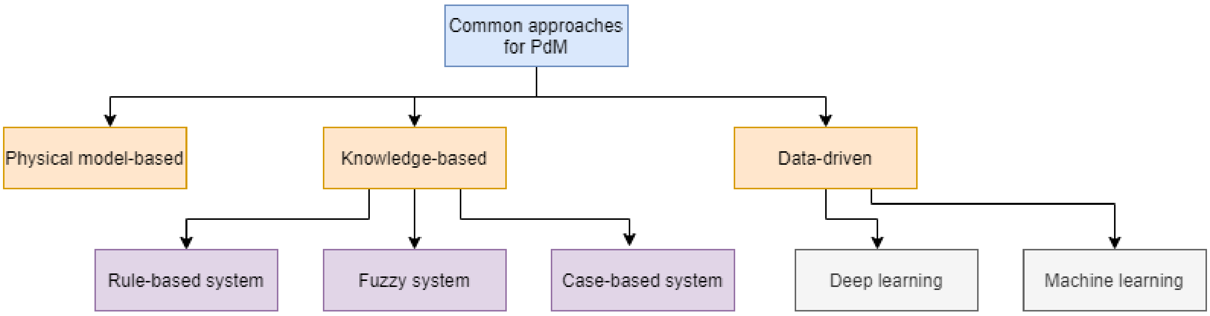


Figure 1: Classification for commonly used PdM methods [24]

Physical models quantitatively characterise the behaviour of a failure mode using physical laws [25]. It normally uses a mathematical representation of the physical behaviour of a machine. The mathematical representation reflects how the monitored system responds to stress from both macroscopic and microscopic levels. To obtain an accurate description of the system, it is important to identify one or several system diagnostic parameters that are specific to the predictive maintenance task [24].

A knowledge based system contains a knowledge base that stores the symbols of a computational model in the form of statements about the domain and performs reasoning by manipulating these symbols [24]. Knowledge based systems can be further classified into expert systems and fuzzy systems. Expert systems can be rule-based systems or case-based systems. An expert system simulates the performance of human experts in a particular field, it generally consists of a knowledge-base containing accumulated experience from subject matter experts and rule or case base for applying that knowledge to particular problems [25].

Data-driven methods are based on large amounts of data from systems where data analytics is applied, for example statistics-based, artificial intelligence (AI) or machine learning algorithms [21]. According to [26] these techniques can discover patterns and relationships in data sets which in turn can indicate faults or no faults. An advantage is that no prior knowledge of faults has to be known, the model will recognise this from the patterns. The downside is that incorrect conclusions can be drawn. [24] and [26] have devided the methods for data-driven approaches into machine learning and deep learning methods.

In practice it is found that the effects of predictive maintenance are primarily seen in the following areas [4, 27]:

- Higher reliability
- Higher availability
- Improved product quality
- Less costs for parts an labour
- Less waste in terms of raw materials and consumables

The effect of predictive maintenance is largely due to the fact that it is very well suited for reducing the number of stops, or even eliminating them [21]. Also, maintenance will only be performed if needed, but unlike with corrective maintenance it will be performed in time to prevent a breakdown from happening. If maintenance is only performed when needed it can save time and costs.

Connection between OEE and active maintenance

From the found knowledge on the OEE, what influences it and how it is used and the knowledge about active maintenance and it's effects, a connection between these two can be drawn.

The link between the OEE and active maintenance can mainly be found in the improvement of the availability rate when implementing predictive maintenance. With predictive maintenance, maintenance is only performed when needed, resulting in less planned stops. Also, less unplanned stops, like breakdowns, are supposed to occur with both preventive and predictive maintenance. This will have an effect on the unplanned and on the planned stops. These types of stops effect the availability rate, as it is calculated with the actual operating time, the unplanned stops and planned stops:

$$\text{Availability Rate} = \frac{\text{Actual operating time}}{\text{Planned operating time}} * 100\%$$

where the actual operating time equals:

$$\text{Actual operating time} = \text{Planned operating time - planned stops - unplanned stops}$$

When decreasing the unplanned stops and planned stops, the availability rate will increase. This effect on the availability rate of PdM would be the same in every type of industry.

In the performance rate and quality rate the effect of active maintenance is mostly secondary. In the dairy industry a reason for quality losses is if the dairy stood still for too long in the production line and has perished [8]. These produced cups have to be thrown out, resulting in quality losses. PdM would lead to less unplanned stops, or even no unplanned stops. Meaning this problem will be eliminated, resulting in less quality losses. Less quality losses is an increase in the quality rate.

So, to conclude active maintenance will positively impact the availability rate in any production line. In the dairy industry especially it will also have a noticeable effect on the quality rate. When the availability rate, quality rate and performance rate increase, so does the OEE.

3 Modelling

From literature it was found that the biggest influence of PdM would be on the availability rate, and due to that increase the quality rate would also increase. However, it was not found how large this increase could be. To be able to research this a predictive maintenance strategy will have to be implemented on a dairy cup line. However, as mentioned is the implementation of this strategy difficult, timely and costly. To be able to still research this effect, a simulation of the in scope production line 14 will be build. On this simulation model an predictive maintenance model will be implemented.

Dairy cup line analysis

The steps that need to be followed for PdM are stated in section 2. These start with the determining of vital components to be monitored. As this research is conducted with a case study of the dairy cup line of Friesland-Campina Maasdam. that production line will be analysed to find this vital component. To see if the production line was actually suited for PdM, an analysis into the OEE and the different rates was conducted. First an understanding of the working of the production line will be given. In the figure below, see figure 2, the different machines in the production line can be seen.

The cup feeder is the start of the production line, here the cups are placed into the magazine which leads to the filling machine. The filling machine is depicted in blue, this machine consists of different sections which will all be viewed as different machines. In yellow all the different in-feeds of materials or product are visible into the filling machine. In red, the conveyors used are depicted. These are the conveyors which transport the tray's to the filling machine and after the tray's have been filled transport them away to be stacked on a pallet and then transport the pallet to the distribution center. In green are the other machines in the production line, the tray folder, the palletizer and the pallet wrapper. Here the tray's are folded, the tray's are stacked on the pallet and the pallet is wrapped in foil.

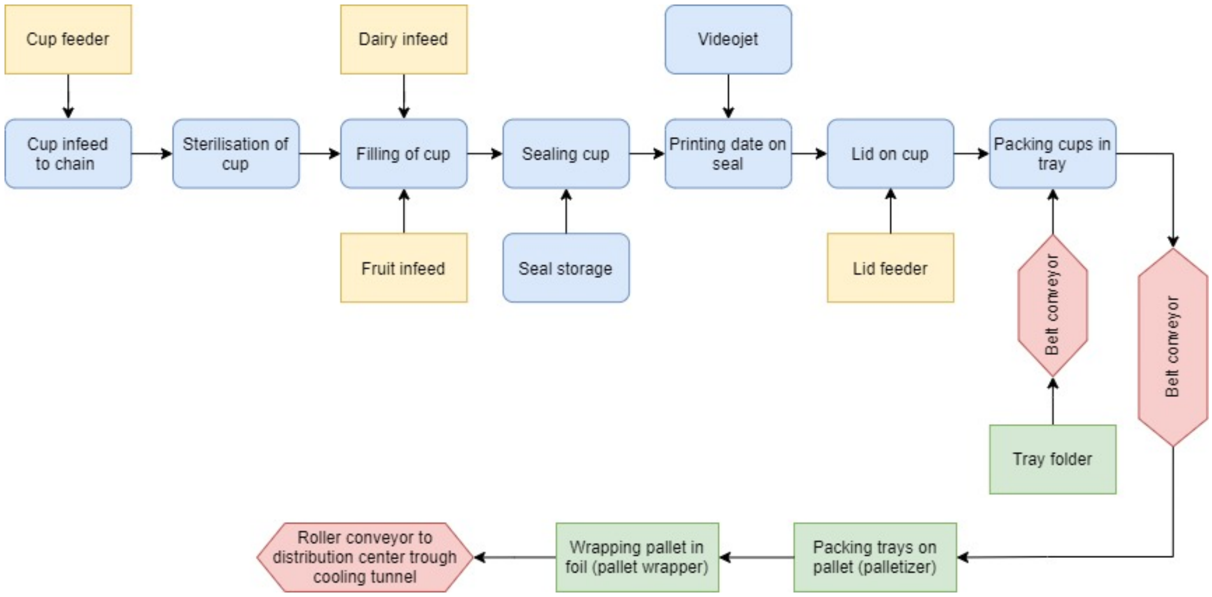


Figure 2: Flow diagram of production line 14 with different in- and out-feeds and components

Data was collected from October '21 until February '22 about the performance, availability and scraps produced by the production line. From this data the average availability rate, performance rate and quality rate were determined. From this the OEE was calculated, as can be seen in table 2. The world class values seen in the table are the values which were determined by Nakajima and are the ultimate values to strive towards.

Table 2: OEE values for production line 14, (average over October'21 - February'22) vs. World Class values

	Availability rate	Performance rate	Quality rate	OEE
Average	**24.6%**	**98.22%**	**99.09%**	**23.94%**
World Class	90%	95%	99%	85%
Difference	- 65.4%	+ 3.22%	+ 0.09%	- 61.06%

It can be seen that the availability rate is way below the world class target. Because PdM would have the largest effect on the availability rate and is very suited to improve this, it would seem that PdM is a suited strategy to improve the availability rate and OEE.

From here the vital component to be monitored has to be found. This is done by analysing all the breakdowns that occurred from October '21 until February '22. In figure 3, the total time spend on breakdowns per section in the production line can be seen. It is clear that the sealing station contributes to the most time spend on breakdowns. Within this section it will have to be checked which component will be used for monitoring. To do this, the stops in the seal section were analysed. This lead to the finding that about 1/3 of the total unplanned stop time in the seal section was caused by the fact that the seals could not be extracted from the holder, the seal storage as can be seen in figure 2. The seals are extracted by an arm which has suction cups on it, these suction cups create a vacuum when it touches a seal. If the needed vacuum to extract a seal cannot be achieved, no seal is extracted. The following reasons for not being able to created the needed achieved vacuum were found to be:

- Jamming of seal
- Creasing of seal in holder
- Deteriorating of suction cups

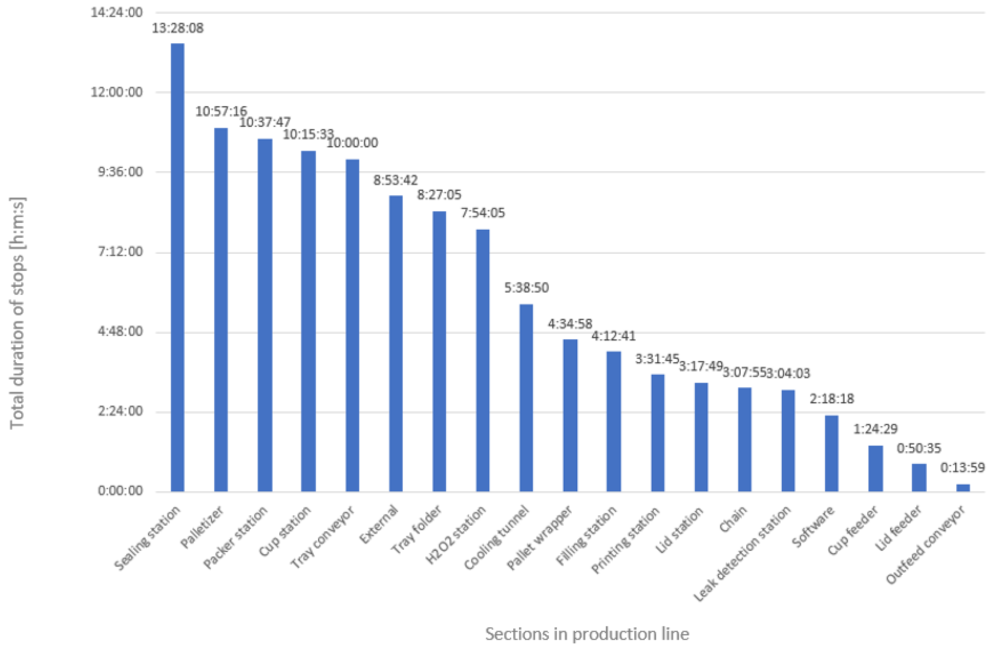
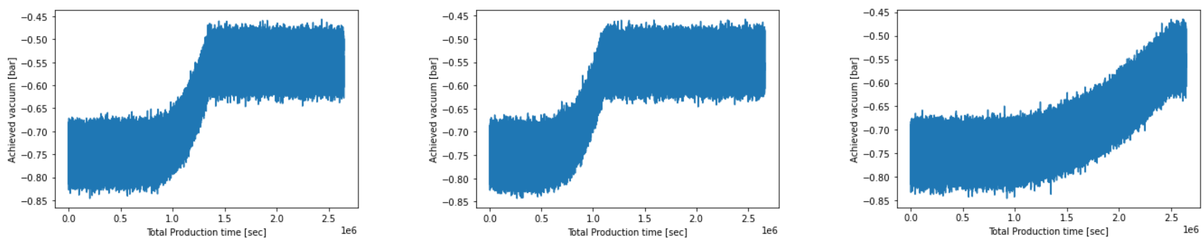


Figure 3: Total time spend on each section caused by breakdowns

When the seal is jammed or creased in the holder, there will only be one stop due to this. If the suction cups have deteriorated, there is the possibility that air can enter the vacuum zone, this will lead to less vacuum being created. If the deteriorated has gone too far, the minimum needed vacuum of -0.65bar cannot be reached anymore and no seals will be extracted. This will lead to stops in the production line, as the whole filling machine works in series, if a stop happens in one section, the whole machine stops.

This gave answer to which vital component of the production line will be used to monitor, the suction cups. These suction cups do not only occur in the seal section but also in the cup and lid section, with the same function of extracting the material from the holder. The next step is to determine the parameter which indicates deterioration. As mentioned, if the suction cups cannot reach the needed vacuum the production line will stop. This achieved vacuum thus indicates the performance of the suction cups, if it is at the set value of -0.75 bar, there is no problem for production, if it is below the threshold of -0.65bar production is no longer possible. When deterioration sets in, the achieved vacuum will slowly increase, this can be seen in figure 4.



(a) Reconstructed change in vacuum for cup station

(b) Reconstructed change in vacuum for seal station

(c) Reconstructed change in vacuum for lid station

Figure 4: Reconstructed change in achieved vacuum for the three sections

The third step is determining the critical threshold. This is set at -0.65bar, when the materials cannot be extracted anymore. Of course, the replacement would have to be performed before this level is reached. This will be Incorporated in the last step, the maintenance decision step.

Simulation model

The information gathered in the simulation of the dairy cup line is needed for the implementation of the predictive maintenance model. Implementing this model on a simulation of a diary cup line is a great way to experiment with the model and gain answers for different scenario's. Simulations are generally seen cheaper, faster, safer, and tests/experiments can be replicated multiple times [28].

The simulation of the production line will need to generate the availability rate and the achieved vacuums of the three sections. The availability rate is the final output in which the effect can be measured when implementing PdM. For the availability rate the planned operating time, planned stops and unplanned stops are needed. The achieved vacuum is the needed input of the predictive maintenance model, or PdM steps 4-8.

There are different simulation techniques which can be used for different types of simulations [29]. The simulation of the dairy cup line will be a mix between continuous and discrete event simulation. With discrete simulations the changes in the system state are discontinuous and each change in the state of the system is called an event, while with continuous simulations the state variables change continuously with respect to time [30]. The production of the cups is a continuous process, this will thus be simulated as continuous events. The occurrence of stops are discrete events, the stops occurring in the production line will be simulated as discrete events.

The simulation of the production line will follow the production of one row of 6 cups. Because the needed parameters are of sections inside the filling machine, this is the part of the production line that will be simulated in more detail. The rest of the production line will be simulated as: other sections. This will be everything outside the filling machine added together, the production time and the stops distributions will thus be taken of the tray folder, conveyors, palletizer and pallet wrapper together. Figure 5 shows how the different sections of the filling machine will be grouped together to make the simulation simpler. For example, the H2O2 section and the filling section, both shown in orange, will be modelled as section 1, also shown in orange.

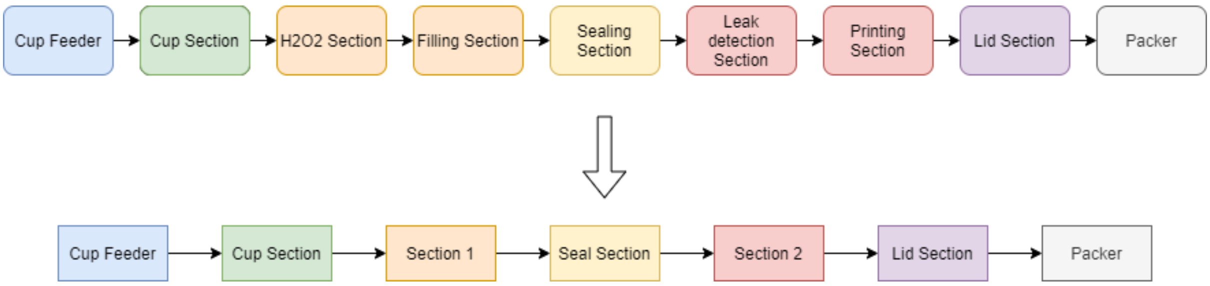
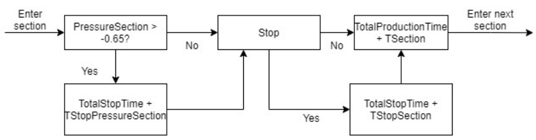
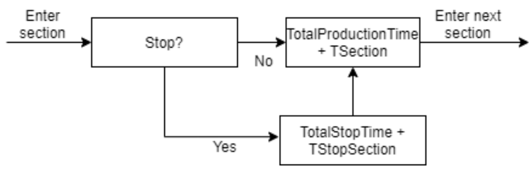


Figure 5: Sections in model L14

There will be two different ways of modelling the sections. There is a distinction between the sections with the parameter achieved vacuum and without. In figure 8 the difference between these can be seen. For the sections with the achieved vacuum parameter, see figure 6a, the rows enter the section, first it is checked if the achieved vacuum is sufficient, if this is the case there is no stop, if this is not the case there will be a stop. Then it is checked if there is any other stop in the section, if this is not the case the rows are processed and leave the section, if there is a stop, the process waits for the duration of this stop and the row is then processed and leaves the section. For the sections without the achieved vacuum parameter, see figure 6b the only the part where a 'normal' stop is checked is modelled.



(a) Modelling of the cup section, seal section and lid section



(b) Modelling of the cup feeder, section 1, section 2 and packer

Figure 6: Modelling of sections of dairy cup line

Unplanned stops can be either stops in the different sections or routine stops. Routine stops are stops in between the production of different products where the production line needs to be cleaned or changed in size. Planned stops include the preventive maintenance which is performed every 4 weeks. In the week prior and after the week when maintenance is performed an extra buffer of products needs to be made.

Of the simulation model a mathematical model is made which can be implemented as a computer model. For this mathematical model the following indices, parameters and variables are used:

Table 3: Indices and sets for simulation model

K	Number of weeks
I_k	Number of rows in week k
J	Number of sections

Table 4: Parameters and variables for simulation model

pt_j	Time to process a row in section j
p_{kij}	Production in week k of i number of rows in section j
mr_k	Rows not produced due to maintenance in week k
b_k	Buffer rows produced before and after maintenance in week k
c bw_k	Weeks k in which buffer is created
m_k	Maintenance in week k
st	Setup Time after maintenance
PPT	Planned Process Time
TPT	Total Process Time
rst_{ki}	Time spend on routine stops in week k after i rows
rs_{ki}	Routine stop in week k after i rows
sr_{kij}	Stop in week k in row i in section j
ttr_{kij}	Time to restart in week k during row i for section j
TST	Total Stop Time

With these, the equations for the mathematical model are drawn up. Parameter m_k,bw_k, rs_{ki} and sr_{kij} are binary. For m_k the parameter equals 1 if there is maintenance, this is every 4 weeks. The parameter equals 0 if there is no maintenance, this is in all the other weeks.

$$m_k : \begin{cases} 1 & : \quad \text{maintenance performed in week k,} \\ 0 & : \quad \text{no maintenance performed in week k} \end{cases} \tag{1}$$

For bw_k the parameter equals 1 if buffer has to be created in week k, and equals 0 if no buffer has to be created:

$$bw_k : \begin{cases} 1 & : \quad \text{Buffer created in week k,} \\ 0 & : \quad \text{no buffer created in week k} \end{cases} \tag{2}$$

For rs_{ki}, the parameter equals 1 if a routine stop occurs and equals 0 if no routine stop occurs:

$$rs_{ki} = \begin{cases} 1 & : \quad \text{routine stop in week k after i rows,} \\ 0 & : \quad \text{no routine stop in week k after i rows} \end{cases} \tag{3}$$

For sr_{kij}, the parameter equals 1 if a stop, due to failure or minor stoppage, occurs and equals 0 if no stop occurs:

$$sr_{kij} = \begin{cases} 1 & : \quad \text{in week k, row i has a stop in section j,} \\ 0 & : \quad \text{in week k, row i does not have a stop in section j} \end{cases} \tag{4}$$

The mathematical equations for production, stops and total process time will then be the following.
The Planned Process Time is calculated in three parts. First the sum over the weeks, rows and sections is taken over the product of production and time to process, this gives the actual production time. Then the sum over

the weeks is taken of the product of the maintenance weeks, maintenance rows plus the buffer weeks times the buffer needed, this is then multiplied by the production time, this gives the total time spend on maintenance. Lastly the time spend on startup after maintenance is calculated by taking the sum over the weeks of the product of the maintenance weeks and the setup time.

$$PPT = \sum_k \sum_i \sum_j (p_{kij} * pt_j) + \sum_k (m_k * mr_k + bw_k * b_k) * \sum_j pt_j + \sum_k (m_k * st) \tag{5}$$

The Total Production Time is calculated in two parts. Here the first part is again the total production time, the same as calculated in the equation for PPT. However, here the maintenance time is subtracted from the production time and the buffer production time is added. This is because the production per week does not encounter for the time spend on maintenance.

$$TPT = \sum_k \sum_i \sum_j (p_{kij} * pt_j) - \sum_k (m_k * mr_k - bw_k * b_k) * \sum_j pt_j \tag{6}$$

The Total Stop Time, this is only the unplanned stops, is calculated in two parts. Here the first part is regarding the breakdowns and minor stoppages. This is calculated by taking the sum over the weeks, rows and sections of the product of the time to restart and the occurrence of a stop. The second part is regarding the routine stops. This is calculated by taking the sum over the weeks and rows of the time spend on a routine stop and the occurrance of a routine stop.

$$TST = \sum_k \sum_i \sum_j (ttr_{kij} * sr_{kij}) + \sum_k \sum_i (rst_{ki} * rs_{ki}) \tag{7}$$

The availability rate is then calculated with equation 8.

$$AR = \frac{TPT}{PPT + TST} * 100\% \tag{8}$$

The available time for maintenance per week is also needed for the predictive maintenance model. This is calculated as following:

$$AvailableTime_k = TotalShift_k - TST_k - PPT_k \tag{9}$$

Where the total shift time is 14 shifts of 8 hours in one week.

For the stops occurring distributions have been set up- based on historic data. This way the stops can be generated over a longer or shorter period of time than the historic data used. In table 5 the needed input for the different parameters used in the mathematical model can be seen.

Table 5: Parameter input for simulation model

Parameter	**Distribution**	**Needed input**
pt_j	Constant	Production time
p_{kij}	Uniform	Order per week
mr_k	Uniform	Maintenance time
b_k	Uniform	Buffer needed
st	Constant	Setup time
sr_{kij}	Chance	Number of stop & total events
ttr_{kij}	Exponential	Lambda

The orders per week are an uniform distribution between 41817 and 51283 rows. The time spend on maintenance per week is an uniform distribution between 6 to 7 hours or 5000 and 6000 rows. The buffer time is a uniform distribution between 2500 and 3000 rows. The setup time is constant at 1 hour. The time to restart uses the equation for the exponential variates to be able to generate different restart times. The equation for this is: $ttr = \frac{-ln(U)}{\lambda}$, where U is a uniform distribution between 0 and 1. The other parameters are defined for every section, as can be seen in table 6.

Table 6: Parameters for process time, lambda, chance of stop for different sections

	Process time [sec]	Lambda	Chance of stop
Cup Feeder	2	0.0052	0.000192
Cup Section	2	0.0081	0.000569
Section 1	4	0.0079	0.001771
Seal Section	2	0.0042	0.00054
Section 2	2	0.0086	0.001027
Lid Section	2	0.0041	0.000333
Packer	2	0.0025	0.00557
Other Stops	0	0.0073	0.0121

The mathematical model with all its different inputs will be implemented as a computer model. This way the model can be executed multiple times under different circumstances. The model's outputs can be seen in figure 7, here the interaction between the simulation model and predictive maintenance model is also illustrated.

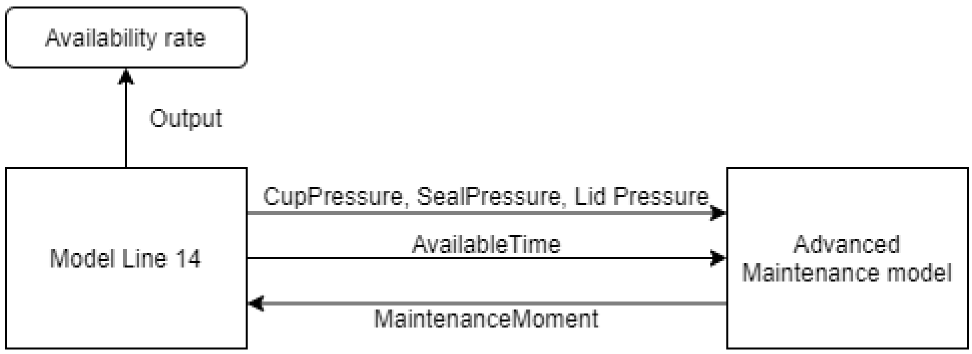


Figure 7: Interaction between Model Line 14 and predictive Maintenance Model

Predictive maintenance model

With steps 1,2 and 3 of PdM being done, steps 4 to 8 still have to be executed. The simulation model generates the achieved vacuum for the three sections for the production of every row. This is the data that enters the PdM system. Unlike in a physical system, when data needs the be read from sensors, the data is already generated in the needed format. The data will be processed, as can be seen in figure 4, there is noise around the achieved vacuum data. This noise will need to be removed to be able to accurately use the change in vacuum. This is done using the moving averages of the achieved vacuum. These are calculated with equation 10.

$$MA = \frac{1}{k} \sum_{i=n-k+1}^{n} p_i \tag{10}$$

Where k is the window size over which the average is taken, n is the size of the data set and p_i are the data points. The moving averages will be used in the fault detection of the PdM strategy.

Steps 6, 7 and 8 use the input from the simulation model, the interaction between these steps is illustrated in figure 8

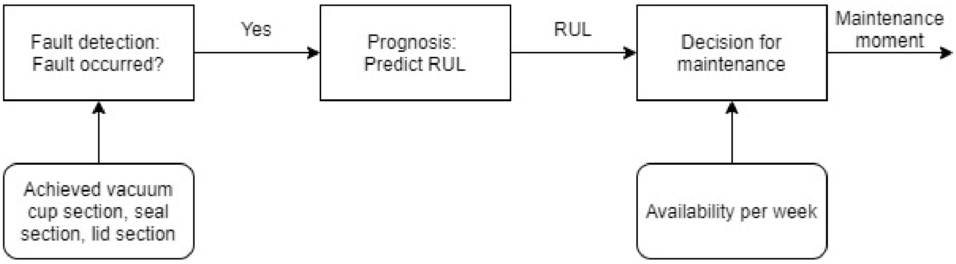


Figure 8: Interaction of different parts of maintenance model

Fault detection

For the fault detection it was chosen to use a knowledge based method, rule based reasoning. Rule-based reasoning normally encodes problem solving knowledge of the domain experts in terms of a set of situation actions, IF-THEN rules. These rules are written in the following format:

if A and B, then C

If C or D, then E

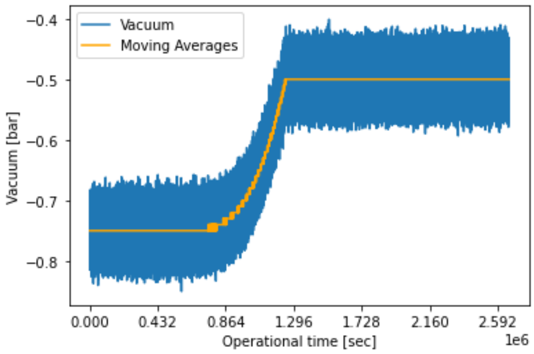
Here the *if* portion is called the antecedent and the *then* portion is called the consequent [31]. The rules are often based on heuristic facts acquired by one or more experts. To be useful, a knowledge base must be as complete and exact as possible, meaning each set of inputs must provide only one output and an output must be provided for any possible combination of input values [25]. The drawn up rules can be checked against the physical systems output and can give the condition of the current state, fault or no fault.

To compute these rules the achieved vacuum, moving averages and the computed Delta of the moving averages is used. The calculation of delta, is done as follow:

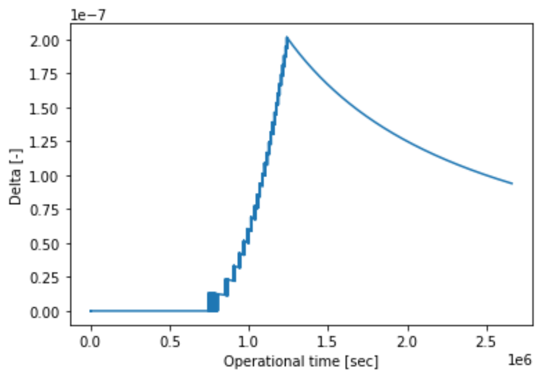
$$Delta = \frac{1}{i}(MA_i - MA_0) \tag{11}$$

Where MA is moving averages and i is the current data point. Equation 11 calculates the delta between every new point in the MA set and the first point in the MA set. This produces the delta between the first data point and every other data point, resulting in figure 9b.

Using the moving averages takes out random occurring failures in achieving the vacuum due to for example creased materials. If the moving averages are not a constant -0.75bar anymore, deterioration has set in, see figure 9a. If delta is 0, no change in the values between MA_1 and MA_2 has occurred. If delta is not 0, it means there is a difference between the values of MA_1 and MA_2.



(a) Achieved vacuum (blue) and moving averages (orange)



(b) Computed delta of the moving averages of the achieved vacuum

Figure 9: Achieved vacuum and the computed delta

The following rules for the fault detection and deterioration detection have been set up:

Mode	Rule	Meaning
Cup section	$P_{k,1} \geq -0.65$	Stop due to lack of vacuum in cup section
	$ma_{k,1} > -0.75$	Deterioration of suction cups in cup section started
	$Delta_{k,1} \neq 0$	Deterioration of suction cups in cup section started
Seal section	$P_{k,2} \geq -0.65$	Stop due to lack of vacuum in seal section
	$ma_{k,2} > -0.75$	Deterioration of suction cups in seal section started
	$Delta_{k,2} \neq 0$	Deterioration of suction cups in seal section started
Lid section	$P_{k,3} \geq -0.65$	Stop due to lack of vacuum in lid section
	$ma_{k,3} > -0.75$	Deterioration of suction cups in lid section started
	$Delta_{k,3} \neq 0$	Deterioration of suction cups in lid section started

Prognosis

If a fault is detected, step 7 prognosis starts. For this step it was chosen to use the data driven method.

The Remaining Useful Life (RUL) has an easy correlation with the vacuum achieved. With the prognosis the load is also taken into account, as this is the same for every for every row of production, the load does not make a difference in the prognosis of the RUL. This leaves the achieved vacuum parameter as an indicator for the remaining useful life. Within the data-based reasoning there are multiple methods, because this is a simple correlation between two variables it was chosen to use a regression analysis using Neural Networks. Neural Networks (NN) are Artificial Intelligence tools which are able to learn and generalise from examples and experience to produce meaningful solutions to problems [32]. Python has a build in library for training and using a NN, this was used for the prediction of the RUL.

In figure **??** the determined RUL with the corresponding vacuum can be seen. In figure **??** the predicted RUL with the corresponding vacuum can be seen.

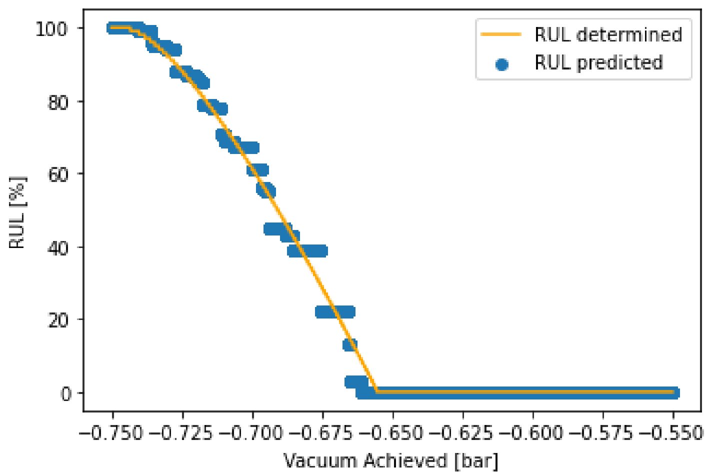


Figure 10: Determined and predicted RUL

With the predicted RUL a maintenance decision can be made.

Decision making

The decision making is the last step. Normally there would be a decision into what maintenance action is needed and when to perform this. Because the only maintenance action in this case is the replacement of the suction cups, this part of the decision making does not have to be modelled. The decision making is based on the maintenance planning and scheduling decision method defined by [33]: *Algorithms that are able to recommend the most appropriate maintenance actions according to the company's policies and the estimations regarding the potential impacts and risks of the candidate actions.* To do this an optimisation equation to maximise the available time per week is drawn up.

The predicted RUL is checked to see if it has reached 60%, if this is the case there is a time frame for performing the maintenance action, this time frame differs for every section. The maximising equation is:

k:	Weeks
i:	Rows
j:	Sections
l:	Maintenance time frame

$S_{k,j}$	Decision variable: stop in week k for section j
AT_k	time available in week k
$RUL_{k,i,j}$	Remaining useful life in week k during production of row i in section j
MT_j	Time spend on maintenance for section j
SW_k	Stop weeks k in which maintenance is performed
ST	Setup time for production after maintenance
TS_k	Total number of stops in week k

$$Max : \sum_k AT_k - \sum_k \sum_j (S_{k,j} * MT_j) - \sum_k (SW_k * ST) \tag{12}$$

The AT_k is determined as in equation 9. $S_{k,j}$ is the decision variable which can either take 1 or 0 as a value:

$$S_{k,j} = \begin{cases} 1 & : \quad \text{Stop for maintenance of section j in week k,} \\ 0 & : \quad \text{no stop} \end{cases} \tag{13}$$

MT_j is the time it takes to replace the suction cups in one of the section (j). The setup time is only used once if maintenance is performed, so if three different maintenance actions are performed in the same moment, there will only be 1 hour of setup time. If these actions were performed during three different moments, there would be 3 hours of setup time. This makes it interesting to perform as many actions at the same time. This is modelled using equations 14 and 15.

$$\sum_l S_{l,j} \geq 1 \tag{14}$$

For the stop weeks, SW_k, the sum of the stops in each week have to be taken:

$$TS_k = \sum_j S_{k,j} \tag{15}$$

And then the following will apply: If $TS_k \geq 1; SW_k = 1$.

This will give the advised moment to stop for every section. This advised maintenance moment will in return be used in the simulation model, as can be seen in figure 7. The maintenance moment will be added to the binary array of maintenance occurrence and the time used for the action to the maintenance time. This way it will have an influence on the availability rate.

4 Results

A few experiments are conducted to see what the quantified effect is of implementing this predictive maintenance strategy on the OEE. All experiments have been run 10 times. The presented results is the average of these runs.

Corrective maintenance

In the historic data used for the simulation model, the used maintenance strategy was corrective maintenance. With this strategy, maintenance was performed when the stops occurring due to deterioration became too much instead of at the advised replacement moments. This leads to less maintenance moments but more stops. To give a basis in how the maintenance was performed during the period of October '21 until February '22, this base experiment is conducted. Against this corrective strategy the current situation, preventive maintenance, and the strategy in this research, predictive maintenance, can be compared.

This experiment resulted in an average OEE of 24.14%

Preventive vs. Predictive maintenance

In this experiment the effect on the OEE of preventive and predictive maintenance are compared. Preventive maintenance is the newest implemented maintenance strategy on the suction cups, but no maintenance actions have yet been performed on the suction cups. There is no historic data about the effect, so an experiments with the known maintenance intervals are performed.

Predictive maintenance would be the next step in maintenance strategy. The advanced maintenance model will be implemented on the simulation.

The simulation will simulate different scenario's for deterioration of the suction cups. First the base will be determined, this is with the historic periods of deterioration. Next, the duration of normal operation experimented with is 10 weeks, 20 weeks and 30 weeks for the different sections. Lastly, a worst case scenario will be simulated. In this case the deterioration of the suction cups will set in immediately after replacement. This experiment will show the difference in availability if a different change in achieved vacuum is happening between the two strategies. This will give an insight into the importance of the predictive maintenance strategy when unusual deterioration occurs, which can be due to bad suction cups or other factors.

In table 7 the results of these experiments are visible.

Table 7: Results expressed in OEE of the different experiments with different deterioration rates

	Base	**10 weeks**	**20 weeks**	**30 weeks**	**Worst case**
Preventive Maintenance	27.51%	27.46%	27.48%	27.46%	2.54%
Predictive Maintenance	27.88%	27.86%	27.91%	27.96%	27.3%

When comparing the corrective maintenance results and the outcome of the base experiment of predictive maintenance, it can be seen that the availability rate has increased on average with 3.85%, and the OEE with an average of 3.74%. This increase is even-though there are 2 more maintenance moments used. This means that with the implementation of predictive maintenance, maintenance is performed before the effect of the deterioration of the suction cups is noticeable in the availability of the production line.

When comparing the corrective maintenance result to the base experiment of preventive maintenance, it can be seen that the availability rate increases. Even-though, with preventive maintenance there are more maintenance moments, 5 in total for the corrective maintenance strategy and 9 in total for the preventive maintenance strategy, the availability rate increases. And this is clearly visible, with an increase of 3.87% in the availability rate and 3.37% in OEE.

When comparing the preventive maintenance strategy to the predictive maintenance strategy some interesting things become clear. With preventive maintenance, maintenance is still performed in the periodic intervals, meaning that, for example with the experiments with normal operation for 20 or 30 weeks, the deterioration of the cup and seal suction cups only starts after the replacement moment. This results in replacing parts when nothing is wrong with them when implementing preventive maintenance. This leads to more maintenance actions done with preventive maintenance than with predictive maintenance. However, no significant effect can be seen in the OEE. This would mean that the reduction in stops weighs much more in the increase in the OEE than the reduction in maintenance time, for this part of the production line.

In the worst case scenario deterioration sets in immediately after replacement of the suction cups. With the PM strategy it can be seen that maintenance is performed too late, the OEE has decreased significantly, to an average OEE of 2.54%. Of course this would not happen in practice, if it was found that deterioration has impacted the production line the suction cups will be replaced. This would lead to the corrective maintenance case, with an OEE of 24.13%. While with the PdM strategy applied, the OEE is still 27.30%, even-though there are more maintenance moments needed.

5 Conclusion

From these results it is concluded that the biggest effect on the availability rate is due to the reduction of stops and not due to the reduction in maintenance activities. This can be seen in the experiment with a degradation period of 30 weeks, with the implementation of predictive maintenance there are only 3 maintenance actions needed for the scenario of degradation of 30 weeks, while with preventive maintenance still 9 moments are used. However, the difference in OEE is minimal. In the worst case scenario the reduction in stops with predictive maintenance is very good, but more maintenance moments are needed. With preventive maintenance, the actions are only performed at the set moments, resulting in a lot of stops and even not being able to operate, resulting in an extremely low OEE. In real life this would be prevented by switching to corrective maintenance. This could then result in an increase more than 3% OEE, while the switch from preventive to predictive maintenance in a normal, or 'better' scenario does not not result in a high increase.

So to conclude, changing from corrective to predictive maintenance for the analysed part, the suction cups, can lead to an increase of 3% in the OEE. Compared to preventive maintenance, the implementation of predictive maintenance on the suction cups does not make a significant difference in the normal deterioration situation. When the worst case scenario happens, predictive maintenance is very suited to detect the deterioration in time and plan a replacement moment. Leading to an increase of 24% compared to preventive maintenance.

Further research

In this case the effect on the OEE when implementing PdM is only analysed for one part of the production line. The replacement of this part can be done in a fairly short time. It would be interesting to see if the effect of on the OEE would be different when choosing a part, which in breakdowns is maybe less critical, but does take relatively long to replace or perform maintenance on. This way it could be seen if a difference in OEE can be made when less maintenance actions are performed but those take a long time.

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B OEE data

Table B.1: Performance rate data

	#	time	time (sec)	#/sec	sec/#
Camp Yogh 1.8% Nat Tr 6x150g Cup	23778	2:09:56	7796	3	0,33
Camp Yogh GrSt TopCup Aard Fram Tr 6x170g	16272	1:29:48	5388	3,5	0,29
Camp Yogh GrSt TopCup Amandel Tr 6x170g	8226	0:48:51	2931	3,5	0,29
Camp. gortepap 500gr cup Tr6	9456	1:02:55	3775	2,5	0,4
Camp. griesmeelpap 500gr cup Tr6	68724	7:35:01	27301	2,5	0,4
Camp. havermoutpap 500gr cup Tr6	84312	9:21:49	33709	2,5	0,4
Camp. Magere kwark Naturel Tr 6x220 gr Cup	9708	0:52:45	3165	3	0,33
Camp. Magere kwark Naturel Tr 6x500 gr Cup	203778	18:04:18	65058	3,3	0,30
Camp. rijstepap 500gr cup Tr6	27324	3:02:03	10923	2,5	0,4
Camp. Volle kwark 8,8% Tr 6x500 gr Cup	142038	12:28:27	44907	3,3	0,30
Jumbo yogh / vez Bosbes 450gr cup Tr6	2760	0:15:23	923	3	0,33
Jumbo yogh / vez Mango 450gr cup Tr6	4512	0:25:02	1502	3	0,333
Mona VLY Aardbei Tr 6x450g Cup	26298	2:33:36	9216	3	0,33
Mona VLY Bosbes Chc Tr 6x450g Cup	23130	2:15:34	8134	3	0,33
Mona VLY Perzik Tr 6x450g Cup	31986	3:07:51	11271	3	0,33

Table B.2: Quality rate data

	# produced	# rejected
Camp. griesmeelpap 500gr cup Tr6	68724	777
Camp. havermoutpap 500gr cup Tr6	84312	953
Camp. rijstepap 500gr cup Tr6	27324	309
Camp. gortepap 500gr cup Tr6	9456	107
Camp Yogh 1.8% Nat Tr 6x150g Cup	23778	269
Camp Yogh GrSt TopCup Aard Fram Tr 6x170g	16272	184
Camp Yogh GrSt TopCup Amandel Tr 6x170g	8226	93
Mona VLY Perzik Tr 6x450g Cup	31986	361
Mona VLY Aardbei Tr 6x450g Cup	26298	297
Mona VLY Bosbes Chc Tr 6x450g Cup	23130	261
Camp. Magere kwark Naturel Tr 6x220 gr Cup	9708	55
Camp. Volle kwark 8,8% Tr 6x500 gr Cup	142038	802
Camp. Magere kwark Naturel Tr 6x500 gr Cup	203778	910
Jumbo yogh / vez Mango 450gr cup Tr6	4512	51
Jumbo yogh / vez Bosbes 450gr cup Tr6	2760	31

C Production line sections

Cup station

The filling machine starts with the cup station. In this station the cups are placed from the cup storage into the chain which moves through the whole machine. With suction cups the cups are retracted from the storage and placed into the chain. The chain has 6 cups in each row. The level of the cups in the storage is checked, if this level is low a warning will be send and if it is almost empty the machine will stop. The cup storage has to be filled by hand. When the cups are placed into the chain, a check is done to see if in all the cup holes are filled. If cups are missing the machine stops and cups can be placed in the holes by hand. If double cups are detected the machine stops and the extra cups have to be taken out. The cup station consists of the following parts:

1. Cup storage - 6 lanes
2. Light sensor - level of cups in cup storage
3. Servo motor - lifting movement forced unstacking
4. Servo motor - holding strips open/close
5. Cup break (pneumatic driven)
6. blocking and holding strips
7. Cup check
8. Cup suction
9. Servo motor - forced unstacking open/close
10. Servo motor and adjustment belt - height setting cup unstacker

Cup sterilisation

From the cup station the cups are transported to the cup sterilisation. Here the cups are sprayed with a combination of H2O2 and sterile air. This will be repeated a few times. After this the cups will be transported under the drying pipes and will be dried with hot sterile air. This is all done in an airtight compartment to prevent unsterile air from mixing in the sterile zone. The station consists of the following parts:

1. Cup drying
2. Cup sterilisation - H2O2 measuring unit
3. Cup sterilisation - Evaporator
4. Pressure regulator
5. H2O2 tank
6. Membrane valves
7. Membrane pump
8. Connection sterile air/steam/CIP
9. H2O2 extraction
10. Extraction hose

Filling station

The filling station consists of a dosing unit. This dosing unit can dose two product types at the same time, for example a fruit prep and a yogurt. The product is transported from the plant product supply to a product tank. From the product tank the product is dosed into the cups with mechanical piston valves. The cups get lifted to the dosing nozzles by the cup lifter with a twister unit. This twister unit can stay still or turn for a wanted swirl in the product. After filling the cups are lowered into the chain holes again.

The station consist of the following parts:

1. Cleaning tube
2. Supply of sterile air
3. Product tank
4. Dosing system
5. Cup lifter with twister unit

Seal station

After the cups are filled they will be sealed. The sealing can be done with a aluminium or a PET seal. The seals get extracted from the seal storage by suction cups on a rotatory arm. The seals get sprayed with H2O2 and dried with hot air. The arm rotates until the seals are placed above the cups and are placed on top of the cups. With heated sealing heads the seals are melted on top of the cups. This station consists of the seal applier and the sealing unit.

The seal applier consists of the following parts:

1. Servo drive with rack and pinion
2. Chutes for suction strips
3. Drum drive
4. Suction strips
5. Drums
6. Suction connection drum
7. Approach switch to detect drum position
8. Ejector
9. Suction cups

The sealing unit consists of the following parts:

1. Servo drive for base frame with sealcradle/-bridge
2. Base frame - vertically movable
3. Sealcradle
4. Chain hole support with movable seal support
5. Frame for cleaningcap
6. Sealbridge with sealing heads
7. Connection part sealbridge

Leak detection station

When the cups are sealed they are tested for leaks. The leak detection station has two ways of doing this. The first one is heating the air between the product and the seal, this way the air will expand and the seal will bulge. If the cup is not sealed properly, air will escape and the seal will not bulge. The other way of testing to by squeezing the cup. If the cup is sealed properly the seal will bulge and if not sealed properly, air will escape and the seal will not bulge. Both ways the bulge is measured the same way. If the seal touches the sensing finger, the cup is sealed properly. If the seal does not touch the sensing finger, the cup is not sealed properly and rejected.

The following parts are in the leak detection station:

1. Connection pneumatics/eclectics
2. Test bridge with test heads
3. Squeeze rails with holder
4. Height adjustment for squeeze direction

5. Chain hole support
6. Servomotor height adjusting squeeze direction
7. Servomotor squeeze movement
8. Servomotor lifting movement test bridge

Printing station

If the cup is properly sealed, some information is printed on the seal. If the cup will also get a re-close lid, the same information will also be printed on the lid. The station for the printing on the seal and on the lid is identical and will be explained here. The sealed cups are transported by the chain and placed under the printing heads. The printing heads move transversely over the cups en print on each cup in the row. The printing heads are supplied with ink via a tube, the tubes move together with the heads via a suspension with a cradle in the top of the machine. The movement is driven by a servomotor with a toothed belt.

The printing station consists of the following parts:

1. Suspension/cradle for ink supply pipe
2. Servomotor for drive
3. Collection tray for excess ink
4. Axis of movement
5. Printing head
6. toothed belt

Lid station

From the printing station the cups are transported to the lid station. Not all products require lids. If they do not require a lid, this station is just passed through without anything happening to the cups. The chain moves the cups over the cup lifters. The cup lifters are moved upwards by a servomotor, this way the cups are lifted slightly out of the holes. The lids are extracted from the lid storage by a row of suction cups. They take the lids and with a rotary movement of 180 degrees, the lids are placed on top of the cups. The lids are then pressed on the cups to snap on. The cup lifters lower the cups again into the holes. The cups now rest on the rims of the lids in the chain holes and are positioned slightly higher. This is also the test to see if the lid has been applied correctly. If the lid has not been applied (correctly), the cup will be positioned higher, leaving a small area underneath the cup. With a 'light curtain' it is check if light is visible underneath the lid, if this is the case the lid is applied correctly. If there is no light visible, the lid has not been placed correctly, the machine will stop and give the error that a lid is missing. Double lids are detected the same way but with a light sensor above the chain. After lids have been placed the cups are transported to another printing station which works the same was as explained above.

The cup lifters which are underneath the lid appliers consists of the following parts:

1. Cup lifting bridge
2. Exchangeable strips with lifters
3. Servo drive bridge
4. Lifters
5. Suction cups
6. Clamp strips
7. 'Light curtain' lid check

The lid applier consists of the following parts:

1. Cam disk
2. Suction bridge

3. Suction cups
4. Guide roller
5. Gear wheel rotary direction
6. Servo drive suction bridge
7. Rack and pinion

Packer station

From the printing station, with or without lid, the cups are transported to the packer station. Here the cups are lifted slightly and with a robot arm they are picked up and placed inside the trays. In every tray 6 cups can be placed. The trays arrive with a conveyor belt in the side of the packer station and are transported again by conveyor belt to the palletizer.

The packer station consists of the following parts:

1. Packer robot
2. Conveyor belt
3. Control panel packer

In the cup station, seal station and lid station the packaging materials are extracted from their storage with the use of suction cups. These suction cups get their under-pressure from the vacuum system. Inside the machine 3 vacuum pumps are placed, see figure C.1.

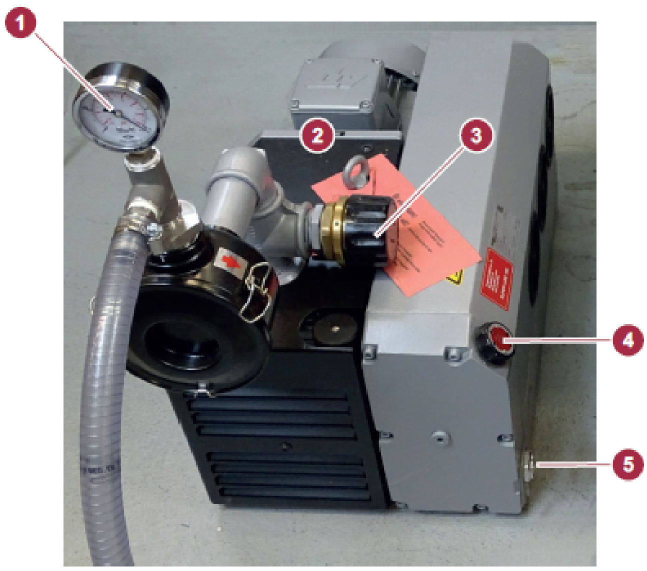


Figure C.1: Vacuum pump

The pump is provided with the following parts:

1. Manometer
2. Vacuum pump
3. Knob for adjusting pressure
4. Oil filling opening
5. Viewing window

The pumps are connected to see through tubes which are connected to the suction cups in the different station. A valve is used to build the under pressure at the right time and decrease when the cup, seal or lid has to be placed.

D Results

Corrective	exp 1	exp 2	exp 3.1	exp 3.2	exp 3.3	exp 3.4	exp 4.1	exp 4.2	exp 4.3
24,88	29,06	29,64	28,20	28,90	28,74	27,97	29,25	28,66	29,50
24,68	29,61	28,53	27,95	29,19	27,47	28,05	28,90	29,25	28,65
25,24	28,34	27,66	28,25	27,98	29,47	27,57	29,54	27,51	27,59
25,27	29,49	29,12	29,95	28,89	28,75	28,01	28,36	28,38	28,78
25,55	26,96	28,31	28,19	28,70	29,35	28,37	28,57	29,18	28,46
25,08	29,61	29,19	28,06	28,12	29,44	28,06	28,32	26,93	29,36
24,50	27,87	28,14	28,43	28,60	27,82	28,35	29,11	28,56	28,19
23,74	27,62	28,22	28,86	29,37	28,84	27,60	29,40	28,20	29,29
24,04	28,43	29,20	28,94	29,38	28,58	27,96	27,53	28,30	27,02
26,17	28,04	28,57	28,74	29,50	29,62	28,37	28,59	28,88	29,33

# Experiments	**Standard deviation**
5	0,31201
6	0,279189
7	0,340315
8	0,548941
9	0,580534
10	0,562318

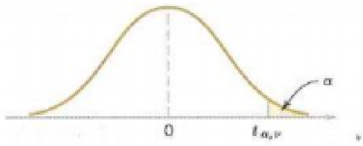


TABLE • V Percentage Points $t_{\alpha,\nu}$ of the t Distribution

ν \ α	.40	.25	.10	.05	.025	.01	.005	.0025	.001	.0005
1	.325	1.000	3.078	6.314	12.706	31.821	63.657	127.32	318.31	636.62
2	.289	.816	1.886	2.920	4.303	6.965	9.925	14.089	23.326	31.598
3	.277	.765	1.638	2.353	3.182	4.541	5.841	7.453	10.213	12.924
4	.271	.741	1.533	2.132	2.776	3.747	4.604	5.598	7.173	8.610
5	.267	.727	1.476	2.015	2.571	3.365	4.032	4.773	5.893	6.869
6	.265	.718	1.440	1.943	2.447	3.143	3.707	4.317	5.208	5.959
7	.263	.711	1.415	1.895	2.365	2.998	3.499	4.029	4.785	5.408
8	.262	.706	1.397	1.860	2.306	2.896	3.355	3.833	4.501	5.041
9	.261	.703	1.383	1.833	2.262	2.821	3.250	3.690	4.297	4.781
10	.260	.700	1.372	1.812	2.228	2.764	3.169	3.581	4.144	4.587
11	.260	.697	1.363	1.796	2.201	2.718	3.106	3.497	4.025	4.437
12	.259	.695	1.356	1.782	2.179	2.681	3.055	3.428	3.930	4.318
13	.259	.694	1.350	1.771	2.160	2.650	3.012	3.372	3.852	4.221
14	.258	.692	1.345	1.761	2.145	2.624	2.977	3.326	3.787	4.140
15	.258	.691	1.341	1.753	2.131	2.602	2.947	3.286	3.733	4.073
16	.258	.690	1.337	1.746	2.120	2.583	2.921	3.252	3.686	4.015
17	.257	.689	1.333	1.740	2.110	2.567	2.898	3.222	3.646	3.965
18	.257	.688	1.330	1.734	2.101	2.552	2.878	3.197	3.610	3.922
19	.257	.688	1.328	1.729	2.093	2.539	2.861	3.174	3.579	3.883
20	.257	.687	1.325	1.725	2.086	2.528	2.845	3.153	3.552	3.850
21	.257	.686	1.323	1.721	2.080	2.518	2.831	3.135	3.527	3.819
22	.256	.686	1.321	1.717	2.074	2.508	2.819	3.119	3.505	3.792
23	.256	.685	1.319	1.714	2.069	2.500	2.807	3.104	3.485	3.767
24	.256	.685	1.318	1.711	2.064	2.492	2.797	3.091	3.467	3.745
25	.256	.684	1.316	1.708	2.060	2.485	2.787	3.078	3.450	3.725
26	.256	.684	1.315	1.706	2.056	2.479	2.779	3.067	3.435	3.707
27	.256	.684	1.314	1.703	2.052	2.473	2.771	3.057	3.421	3.690
28	.256	.683	1.313	1.701	2.048	2.467	2.763	3.047	3.408	3.674
29	.256	.683	1.311	1.699	2.045	2.462	2.756	3.038	3.396	3.659
30	.256	.683	1.310	1.697	2.042	2.457	2.750	3.030	3.385	3.646
40	.255	.681	1.303	1.684	2.021	2.423	2.704	2.971	3.307	3.551
60	.254	.679	1.296	1.671	2.000	2.390	2.660	2.915	3.232	3.460
120	.254	.677	1.289	1.658	1.980	2.358	2.617	2.860	3.160	3.373
∞	.253	.674	1.282	1.645	1.960	2.326	2.576	2.807	3.090	3.291

ν = degrees of freedom.

Figure D.1: t table

D.1 Base

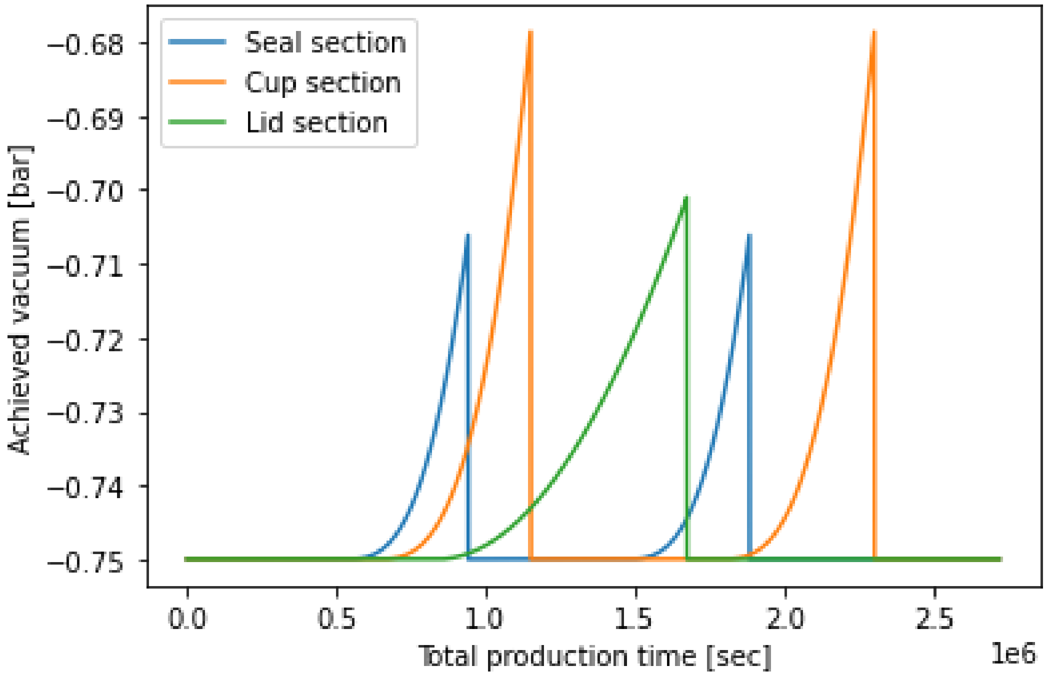


Figure D.2: Results base

D.2 Experiment 1

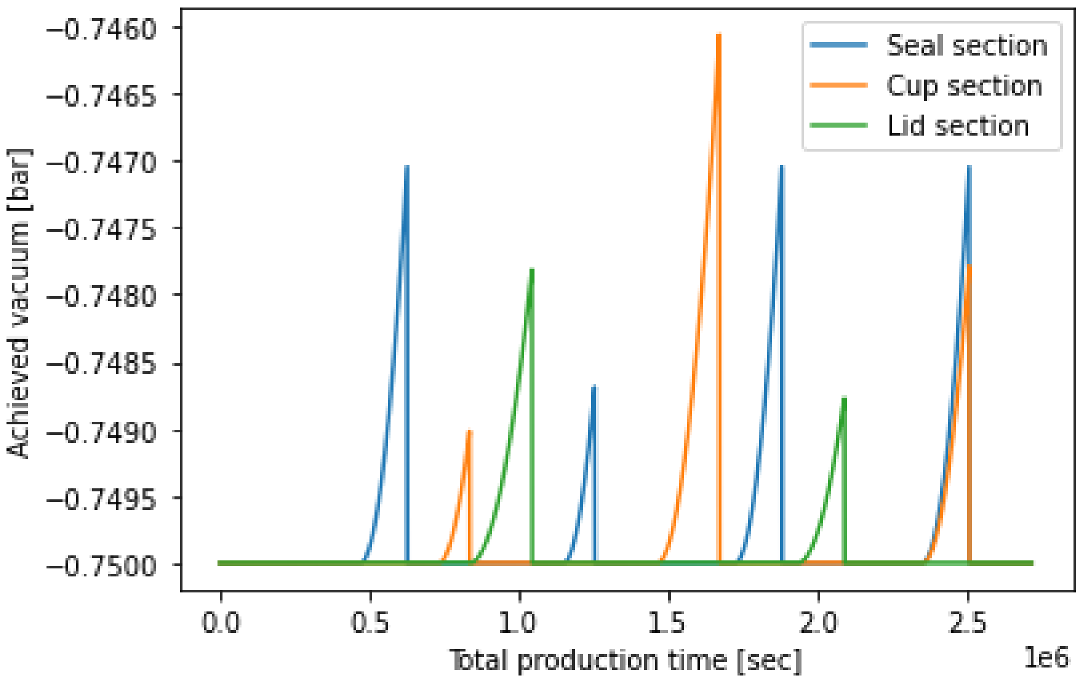


Figure D.3: Results experiment 1

D.3 Experiment 2

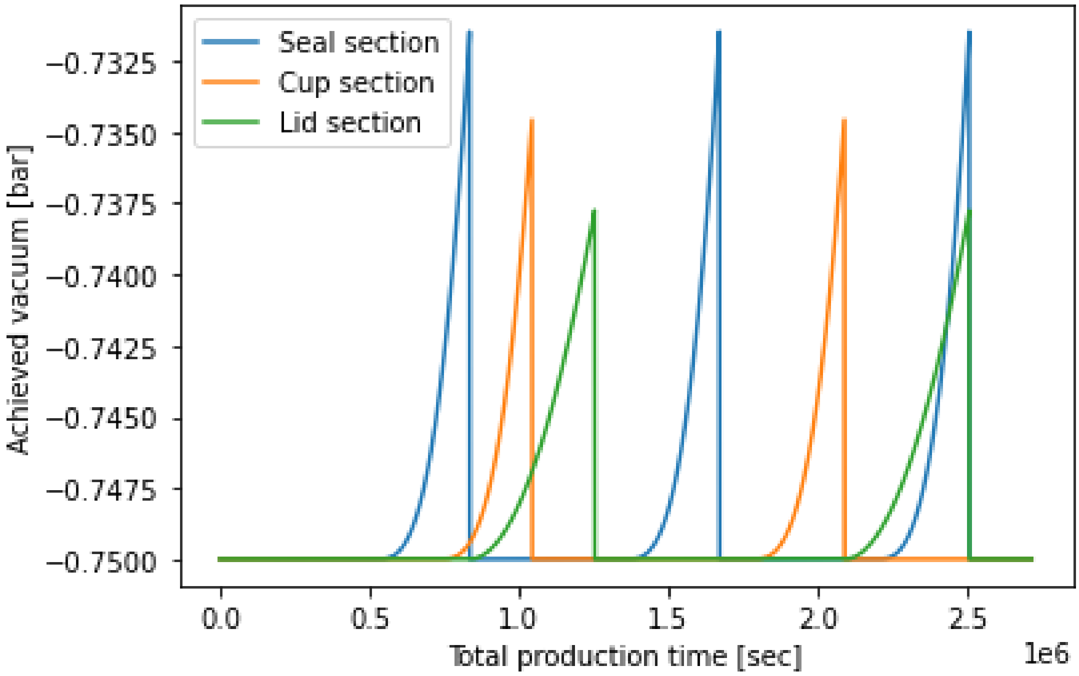
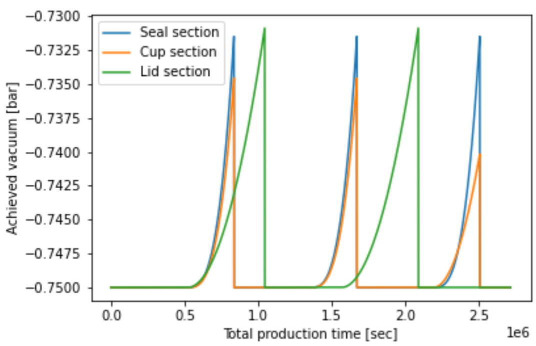
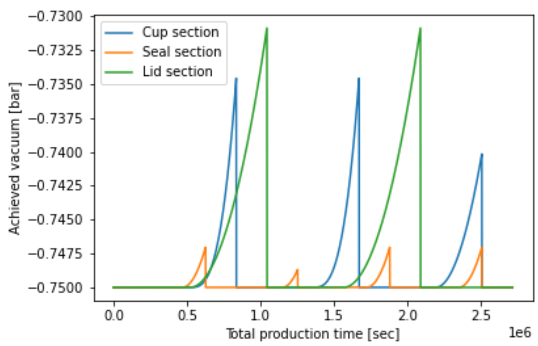


Figure D.4: Results experiment 2

D.4 Experiment 3

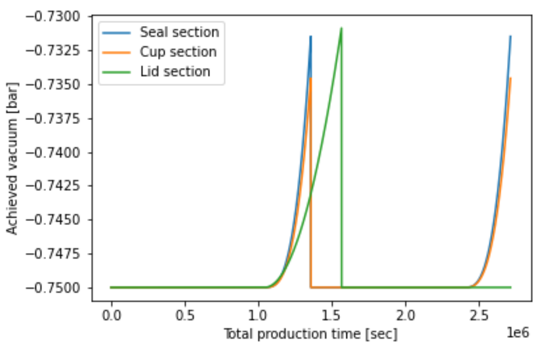


(a) Result exp 3.1 PdM

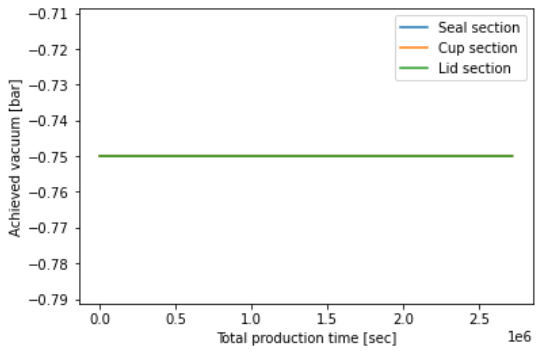


(b) Results exp 3.1 PM

Figure D.5: Results experiment 3.1

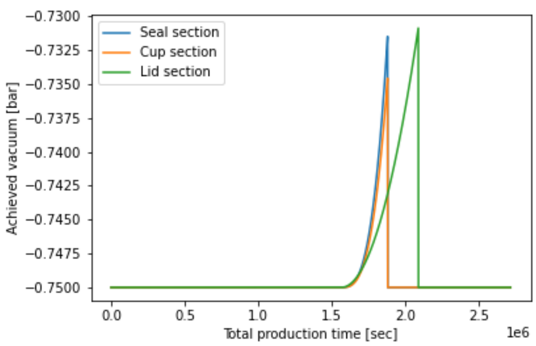


(a) Result exp 3.2 PdM

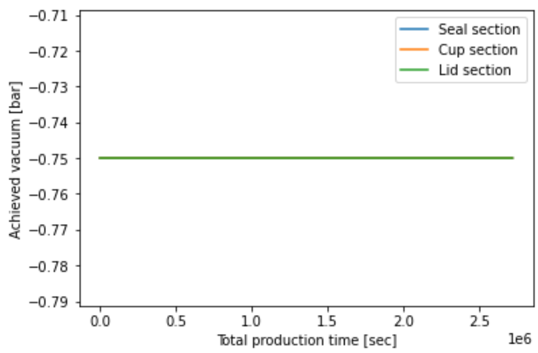


(b) Results exp 3.2 PM

Figure D.6: Results experiment 3.2

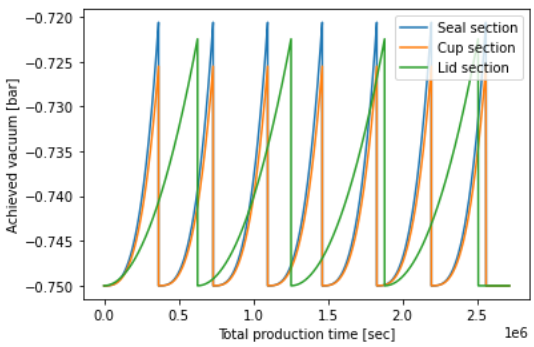


(a) Result exp 3.3 PdM

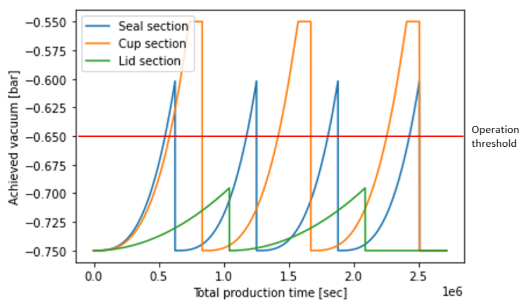


(b) Results exp 3.3 PM

Figure D.7: Results experiment 3.3



(a) Result exp 3.4 PdM



(b) Results exp 3.4 PM

Figure D.8: Results experiment 3.4

D.5 Experiment 4

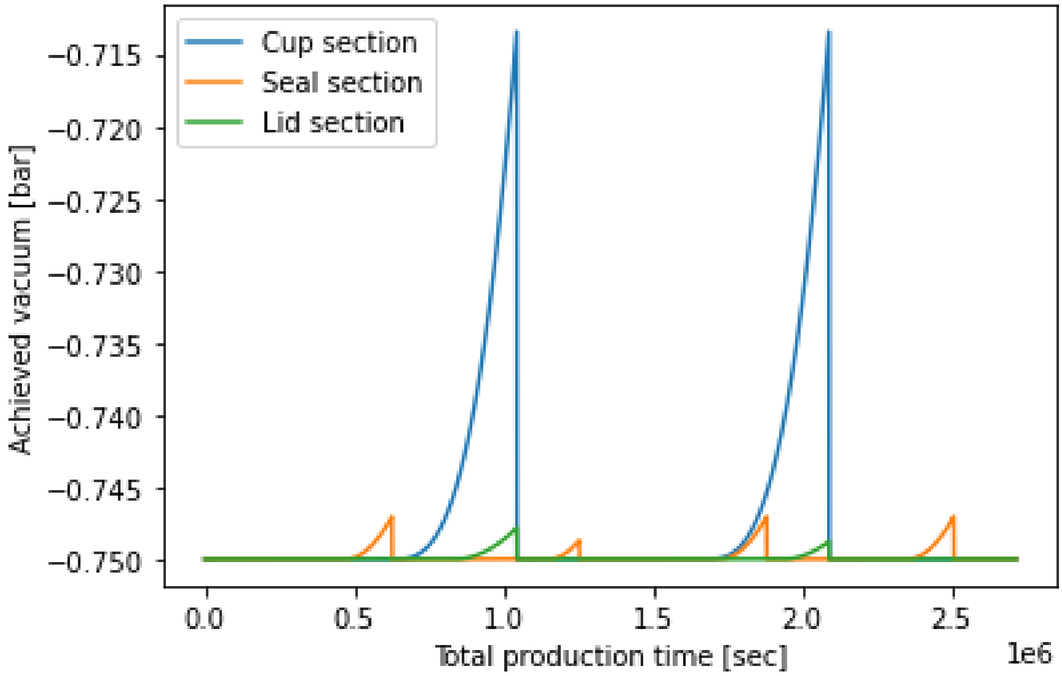


Figure D.9: Results experiment 4.1

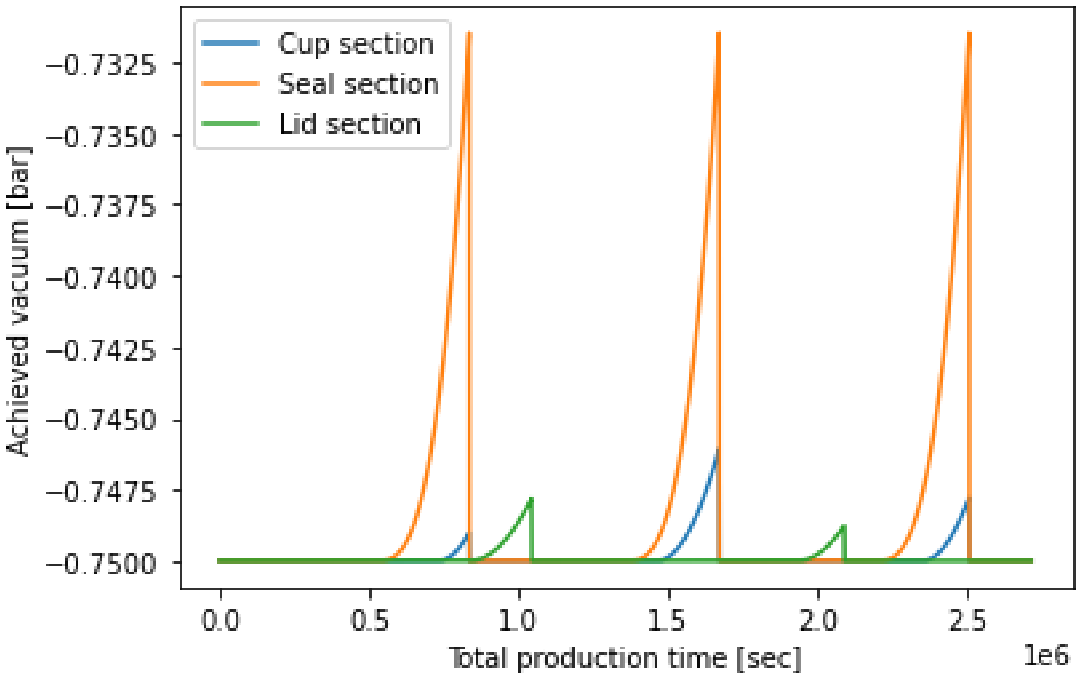


Figure D.10: Results experiment 4.2

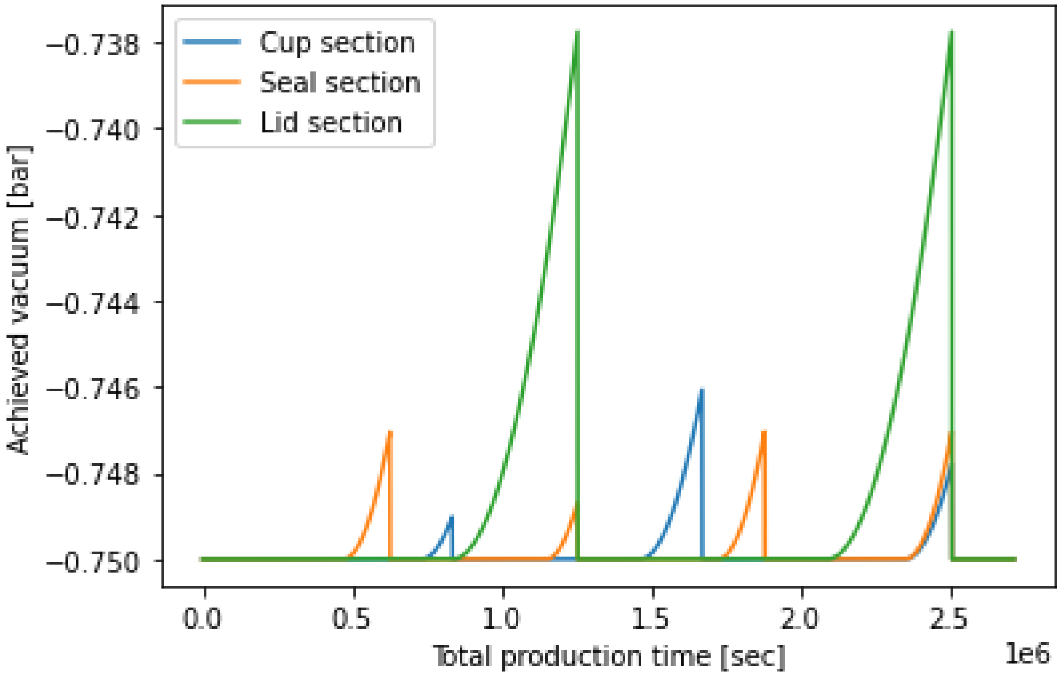


Figure D.11: Results experiment 4.3