OPTIMISATION OF THE WEIGHT STABILIZATION SYSTEM AT JDE

UNIVERSITY OF TWENTE

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Master Thesis of Thomas Anton de Koning

Optimisation of the weight stabilisation system at Jacobs Douwe Egberts

A discrete-event simulation study

Conducted at Jacobs Douwe Egberts
Production location of Senseo, Utrecht, The Netherlands

Supervisor JDE:	Supervisors University of Twente:
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MANAGEMENT SUMMARY

This research is conducted at JDE, production location Utrecht, concerning the rejections on the Senseo pad production lines.

JDE is a global coffee & tea company and sells vacuum packed coffee, liquid coffee, beans, coffee cups and Senseo pads. It introduced Senseo pads in 2001, in a collaboration with Philips. With this introduction, JDE and Philips changed the way the world drinks coffee.

The process of producing Senseo pads consists of three parts; first the pads are made and put in product carriers (semi-batches), second the product carriers are weighed (first weighing) and either accepted or rejected based on their weight and consecutively the product carriers are transported to the bag filling machine. Third, a bag is filled with the right amount of bags by emptying the product carriers in a bag, the bag is weighed (second weighing) and based on its weight either accepted or rejected. Then the bag is put into a box.

Waste occurs at the two weighing moments caused by rejections and another type of waste is overfill, which occurs when too much coffee has gone in a pad.
In this research, we aim to

i) Decrease the waste caused by rejections of product carriers and bags;
ii) Decrease the amount of overfill

This is done in three ways, first, by optimizing the rejection limits (i.e., how many grams a product may be off the norm weight to accept it), second by optimising the built-in weight stabilisation system within the production lines, the so called ‘feedback loop’. The feedback loop determines the weight of the pads and adjust the weight accordingly. The parameters that determine when and how the weight is adjusted are optimised, these are:

- Sample size (number of product carriers weigh to calculate the average weight)
- Tolerance (amount of grams the average may be beyond the norm, before adjusting)
- Adjustment factor (percent of the weight beyond the norm that should be adjusted)
- Delay (number of product carriers we should wait before the adjustment is finished)

Third, rejections are prevented by introducing statistical process control charts to detect when the system deteriorates and so when action should be taken to correct flaws in the system.

In 2019, x% of the product carriers (semi-batches within the process) and x% of the bags were rejected. That sums up to x product carriers and x bags per year. Rejections occur due to weight fluctuations, because there is not enough understanding of how the feedback loop works and how the weight itself fluctuates. It is unclear whether the rejection limits and the settings of the parameters are set to the best possible values. A better understanding of the feedback loop and the actual weight fluctuations should lead to less rejections.

The aim of this research is to decrease these rejection rates by at least 20%. This also brings us to the research question:

“How can JDE decrease the rejection rates within the process by at least 20%?”

To solve this problem, a simulation model was built. With this simulation model, it was possible to run experiments without affecting the production lines directly. Since all production lines are

fairly similar, the model is representative for all production lines. In this model, sources for stochasticity are included. Like, among others, the distribution of pad weight, the distribution of the weight of product carriers and the distribution of the inaccuracy of the weighing cell.

In the simulation, the rejection limits and the parameters of the feedback loop were varied in experiments.

Resulting in the following recommendations (based on bag of 48 pads):

- Decrease sample size from 10 to 5 product carriers;
- Decrease tolerance from 0.7 to 0.1 grams (i.e. as small as possible);
- Increase adjustment factor from 0.5 to 0.8;
- Decrease delay from 25 to 12 product carriers (i.e. as small as possible);
- Change rejection limit for product carriers from -2.0 & +4.0 to +/- 3.3 grams;
- Change rejection limit for bags from -3.5 & +10.0 to +/- 4.4 grams.

Resulting in the following improvements (based on bag of 48 pads):

- Rejection rate product carriers (simulated) decreases by 88%;
- Rejection rate bags (simulated) decreases by 62%;
- Costs for reworking decreases by 81%;
- Expected overfill decreases by 49%.

The improvements differ per bag size. In Figure 1, the decrease in Coffee in rework costs rate is shown per bag size. The weighted average decrease is 35%.

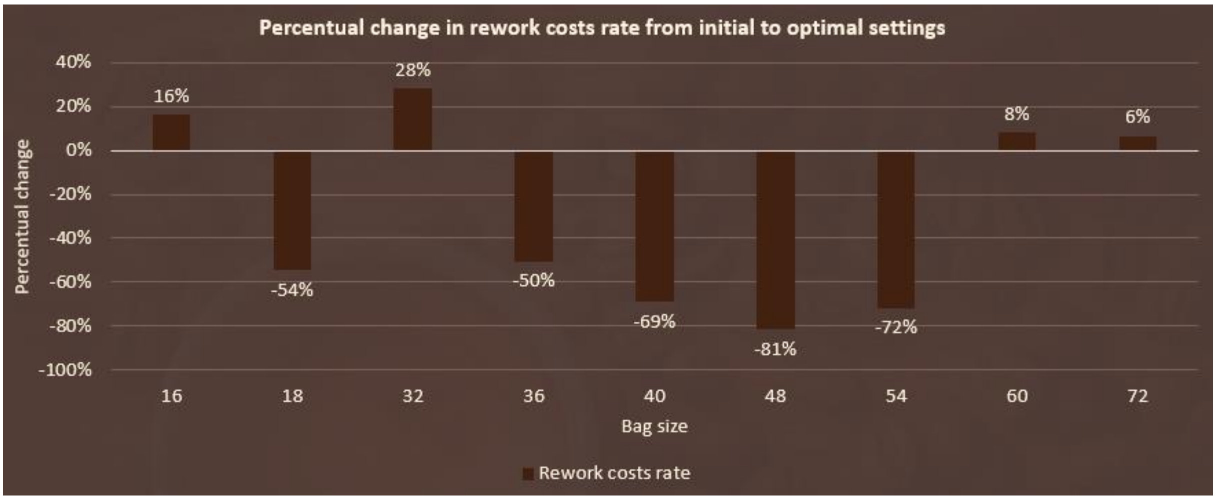

FIGURE 1: CHANGE IN COFFEE IN REWORK COSTS RATE FROM INITIAL TO BEST POSSIBLE SETTINGS

In Figure 2, the decrease in overfill of coffee per bag size is shown. The weighted average decrease in overfill is 22%.

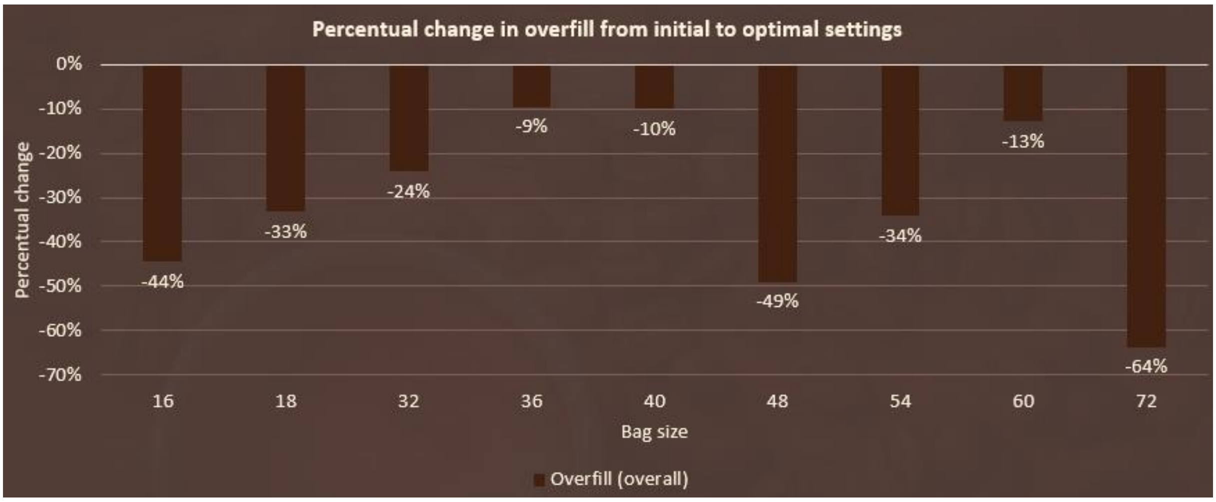

FIGURE 2: DECREASE IN OVERFILL FROM INITIAL TO BEST POSSIBLE SETTINGS

No further redesigns of the production line seems to have a substantial impact on the number of rejections. Redesigning or buying a set of product carriers are both possibilities, which can result in a decrease in Coffee rework costs rate of maximum 4.4%. However, with this minor decrese, the business case seems to be too weak. Though to even further decrease the rejections and better control the process, statistical process charts should be introduced and policies to act on certain behaviour of the system should be designed. The statistical process control charts can help decrease the overfill by 72% and rejections caused by mechanical issues can be reduced.

The results we found can be implemented in five phases, such that imperfections in the model are taken into account. The five phases are described below:

- *Phase 1:* Change the parameter settings, but start by using higher values than the recommended settings; consult the results of the sensitivity analysis and the assumptions described when choosing the values. Monitor the results.
- *Phase 2:* Then, gradually set the parameter settings to the recommended values and monitor the effects to the system. Start with changing the parameters that have the least impact on the results as seen in the sensitivity analysis.
- *Phase 3:* Change the rejection limits to the best possible limits obtained and monitor the rejections.
- *Phase 4:* Implement the settings to other lines and bag sizes while monitoring the results.
- *Phase 5*: Implement the control charts, starting at one line. Monitor results and implement at other lines too.

PREFACE

This thesis marks the end of my career as an Industrial Engineering & Management student at the University of Twente. In the past 6.5 years I completed a Bachelor's and Master's degree, besides contributing to the student life in Enschede by being an active member of several associations and student organisations.

To finalize my Master's degree, I conducted a research at Jacobs Douwe Egberts in Utrecht, The Netherlands, where I had the opportunity to dive deep in the working of their Senseo production lines. During my time at JDE, I experienced great support from the people around me, including supportive staff, operators, my manager and especially my supervisor. The results of my research look very promising, though they are not implemented yet, many valuable insights derived from this research.

I would like to thank Pieter, Nick and Sjors of JDE for their endless willingness to help me during this research. Many sparring sessions, experiments and discussions were conducted to better understand what was happening on the production lines and what causes should be researched and how. Especially Nick, my direct supervisor very proactively contributed to this research and helped me out several times with creative ideas and his proactive mindset.

I would like to thank my family and friends for their support during the time I studied at the University of Twente. Their support always provided an extra motivation for doing well and enjoying my time in Enschede. For the support during this research, Peter and Sander were especially helpful in challenging my understanding of the problem and the discussions, which were very productive and I liked them very much.

I would like to express my gratitude to Ipek Seyran-Topan for providing me with useful feedback and her willingness to put effort giving feedback no matter what the urgent tasks besides this thesis were. Furthermore I want to thank Engin Topan for providing feedback on my work based on a fresh view resulting in the last boost to improve this research.

Lastly, I hope you enjoy reading my thesis.

Thomas Anton (Tom) de Koning,
Utrecht, March 2021

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LIST OF ABBREVIATIONS

DES: Discrete event simulation

DOE: Design of experiments

JDE: Jacobs Douwe Egberts

KPI: Key performance indicator

PC: Product carrier

SPC: Statistical process control

1. INTRODUCTION

This section introduces the company to provide an idea of its corporate environment and goals. In section 1.1 the goals of the company and some of the pillars that it is focusing on. In section 1.2 the department the research relates to is described. In section 1.3 the overall process of producing Senseo pads is then described. In section 1.4 the problem within this production process is introduced. Finally, in section 1.5 the research along with the research questions is to be answered.

1.1 INTRODUCTION TO JACOBS DOUWE EGBERTS

In this section, the structure of Jacobs Douwe Egberts (JDE) is described from the highest level down to the department to this research relates.

Founding of JDE and general information

Jacobs Douwe Egberts Peet's is a coffee, tea and hot-chocolate manufacturer, listed on the Amsterdam Stock Exchange (AEX) and its headquarters are located in Amsterdam. The company was founded in 1753, in Joure, the Netherlands, where it traded coffee, tea and tobacco. Today, JDE owns numerous beverage lines, and they bring many different types and brands of beverages to the global market. With an annual turnover of around 7 billion Euros, JDE is the world's largest pure-play coffee and tea group by revenue, serving approximately 130 billion cups of coffee and tea in 2019 across more than 100 developed and emerging countries. With a portfolio of more than 50 leading global, regional and local coffee and tea brands, JDE offers an extensive range of products to serve consumer needs across markets, consumer preferences and price levels.[1]

With around 6% of the global market, JDE is the second biggest player of hot drinks in the world, after Nestlé SA (around 17% according to a report by Passport, 2019). The broad range of products and brands is one of the characteristics that make JDE a thriving company in the relative scattered market of coffee and tea. The company is able to serve multiple non-homogeneous markets with its global brands such as Senseo, Jacobs and L'Or (Figure 3), with its regional brands like Douwe Egberts, Ofçay and Carte Noire and its local brands such as Ali, Nova Brasilia and Karat. These scattered brands serving such a non-homogeneous markets make it necessary to fit a strategy for separate markets. Besides the multiple brands, JDE also sells multiple type of products. There is ground filter coffee, beans, as well as pads that were introduced in 2001 under the name Senseo, in addition to the upcoming cups.

[1] https://www.jdepeets.com/

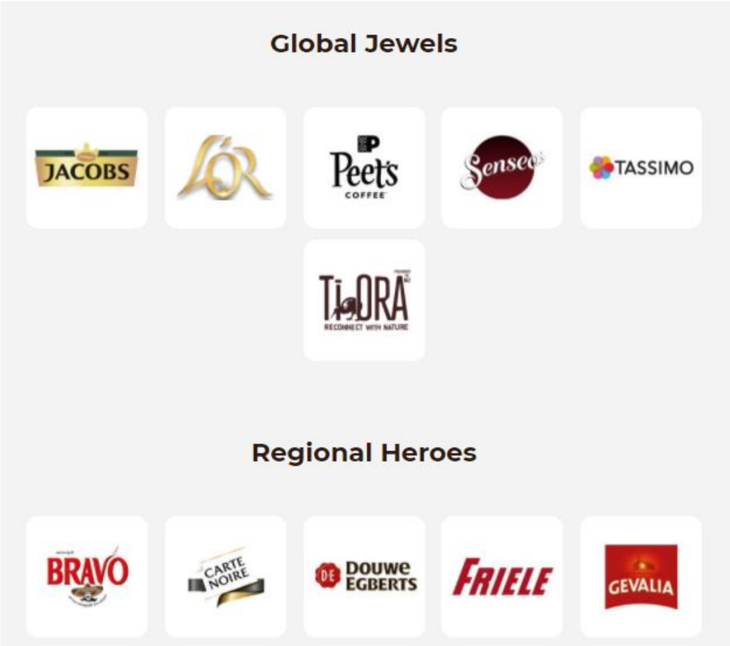

FIGURE 3: SOME OF THE BRANDS SOLD BY JDE.

JDE' strive for operational excellence

JDE strives for operational excellence by inducing internal competition between production sites. Retailers can buy their products at one of the production sites, and the costs of production and transport influence the competency of a production location. This internal competition gives production sites incentives to innovate and improve their processes, which can paradoxically be shared among all production sites after a successful improvement. For example, the Senseo production site in Utrecht, the Netherlands is competing with the Senseo site in Valasske, the Czech Republic, to serve parts of the same European market.
In 2016, JDE introduced the Manufacturing Operating System (MOS) project. This project aims for operational excellence across all the European production sites. For Utrecht, this means that the improved operations should result in a decrease in costs of €x million from 2016 to 2021. Currently, JDE Utrecht has finished the Extension phase and is working on the Advanced phase. This project should contribute among others, to reducing material losses.

1.2 JDE SENSEO PRODUCTION UTRECHT

In this section, the various sites of JDE in The Netherlands are described.

Head office

The head office of JDE is situated in Amsterdam, the Netherlands. In Joure, JDE produces mainly tea, liquid coffee and freeze-dried coffee. The other production site in the Netherlands is located in Utrecht. At this production site, vacuum-packed coffee is produced and packaged in the area indicated by 'Unit 1'. In 'Unit 2' in Utrecht, JDE produces around 3.5 billion Senseo pads per year.

Senseo department Utrecht

This research involves 'Unit 2' in the Utrecht production site (i.e. the production department of Senseo pads). In this unit, there are 11 production lines available, from which normally 10 are in operation. One line is preferably not in use, since its equipment differs from that of other lines, causing a relatively high risk of failures. The factory starts producing on Sunday night at 10 p.m. and stops on Friday at 10 p.m., so it produces Senseo pads for five days per week, 24 hours a day. The production times are split in three time slots: three different shifts of operators take care of one of the time slots of 8 hours per day.

Operators, process engineers and planning

The group of operators switch their working times every week. Every group has a shift lead. Besides these groups, there are other employees who are also essential to the business. These include the mechanics who solve mechanical issues and perform maintenance on the machines, as well as the process engineers who continuously seek new opportunities to increase the efficiency of the machines. Besides the process of pad production, the quality department checks among others the quality of the ground coffee and whether finished pallets of boxes with customer units meet the weight requirements. There is also a production planning department that decides on when to produce what kind of products on what production line. The number of units to be produced is determined by a central demand planning team operating from the headquarters.

Product variations

The Senseo production unit in Utrecht produces bags with Senseo pads of eight different sizes, namely 16, 18, 32, 36, 40, 48, 54 and 60 pads per bag. The production unit produces over 10 different blends, a blend being a mix of certain types of coffee beans that are roasted and ground in a particular way. In addition, the unit produces pads for several brands, of which Senseo, Douwe Egberts, Kanis & Gunnink are the most frequently produced. With these combinations, changeovers to different sizes or blends do not occur, or they occur several times per day per production line.

1.3 PRODUCTION PROCESS OF SENSEO PADS

In this section, the overall process of pad production is explained, with an emphasis on the moments in which rejections take place.

The process from raw material to packaged product

The process (see Figure 4) starts with the production of a blend. To finish a blend, the beans are roasted, blended with other beans and finally ground. The blend is distributed to the pad making machine in the packaging department. In the packaging department, the pads are filled with coffee, checked on certain quality measures and finally packed in boxes and the boxes are finally stacked on a pallet.
The quality measures, indicated in Figure 4 are:

1: Check whether there is coffee in the rim of a pad;
2: Check whether the weight of a full product carrier is within the rejection limits for product carriers;
3: Check whether the header of the bag is correctly folded;
4: Check whether the weight of a bag is within the rejection limits for bags.

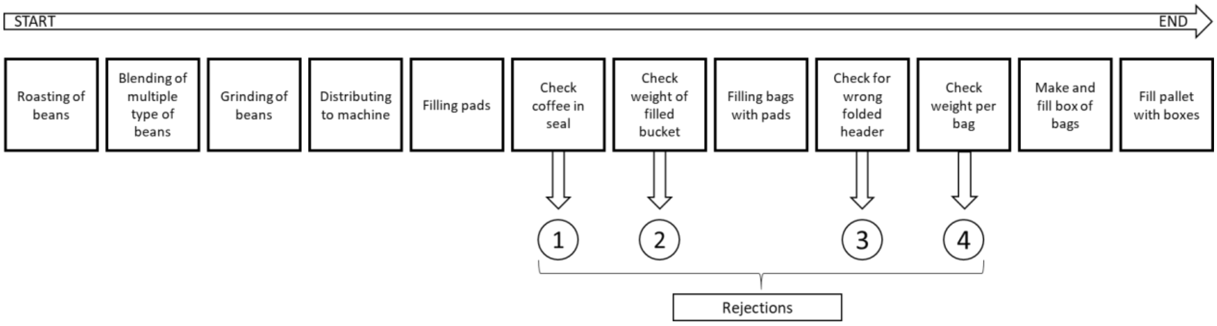

FIGURE 4: PROCESS OF PRODUCING SENSEO PADS FROM ROASTING TO PACKAGING.

The filling of pads by the pad making machine and checks on quality

Number 1: Hopper
This distribution is done by a screw which distributes the coffee into the hopper of the pad making machine (nr 1 at Figure 5). The screw' speed is controlled using a proportional-integral-derivative (PID) controller and a laser level sensor.

Number 2 and 3: Dosing drum and Forming drum
The coffee is sucked out of the hopper by the dosing drum (nr 2 at Figure 5). From the dosing drum, it is dropped in a piston of the Forming drum (nr 3 at Figure 5). The pad making machine can make up to x pads per minute. This dosing drum which consists of 40 pistons in total, 20 each on the operator and the machine side. Pads are filled in a volumetric process (i.e. the amount of coffee that end up in a pad depends on the volume of the cavity).

Number 4: Pad is sealed
Just after the pistons are filled with coffee, the pads are sealed (nr 4 at Figure 5).

Number 5: Pad vision control
Just after the pads are filled, the pads are checked on nine different criteria by a camera (nr 5 at Figure 5), known as the 'vision', (see check nr. 1 in Figure 4). The most common criterion is 'coffee in the seal' (CITS), which indicates the presence of coffee grounds in the rim of the pad. A pad may have coffee in the seal up to certain limits; if the amount of coffee in the seal exceeds these limits, the pads are rejected.

Number 6: Pad laydown
Rejected pads are cut and dropped out of the machine. Accepted pads are cut from the filter paper, collected in a stack and dropped into a product carrier. This collection and dropping of a stack of pads into a product carrier is called the 'lay-down' (nr 6 in Figure 5).

Product carrier weight check
Next, the product carrier is weighed (check nr. 2 in Figure 4). If the product carrier does not meet certain weight specifications, it is rejected. Otherwise, it is transported to the location where the accepted product carriers are emptied.

Filling the bag
The bags are filled by emptying product carriers and dropping the pads of that product carrier in a tube. Via the tube, the pads end up in the bag. Then the bag is filled.

Folding the header
After filling the bag, the header of the bag is folded, and the fold is subsequently checked (nr. 3 in Figure 4). If the fold is accepted, the bag is transported further.

Bag weight check
Then the full bag is weighed and based on its weight either rejected or accepted. This is the final check (nr. 4 in Figure 4). Then the bags are processed further and put in a carton box to be send to retailers.

The product carrier weighing check and the bag weighing check are the focus of this research.

X

FIGURE 5: DETAILED PICTURE OF THE PAD MAKING MACHINE.

1.4 PROBLEM DESCRIPTION

This section introduces the problem, the losses caused by the system, the types of losses and the severity of the losses.

1.4.1 INTRODUCTION TO THE PROBLEM

The whole weighing process needs to achieve the goal of having the exact net weight in each bag, no more and no less to prevent rejections in the process and overfill in the end. In an ideal situation, no rejections of product carriers or bags and no overfilling/underfilling is present in the system. Currently, hourly underweighting still occurs as part of the process, as do bag and product carriers rejections as well as overfilling. Depending on the bag size, the weight may be 3.5-6 grams less than the norm or 9-15 grams above it.

Material losses and reworking

As shown in Figure 4, the coffee pads are checked at four different checkpoints. The first is related to the coffee in the seal, the second check verifies the weight of a product carrier, the third evaluates whether the header of the bag and in the fourth is again a weight check to ensure that the product meets EU regulations. The rejected pads are reworked (see Figure 6 for the activities that result in the most reworking). During this reworking process, the filter paper is separated from the coffee and the coffee then flows into the supply in the machines. This reworking causes losses in terms of materials (see Figure 7), the amount of coffee and filter paper is substantial (Figure 8) and can be reduced by decreasing the proportion of rejected product carriers and bags (Figure 6).

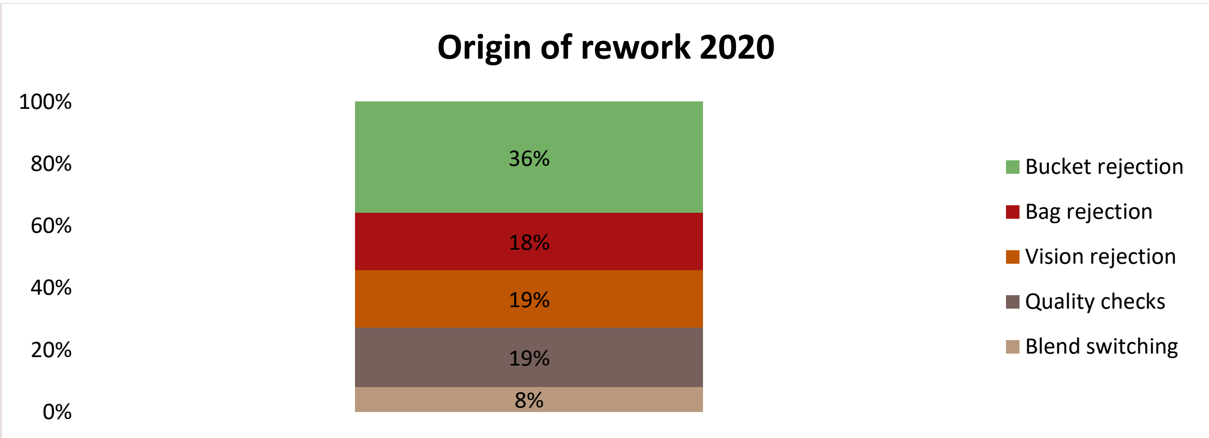

FIGURE 6: CAUSES FOR REWORKINGS.

FIGURE 7: MAIN MATERIALS USED IN THE PAD PRODUCTION PROCESS.

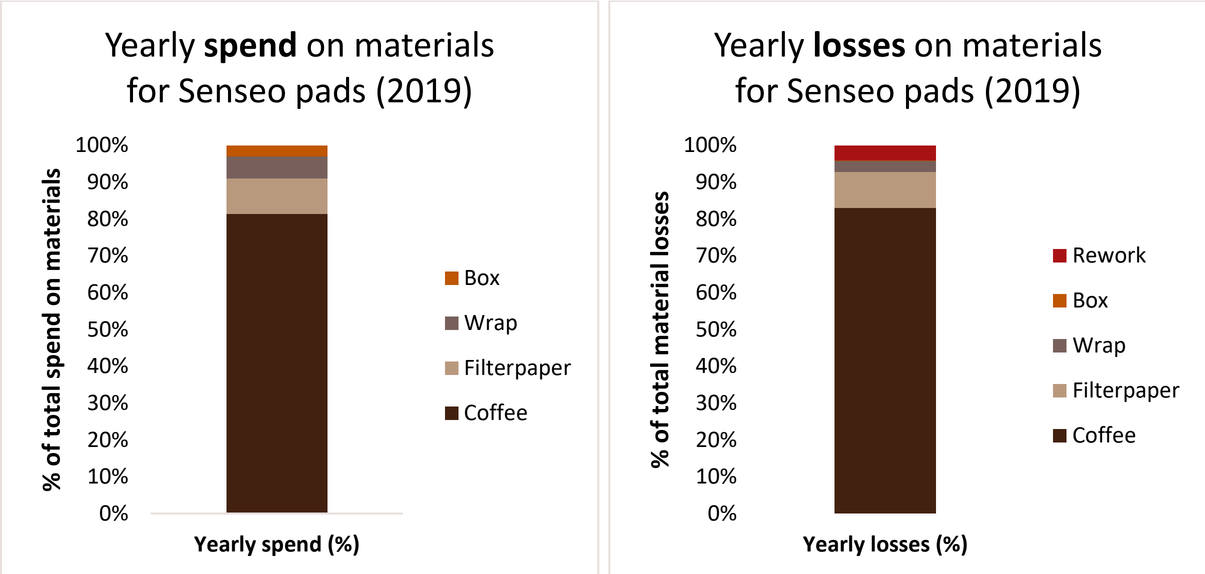

FIGURE 8: YEARLY EXPENDITURES AND LOSSES ON MATERIALS IN PERCENTAGE OF THE TOTAL FOR 2019.

First check: Coffee in the seal

The first check is executed by the ‘vision’ system, in which around x% of the pads are rejected. This accounts for around x% to the total amount of coffee that is reworked. The precise costs related to the rejected pads is unknown. Orbons (2018) conducted a study on the causes leading to the presence of coffee in the seal. Several causes were found, but they are difficult to change, therefore improving the system to reduce the rejections caused by coffee in the seal is a challenging task. Therefore, this cause of rejection is excluded from the present research.

Second and fourth check: Weight checks

The second and final checks are both weight related. The second check weighs the products carriers and rejects them based on internal limits set by JDE, while the fourth check weighs the amount of net coffee in the bag, ensuring that the weight meets EU-regulated specifications. The wider the limits for the weight of the product carriers, the higher the standard deviation of bags should be. Product carrier and bag rejections accounts for x% of the total amount of coffee that is reworked (see Figure 6). These weight checks are to be optimized within the scope of this research, i.e. all aspects related to weight are within scope.

Third check: Incorrectly fold bag header

The third check in the process is whether the header of the bag is correctly folded. This results in 0.27% bag rejections, based data from October 2002 from a counter in one of the production lines. Although this cause is substantial, we have decided to exclude it from this research, since it is self-contained and does not influence the weight.

1.4.2 PROBLEM CLUSTER

The problem JDE faces is that according to their ambition, there is too much rework and waste caused by rejections in the process of producing pads, indicated as the action problem in Figure 9. Rejecting something in the process causes rework. Rework is the process of opening a pad and separating the filter-paper and the coffee. The filter-paper is wasted, the coffee is supplied to the production lines again and therefore not wasted, but the value of the reworked coffee is reduced on average since the reworked coffee should always be of a lower or equal quality compared to the coffee it is mixed with.

This problem mentioned above has two main root causes indicated in Figure 9, i) the best possible limits for when to reject products are unknown and ii) the best possible parameter settings in the feedback loop are unknown.

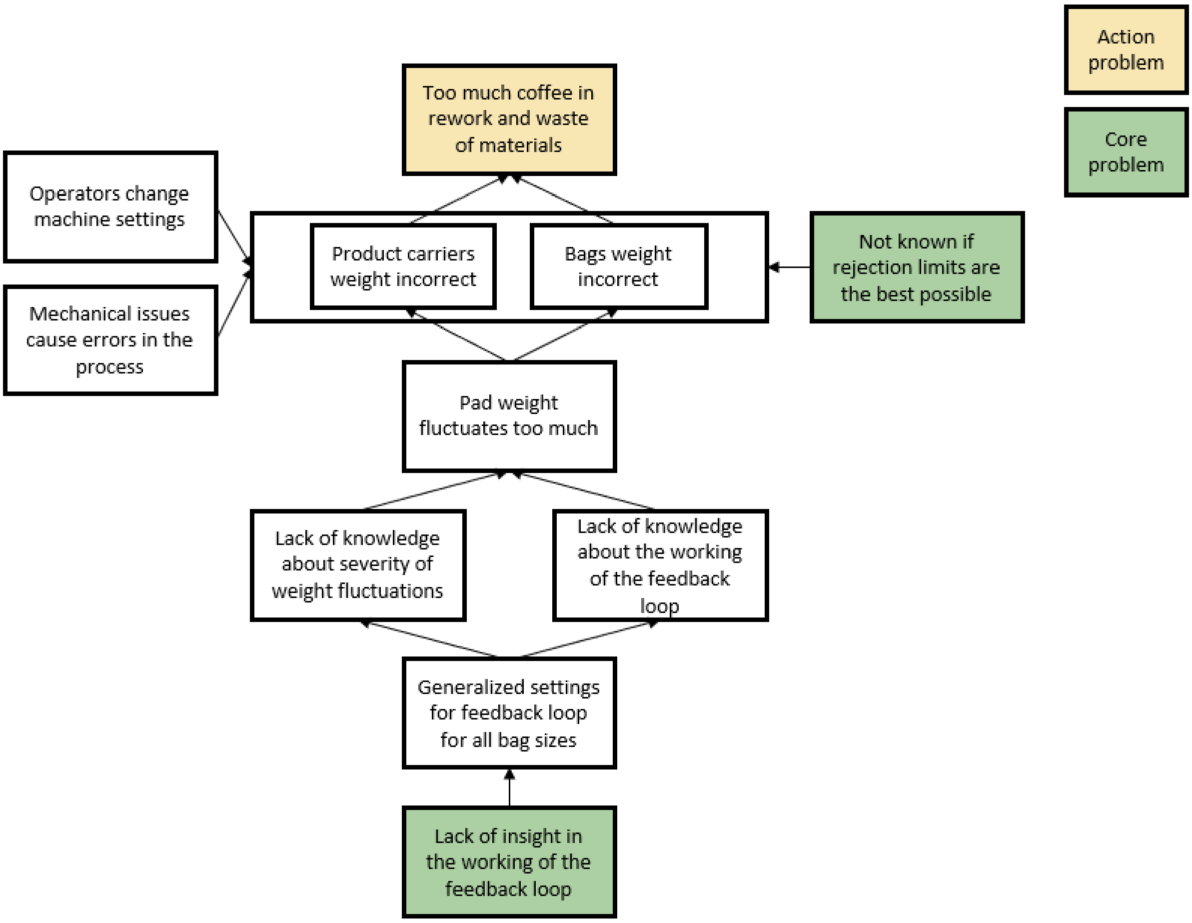

FIGURE 9: PROBLEM CLUSTER OF THIS RESEARCH.

1.4.3 CURRENT PERFORMANCE ON THE PROBLEM

The performance of the system is expressed in the rejection rates of product carriers and bags and in over- and overfill compared to the aimed weight of bags.

Rejection rates

In 2019, an average of x% of the bags were rejected (see Figure 10), which translates into around 340,000 bags. On average x% (see Figure 11) or, around 1.4 million product carriers were rejected that year. This was not solely due to their weight, also caused by other factors such as mechanical issues play a role. When the machine has an error upon the start-up, rejections can occur as well. Based the judgment of experts within JDE, the rate of rejects due to mechanical issues can be substantial, although, the figure is unknown. This figure may be revealed if weight-based rejections can be minimized. Apart from this research, process engineers with a mechanical background are responsible for investigating the mechanical issues. Therefore, the mechanical issues are beyond the of scope of this study.
Based on Figure 10 and Figure 11, one interesting observation is that there seems to be a seasonal influence in the rate of rejections. The rejections rates of product carriers and bags seem to show a similar trend, which seems to increase and decrease for several consecutive weeks, indicating seasonality. Although this effect could be present, the process we are further exploring here should be able to respond accurately to seasonal influences. In Section 2.3 this

is discussed in more detail, there is explained why the seasonal influences are not taken into account.

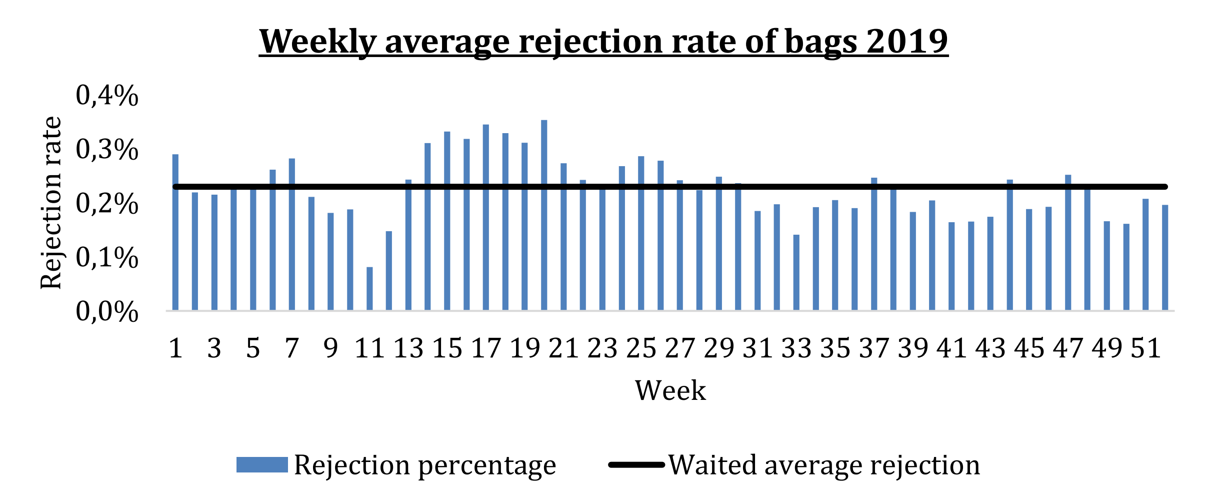

FIGURE 10: OVERALL BAG REJECTION RATES IN 2019.

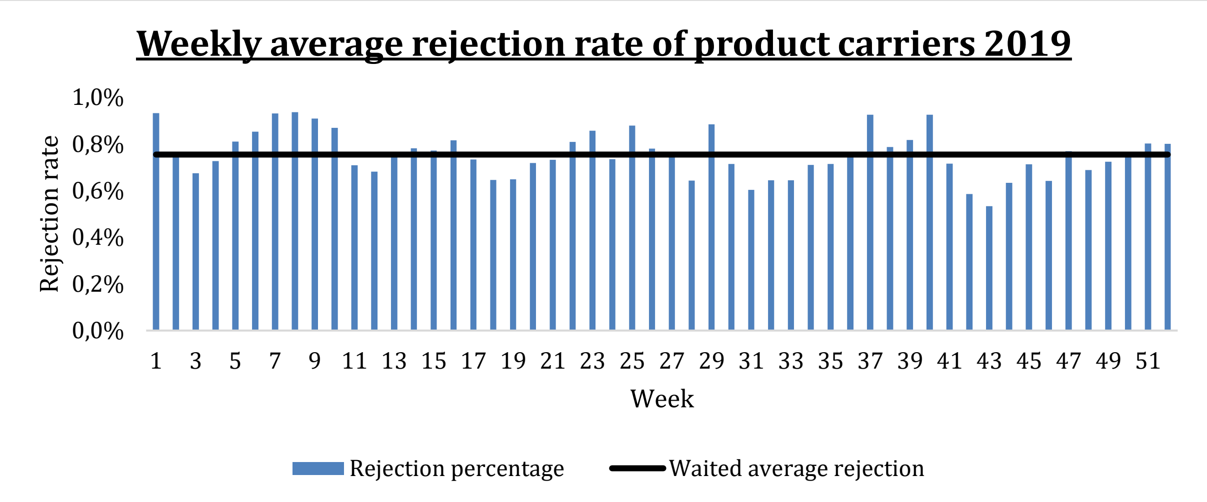

FIGURE 11: OVERALL PRODUCT CARRIER REJECTION RATES IN 2019.

Underfill and Overfill

The amount of overfill and underfill are good indicators of the overall system performance, and they demonstrate the quality of the pads based on weight. Underfilling is an indication that pads have less than 7 grams coffee, while overfilling means that they have more than 7 grams. Therefore, if the feedback loop in the system, is functioning properly, the hourly average of the bags is expected to be exactly equal to the target weight. Currently, overfilling is limited and shows a decreasing trend over the past several years, suggesting that JDE has already improved its processes. Over the first half year of 2020, the amount cumulative overfilling is nearly zero (see Figure 12), still however, the system can be improved because overfill and underfill still occur. Underfilling and overfilling is both present by over 13,000kg of coffee in the first half of 2020. Theoretically, if the system functions properly, the average weight should be exactly equal to the norm. These numbers are calculated based on the hourly averages of the bags compared to the target weight of these bags, multiplied by the number of bags filled in a given hour. Overall, we can conclude that the weight can be more stable such that the under- and overfill can be decreased.

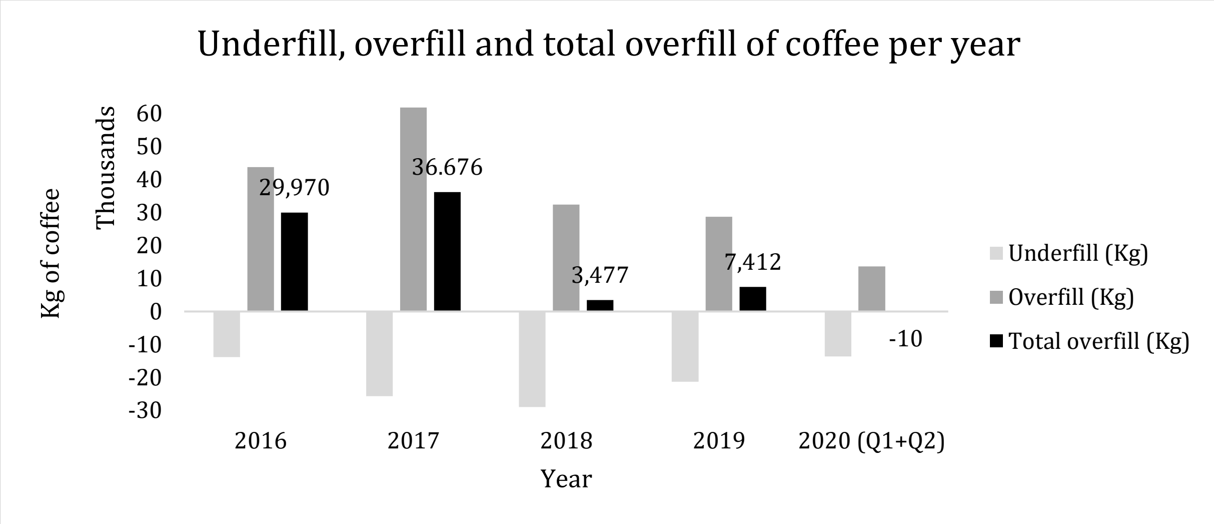

FIGURE 12: ANALYSIS OF UNDERFILLING AND OVERFILLING OVER THE PAST FIVE YEARS.

Costs of wasted materials

Three types of wastes are caused by rejections of product carriers and bags. When a product carrier is rejected, filter paper is wasted and coffee is reworked causing a devaluation. When a bag is rejected, additionally wrapping paper is wasted. Based on the yearly expenses of 2019, on average the filter paper costs €x per pad (total spend on filter paper divided by x pads), the wrapping paper costs €x per pad (total spend on wrapping paper divided by x pads) and the coffee devaluation costs €x per pad (total value devalued coffee divided by x pads). Assuming the rejections rate are also representative for rate of rejected pads, the yearly costs related to rejections are as follows (see Table 1):

TABLE 1: COSTS OF WASTE CAUSED BY REJECTIONS.

Waste (€)	**Product carrier**	**Bag**
Filter paper		
Wrapping paper		
Devaluated coffee		
Total per type		
Total		

Based on these numbers, the business case for eliminating rejections is €x per year. According to the judgment of the production engineer at JDE, the estimated rejections caused by weight being beyond limits is x-x% of the total rejections, making the business case between €x and €x per year, for wasted materials.

1.4.4 OBJECTIVE OF THIS RESEARCH

The aim of this research is to decrease the number of product carrier and bag rejections without accepting bags where a pad is missing, this results in the following realities and norms:

At this moment, the rejection rate for product carriers is x% (reality), the aimed rejection rate for product carriers is 0.6% (norm), which implies a decrease by 20%.
At this moment, the rejection rate for bags is x% (reality), the aimed rejection rate for bags is 0.12% (norm), which implies a decrease by 48%.

To make both happen, an objective that serves both aims is introduced, namely the ‘costs of rework’. The costs of rejecting a product carrier is set equal to the amount of coffee in the product carrier, the costs for filter paper are inherent to its weight. When rejecting a bag, waste of the bag itself also comes with a cost. Since rejected bags cause a wastage of wrapping paper too, the 'costs of rework' of a rejected bag is determined by the amount of coffee in the bag, multiplied by 1.62. Since, the material costs per rejected pad are 62% higher with a rejected bag.

1.4.5 CONCLUSION TO THE PROBLEM INTRODUCTION

The action problem that is tackled in this research is that there are too many rejections causing rework. Through optimizing the weight stabilization system and the rejection limits, this should be reduced. Since most losses come from product carrier and bag rejections, we focus on reducing these rejection rates. Furthermore, as we are focusing on the process side of the problem (rather than the mechanical side), we aim to research the settings of the production line so as to minimize the number of rejections caused by weight discrepancies.

1.5 RESEARCH APPROACH

In this section the aim of the research, the scope and the research questions are introduced.

1.5.1 RESEARCH GOAL

The goal of this research is to improve the weight stabilisation system used within the production line of Senseo pads. The system should be improved by optimising the current parameters. The results of this research should eventually contribute to stabilising the weights of Senseo pads and reducing the rejection rates of product carriers and bags, in addition to reducing waste, reworking and overfilling.

1.5.2 RESEARCH SCOPE

There are several limitations to the scope of this research, which include processing and mechanical issues, slight differences per line and differences per blend. These limitations are discussed below.

1) We limit ourselves to rejections caused by process errors. Occasional mechanical issues are not taken into account. Mechanical issues are for example why too many or too few pads are dropped in a product carrier or when the weight changes because of a mechanical issue like a change in the power of vacuum suction.
2) We focus on a single line, that is where the theoretical model of the real system is based on. Slight differences per line, e.g. are more or less accurate weighing cell, are ignored. The line used is Line 17. There are three reasons to base the research on Line 17: i) It has a product carrier weighing cell that will also be used by other lines in the future. Currently, only Lines 17 and 19 have the latest version of the product carrier weighing cell. ii) It is possible to extract more data from production Line 17 and 19 than from the other lines. iii) Line 17 produces bags of 48 and 54 pads, for which product carriers with the largest number of pads are used and several product carriers are needed to fill one bag. Differences should be taken into account while implementing the recommendations.
3) We ignore differences per blend. Different blends can exhibit different characteristics that may cause variations in weight. For example, the way in which the beans are roasted and ground can influence the density of the coffee. Though, fluctuations in weight are assumed to be similar for all blends.

1.5.3 RESEARCH QUESTIONS

In order to achieve the goals mentioned in Section 1.4.4, several research questions are introduced that must be answered.
First, the main research questions is formulated as follows:

"How can JDE decrease the rejection rates within the process by at least 20%?"

Next, several sub-research questions that must be answered to successfully answer the main research question were formulated. The sub-research questions are listed below.

To address the first research question, the working of the several processes that are incorporated into the production lines are thoroughly explained. Logic flows of the processes will be made and it will be determined which characteristics influence the weight by conducting experiments on the production line. Then, it is assessed whether these factors can be changed. System deteriorations are assessed by looking into the data and on-the-floor interviews. Finally the current performance of the system is analysed.
The answer to this research question is given in Chapter 2.

1. What is the current weighing process and current performance of the system?
   1.1. What are the current rejection rates of the products made?
   1.2. What processes are relevant to the weighing process?
   1.3. What are possible root causes for weight variation?
   1.4. Which factors influence the process of weighing and which one can be changed?
   1.5. What kinds of deteriorations need to be taken into consideration?

To this end, a literature review about how to study systems is conducted, to determine the possible ways to study a system that exists and which one is most appropriate for the problem at hand. Because of the complexity of the system, we will decide to build a simulation model to study the system at hand. Furthermore, the steps to take while building a simulation model and the ways to determine the performance of the system are described.

The answer to this research question is given in Chapter 3.

2. How can we model the described system according to the existing literature?
   2.1. How can we model a system according to the literature?
   2.2. What type of model is appropriate to model the current system?
   2.3. How can the results of the system be verified and validated?

In this research question it is determined how we can build the model. The model is verified and validated before beginning the experiments. These experiments are first conducted with the parameters in isolation, such that all settings remain as they are except for one parameter setting. A small range of possible values remains as a result, and with this small range, design of experiments are conducted to find the best possible values by taking interdependency between the parameters into account.

The first part of the answer to this research question is given in Chapter 4 and the last part about experiments and the best possible settings is given in Chapter 5.

3. How can we redesign the weighing process to decrease variability?
   3.1. What factors and process characteristics should be included in the model?
   3.2. What is the impact of variety within the system on the process objectives?

3.3. Given the objectives taken into consideration, what are the best possible settings?

The last step in optimising the weighing process is to detect when the system is not performing properly. Since the built-in systems cannot detect (and so not correct) certain flaws, statistical process controls can give insights in a flawed system that can be corrected to prevent rejections from happening.

The answer to this research question is given in Chapter 5.

4. What appropriate measures can be used to control the deterioration of the production process?
   4.1. What kind of statistical process control charts are available in the literature?
   4.2. What key performance indicators are relevant for detecting flaws in the weighing system?
   4.3. What process control chart is appropriate for tracking the performance of a key performance indicator?

1.6 READER GUIDE

In this section, the structure of the report is explained. The structure of the report is strongly related to the sequence of the research questions. In Table 2, the research questions and corresponding chapters are listed.

TABLE 2: RESEARCH QUESTION RELATED TO CHAPTERS IN THIS RESEARCH.

Research question	Chapter	Short description
1.1	1.4.3	Problem introduction
1.2	2.1	Process description
1.3	2.2	Root cause analysis
1.4 / 1.5	2.3	Stochasticity and characteristics of the system
2.1	3.2	Ways to study a system
2.2	3.5	Suitable approach for problem
2.3	3.7	Performance measures
3.1	4.1 – 4.5	Inputs, outputs, assumptions, verification and validation
3.2	5.2	Experiments
3.3	5.3	Sensitivity analyses
4.1	5.5	Statistic process controls
4.2	5.5	Key performance indicators
4.3	5.5	Statistic process controls for JDE

1.7 CONCLUSION OF INTRODUCTION

In this section the company and the production site in Utrecht which produces Senseo pads are introduced. Then the high-over process is described, to fit the problem in the bigger picture. The core problem is introduced and its current performances, which has to do with too many rejections causing more waste and rework than desired. Based on this problem, research questions are defined to solve the problem JDE faces.

2. CURRENT SYSTEM ANALYSIS

This chapter provides a thorough description of the system to be researched. In Section 2.1, the processes within the system are described. These processes are relevant for understanding the system. In Section 2.2 the root causes for variation in weights are explained. In Section 2.3 the influences on variation within the weighing process are explained, to get a better understanding of how weight varies.

2.1 WEIGHT-RELATED PROCESSES

The research problem relates to is rejections based on weight. This section delves deeper into the design of the process of weight regulation of the pads, product carriers and bags.

The weighing process & feedback loop

Making of pads

First, pads are made and collected in a semi-batch (i.e. product carrier) which is then transported to the weighing cell of the product carrier (see Figure 13).

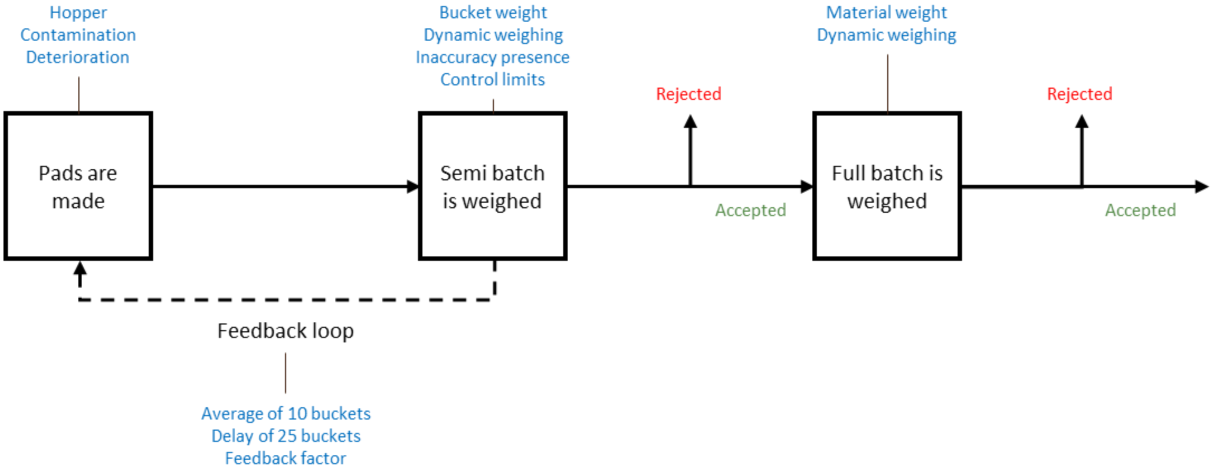

FIGURE 13: PROCESS OF WEIGHT CONTROL WITHIN THE PRODUCTION OF PADS.

Weighing of product carriers

Second, the product carrier is weighed (see Figure 13). Depending on the bag size, these are semi-batches of the final customer unit, since multiple product carriers typically fill one bag (see Table 3). The product carrier containing pads is weighed in a dynamic way (i.e. the product carrier is weighed while it moves on the weighing cell). While weighing, several factors influence the weight. i) The product carriers have an average weight, which is subtracted from the detected weight. The tare (i.e. average weight of the product carriers) is set into the system, so the system ignores any fluctuations in the weights of product carriers, in reality, the weights do fluctuate, the actual fluctuation is explained further in Section 0). ii) The product carrier is weighed dynamically (such that it is transported and weighed on the weighing cell at the same time); therefore, a correction factor is in place to transform the dynamic weight to a static value. iii) The weighing cell contains an inaccuracy, because it returns the weight rounded up to even decimals (i.e. either .0, .2, .4, .6 or .8). The product carrier is rejected when it does not meet the control limits of the weights of pads including the filter paper. These control limits differ based on the product carrier size.

TABLE 3: PRODUCT CARRIER SIZE AND NUMBER OF CARRIERS THAT FILL ONE BAG (CUSTOMER UNIT).

Bag size	Pads per product carrier	Number of product carriers
16	16	1
18	18	1
32	16	2
36	18	2
40	20	2
48	24	2
54	18	3
60	20	3

Filling of a bag
Third, after the product carriers are accepted and emptied, a bag is filled. The net weight of the bag is then obtained dynamically. A correction factor is also in place here.

Feedback loop
Fourth, a feedback loop (see Figure 14) between the pad making machine and the product carrier weighing cell is in place. This feedback loop is the main component that is aimed to be improved in this research. Weighing is performed for every product. But quality check of weighing is done by sampling. At the start of the process, the first 25 product carriers are ignored by the feedback loop, then the average weight of the product carriers is determined based on 10 samples. If this average weight differs by 0.7 grams compared to the target weight of all the pads in the product carrier, the pad making machine receives a pulse (i.e. the feedback factor). This pulse should result in an increase or decrease in the weight per product carrier by the number of grams from which the last calculated average differs compared to the target weight; this is called the ‘feedback factor’. This pulse makes the cavity (see section 1.3) smaller or larger (depending on overfilling or underfilling), and the volume of the cavity determines the amount of coffee that ends up in a pad. After a correction, the system again neglects 25 product carrier measurements, and it then weighs 10 product carriers are used to determine the new average weight.

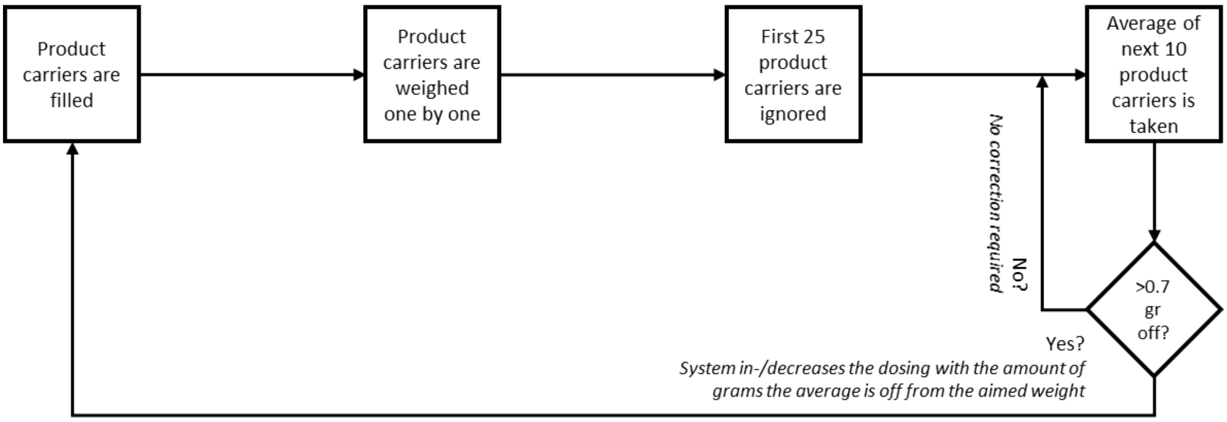

FIGURE 14: FEEDBACK LOOP PROCESS BETWEEN PAD MAKING MACHINE AND PRODUCT CARRIER WEIGHING CELL.

This feedback loop is used to determine the current weight of pads, and it takes action to stabilise the weight; this action can be disrupted by influences from within or outside the process.

Product carrier movement

One consequence of the design of the feedback loop described above, is that the pads weights of two subsequent product carriers are correlated, since, the weight of the filled product carriers exhibits a fluctuation (see Figure 16) upwards and downwards within the accepted tolerance ranges of 0.7 grams around the target weight. Because the product carrier movement (see Figure 15) is designed in such a way that two (or 10, depending on the production line) subsequent carriers are directed to the same packaging line, two or three product carriers that fill one bag are often (but not always) correlated and therefore could all be underfilled or overfilled. Therefore, product carrier weights cannot be assumed to be independent. This is one of the major reasons that the system cannot be analysed by a mathematical model alone. The literature review in Chapter 3, explains that this is one of the reasons for which a simulation model is preferred over a mathematical model.

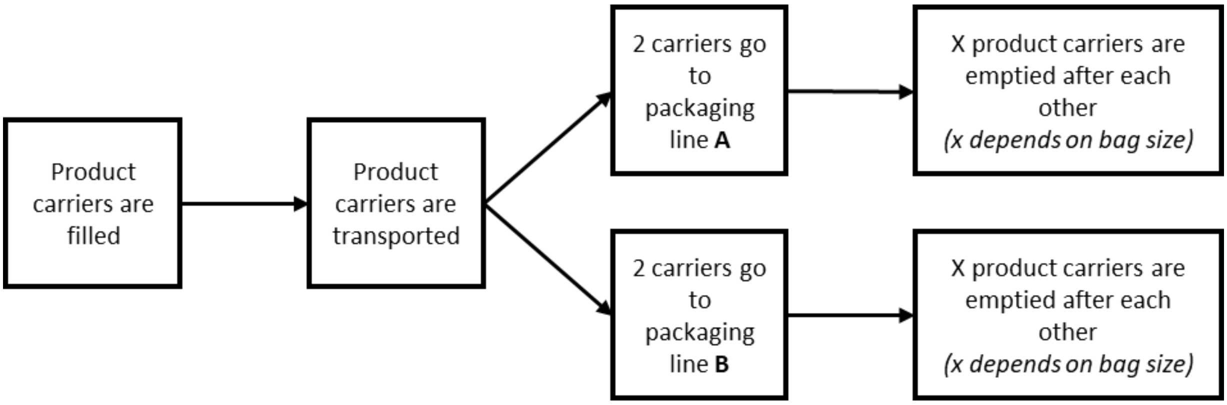

FIGURE 15: PRODUCT CARRIER MOVEMENT FOR LINES 14 TO 19 (LINE 17 INCLUDED).

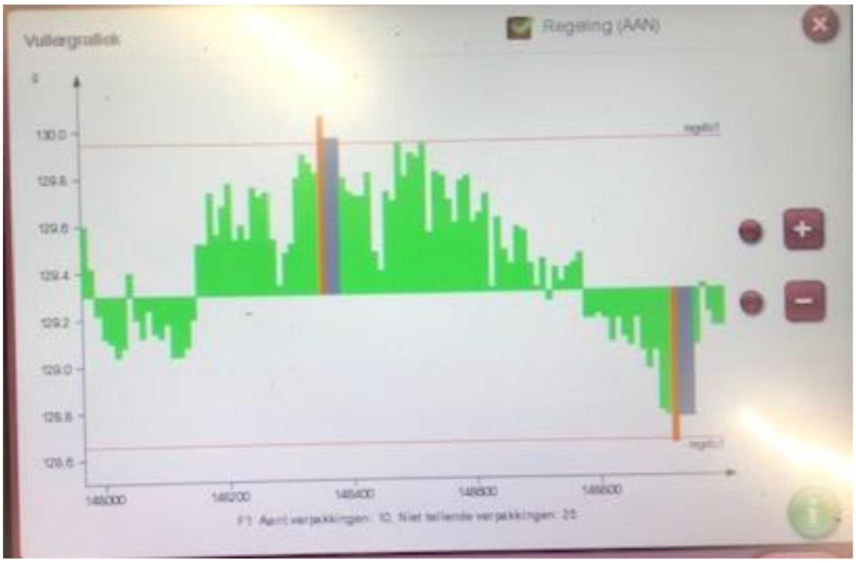

FIGURE 16: EXAMPLE OF FLUCTUATION OF FILLED PRODUCT CARRIER WEIGHT BETWEEN THE TOLERANCES OF +/- 0.7 GRAMS (PHOTO TAKEN FROM LINE 17, NOT POSSIBLE TO TAKE A SCREENSHOT).

Conclusion

With this section, we answered the first research question about the relevant processes. The processes described in this chapter are the weighing process itself, the feedback loop and the transportation policy.

2.2 ROOT CAUSE ANALYSIS FOR WEIGHT VARIATION

This section explains the causes for variations in weight. The factors to be explored and optimised further in this research are explained.

Root causes analysis of the weight variations

When a bag is rejected based on weight, three scenarios can occur (see the second layer in Figure 17). Namely, the bag has too many or too few pads, or the right number of pads are present but the weight is incorrect. In Figure 17*,* a root cause analysis is conducted for the first two cases. Either the product carriers were accepted with too many/too few pads, the product carriers lost a pad or a pad ended up in another product carrier or bag somewhere in the process. In consultation with the production engineers at JDE, losing pads is not considered a major cause of imperfections, although pads occasionally fall out of a product carrier. The root cause that product carriers are accepted with too many or too few pads could be a flaw in the weighing process, which should be further researched.
When a bag has enough pads but is still rejected by weight, the pad weight is beyond the limits; the possible causes of this scenario are shown in Figure 18*.*
If there is a discrepancy between the actual weight and the target weight of JDE, there is an error in the system. Factors that should not change (such as the weight of the filter paper and of the bag foil) could differ from their assumed values. The weights could also be incorrectly calibrated. One other explanation is that the material could absorb air moisture, which causes the weight of the material to vary over time.
Another reason for discrepancy in weight is that the feedback loop built into the system is not functioning properly. During proper operations, there should be barely any rejections by bag weight. On the other hand, if it is not working properly, the feedback factor (i.e. automatic correction in grams) is either too low or too high compared to the discrepancy, such that the real effect of the feedback factor is unknown and should be assessed.
If this feedback factor is correct, the feedback loop receives incorrect information on which it decides its actions. Several factors could cause this problem to occur:

- The sample size (i.e. number of filled product carriers) on which the system calculates the averages may be too small, resulting in low accuracy.
- The delay is too small, and therefore the calculation of the new average includes product carriers on which the last used feedback factor had no influence yet.
- Another potential source of error in the average calculations is that product carriers which should not be included in the calculations have been included. For example, when a product carrier is missing a pad because the die-cut failed, the average of the product carrier is assessed as too low, although in practice this has a mechanical cause instead of a weight-related one.
- The correction factor could be incorrect. This could be the case if the tare of the product carriers is incorrect or if the factor from dynamic to static weight is incorrect.
- The last option is that the limits set in the system, such as the weights at which a product carrier is rejected, are incorrect.

Conclusion

In this section, the factors that influence the process of weighing is researched. The conclusion is that the feedback loop process has the most influential factors, therefore its parameters are chosen as possible changes resulting from this research, so these parameters will be researched. Mechanical issues as contamination, imperfect mechanical processes, and external factors like humidity are not taken into consideration since these factors can’t be changed.

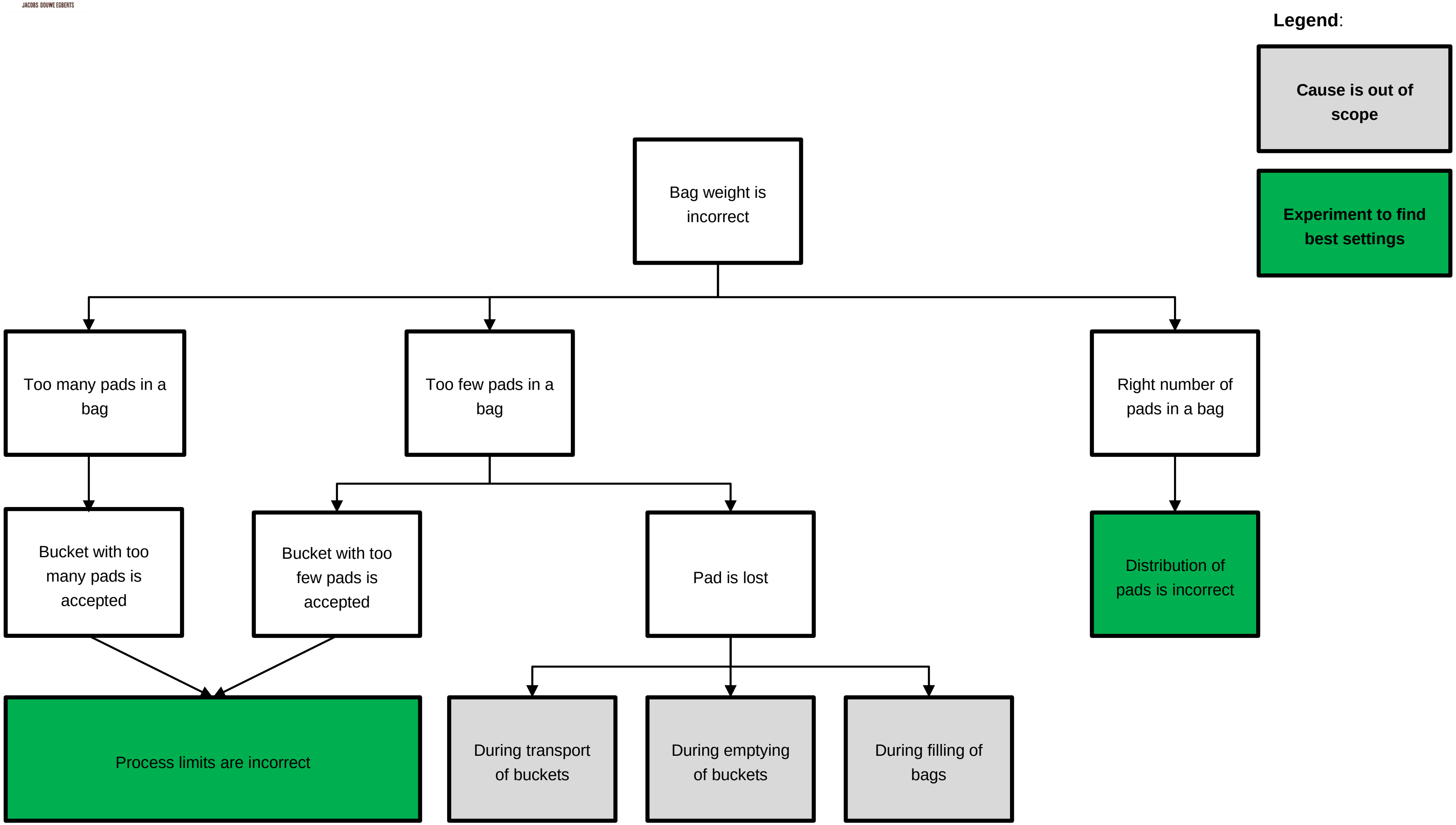

FIGURE 17:ROOT CAUSE ANALYSIS BAG WEIGHT VARIATION.

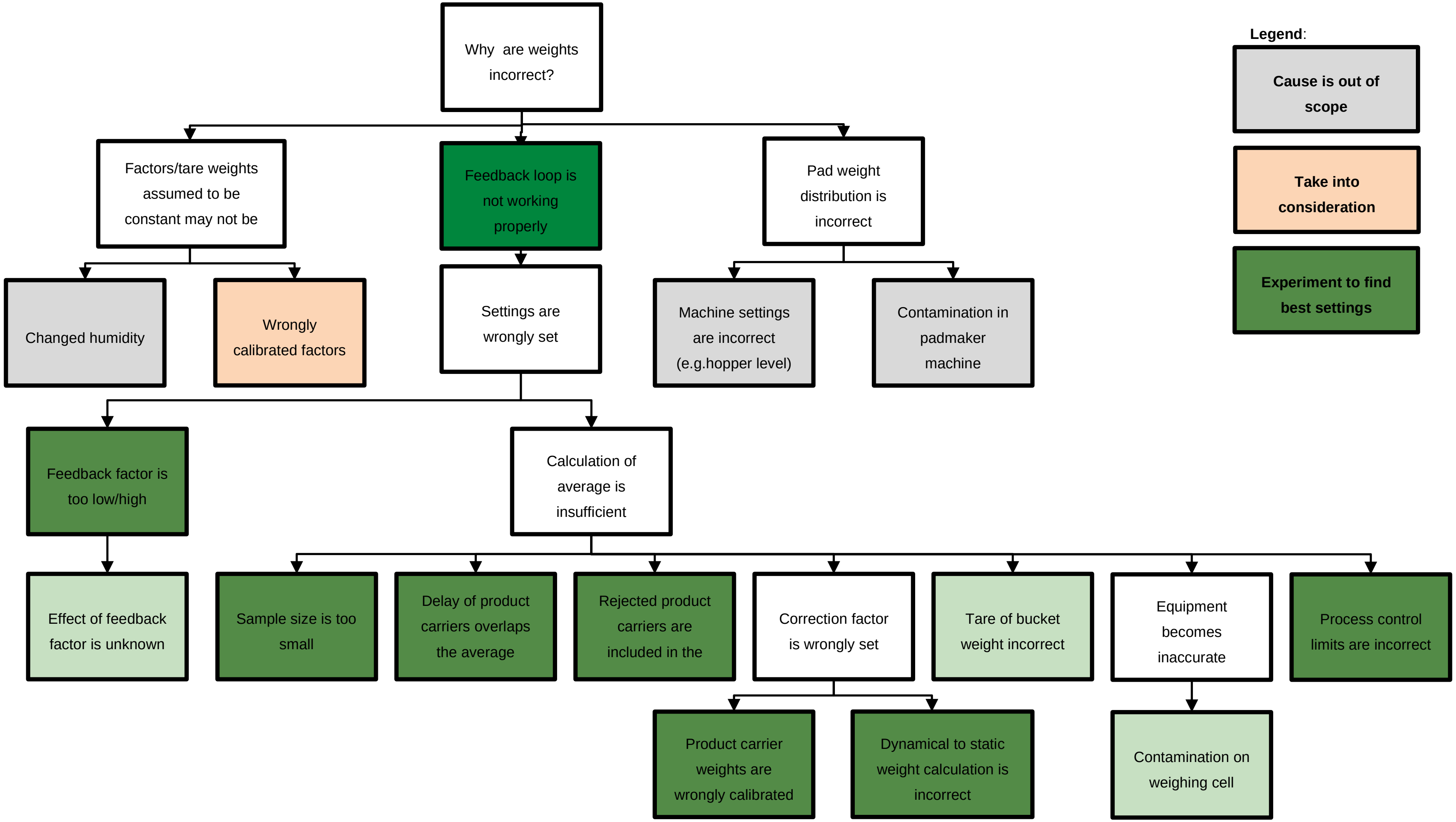

FIGURE 18: ROOT CAUSE ANALYSIS OF MEASURED WEIGHTS BEING OFF LIMITS.

2.3 VARIATION INFLUENCES WITHIN THE WEIGHING PROCESS

There are several causes of variation that influence the process of weighing. Since these sources of variation are independent from each other, they are researched independently. The sources for variation discusses are as follows:

- Weight distribution of pads
- Weight distribution of empty product carriers
- Inaccuracy of product carrier weighing cell
- Inaccuracy of bag weighing cell
- Weight distribution of empty bags
- Volume density distribution of coffee
- Weight adjustment inaccuracy
- Weight adjustment delay
- Trend in weight of product carriers
- Discrepancy between pad weight of operator- and machine side of the dosing drum
- Weight disruption at machine start-up
- Effect of air humidity on rejections

In “Appendix A: System influences on weight stabilization”, any mechanical improvements to stabilize the weight are discussed. Based on that section, the hopper level became more stable. Further details can be found in the Appendix.

Weight distribution of pads

According to internal standards set by the Research and Development department of JDE, a pad should weigh 7.183 grams (7.00 grams of coffee and 0.183 grams of filter paper). Based on the data on manually weighed pads from operators, in June 2018, on all production lines, the weight of pads is normally distributed with a mean of 7.181 and a standard deviation of 0.151 (see Figure 19). Since this data is based over longer period of time (one month) and multiple production lines, this standard deviation is probably overestimated compared to the standard deviation within a product carrier or bag. Therefore, the standard deviation used in the model in Section 4.1 is set to 0.13 grams.
Ten Berge (2017) provided thorough researched on the causes and effects of varying pad weights. Therefore, this research assumes that it is not plausible to improve the inherent performance of the machines in terms of pad weight variation, but it takes the variation in pad weight as a given factor.

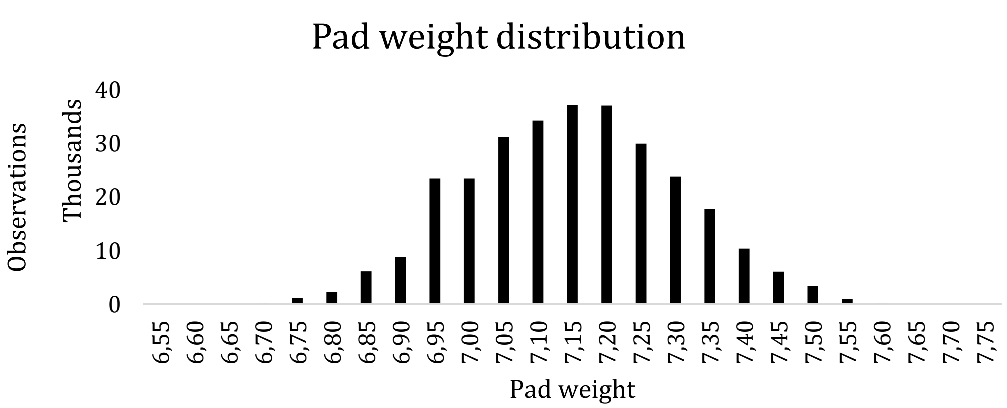

FIGURE 19: PAD WEIGHT DISTRIBUTION, WITH A MEAN OF 7.181 AND A STANDARD DEVIATION OF 0.151 (DATA FROM JUNE 2018).

Weight distribution of empty product carriers

The weights of the product carriers vary. There are around 650 product carriers per line, plus two spare sets, this makes 8450 product carriers in total. Since product carriers are shuffled, a single product carrier can end up on every line, and which product carriers are placed at one line at the same time also differs. Moreover, each product carrier is independent from the others. Therefore, the 8450 product carriers can be seen as a population. To test the distribution of the product carrier weight, a sample is taken from most lines (excluding Lines 21 and 22, since they were in maintenance). The weight of the product carriers is normally distributed (p-value 0.037) with a mean of 390.4 and a standard deviation of 0.2849 (see Figure 20).

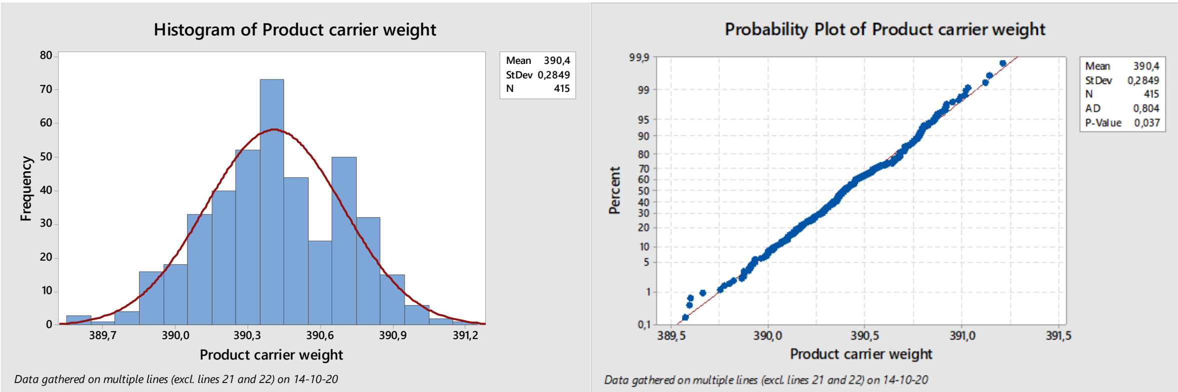

FIGURE 20: WEIGHT DISTRIBUTION OF PRODUCT CARRIERS.

Inaccuracy of product carrier weighing cell

The cell that weighs the filled product carriers is another source of stochasticity in the process. Multiple samples were taken from two different product carriers (light and heavy) on the weighing cell of Line 19, and the data points measured were rounded to two decimal places. Since Lines 17 and Line 19 have the same weighing cell for product carriers, data from Line 19 is representative for Line 17 too. The light product carrier weighed 502.30 grams, which is similar to a filled product carrier with 16 pads:
$Filled\ Product\ carrier\ 16\ pads = 390.4 + 16 * 7.183 = 505.328\ grams.$

The heavy product carrier was 570.00 grams, similar to a filled product carrier with 24 pads:
$Filled\ Product\ carrier\ 24\ pads = 390.4 + 24 * 7.183 = 562.792\ grams.$

The weight obtained is decreased with the set tare of 390.40 grams. When measuring the light product carrier, the standard deviation of the weighing inaccuracy is 0.07711 (see Figure 21); for the heavy product carrier, the standard deviation is 0.07651 (Figure 22). Both values are statistically significant with a p-value of <0.005.

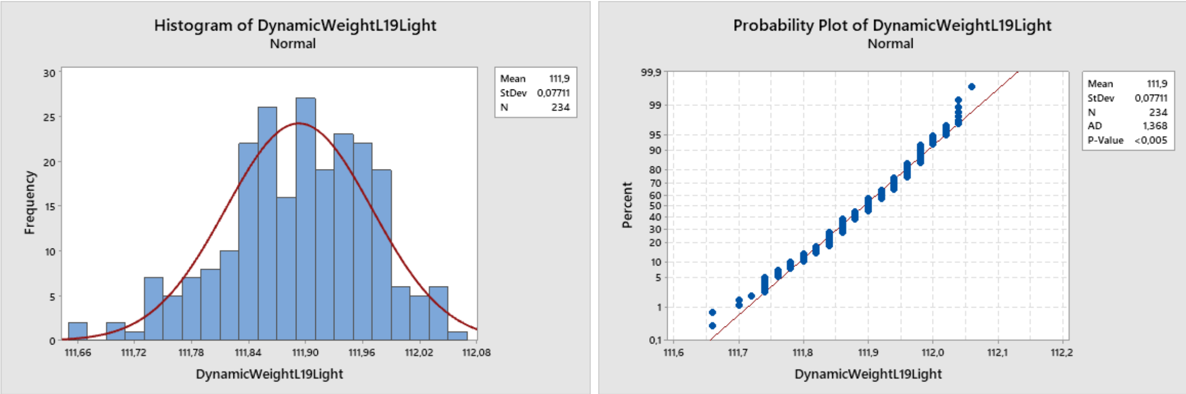

FIGURE 21: DISTRIBUTION OF WEIGHING INACCURACY IN PRODUCT CARRIERS (LIGHT).

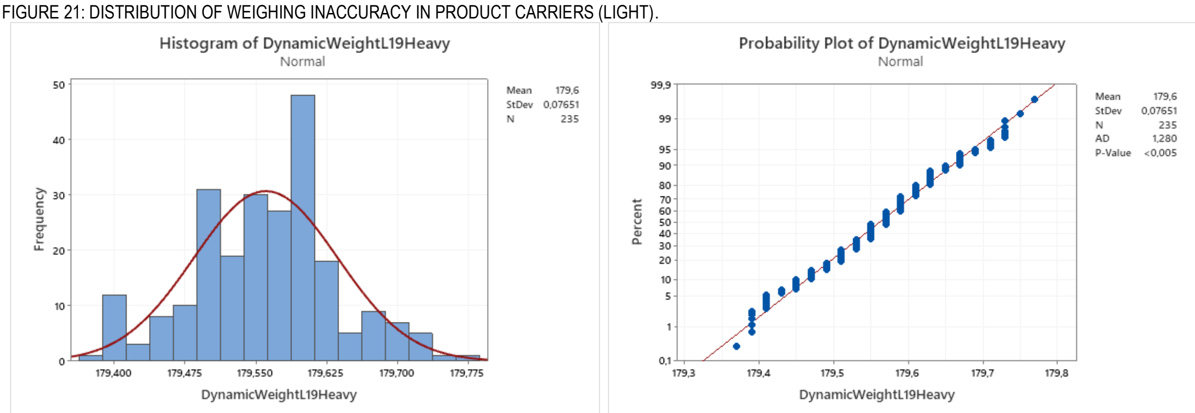

FIGURE 22: DISTRIBUTION OF WEIGHING INACCURACY IN PRODUCT CARRIERS (HEAVY).

Inaccuracy of bag weighing cell

The bag weighing cell is another source of stochasticity, since it is not perfectly accurate. To determine the accuracy, one bag is weighed many times. One bag of 18 pads and one bag of 54 pads is used. The standard deviation of the weight for a bag of 18 pads is 0.1317 grams (see Figure 23), and that for a bag of 54 pads it is 0.2844 grams (see Figure 24). This difference can be explained by the vibrations of the weighing cell, which have more impact on larger bags. It is assumed the difference per bag size to be linear, resulting in an increasing standard deviation with increasing bag sizes increases (see Figure 26). For this calculation, the standard deviation of 18 and 54 pads is used. The numbers in Figure 26 are increased by 14% to be used in the model, which represents the standard deviation of empty bags. This is based on the ratio between weighing cell inaccuracy and the standard deviation of an empty bag for 60 pads. For bags with 54 and 60 pads, however, the speed of the transport band of the weighing cell is set to a lower pace, therefore, it is assumed that the standard deviation for all bags to be higher than that for the bag with 48 pads and equal to that for the bag with 48 pads (i.e. 0.30 grams; see Figure 26).

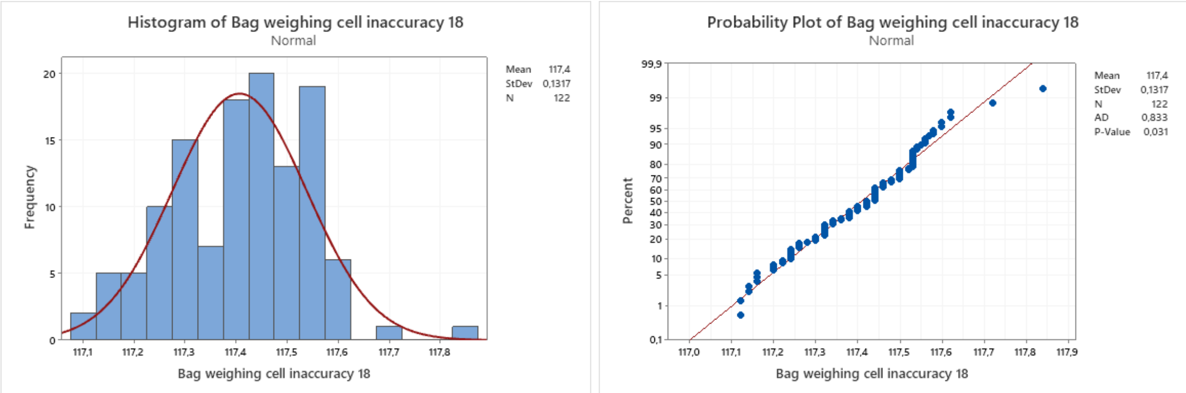

FIGURE 23: DISTRIBUTION OF THE WEIGHING INACCURACY OF THE BAGS WEIGHING CELL (BASED ON A BAG WITH 18 PADS).

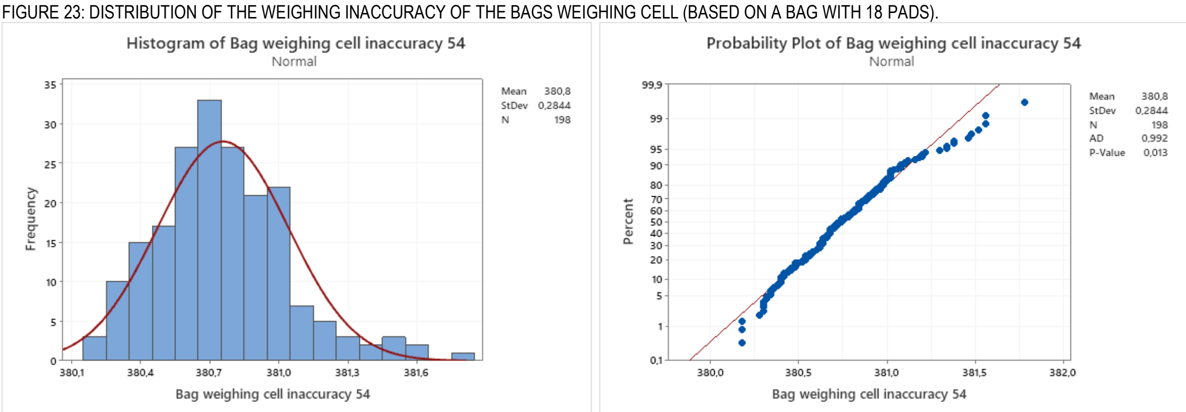

FIGURE 24: DISTRIBUTION OF THE WEIGHING INACCURACY OF THE BAGS WEIGHING CELL (BASED ON A BAG WITH 54 PADS).

Weight distribution of empty bags

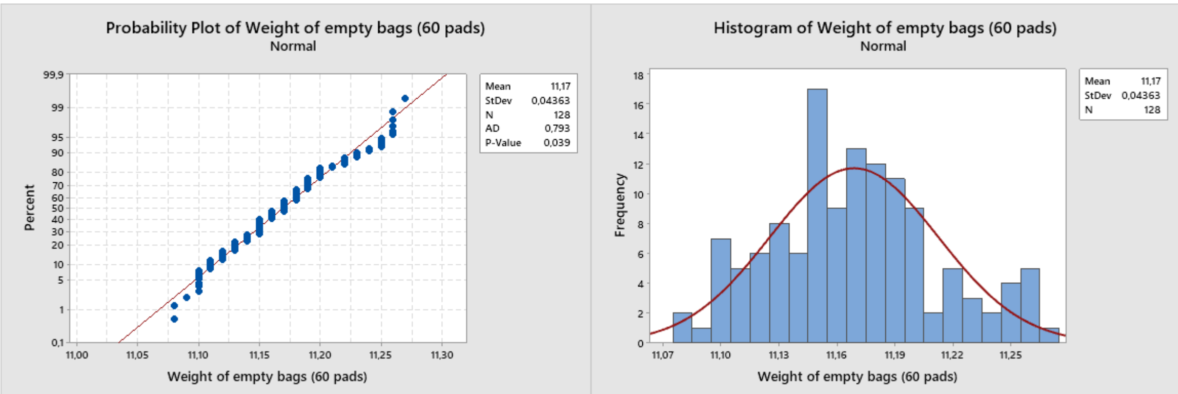

FIGURE 25: DISTRIBUTION OF THE EMPTY BAGS (OF 60 PADS).

Variation in the weight of material is a possible cause of rejections of bags. The weight of the largest bag (for 60 pads) is measured. The bags have a standard deviation of 0.0436 grams, with a p-value of 0.039, see Figure 25. This variation is added to the inaccuracy of the bag weighing cell in the model.

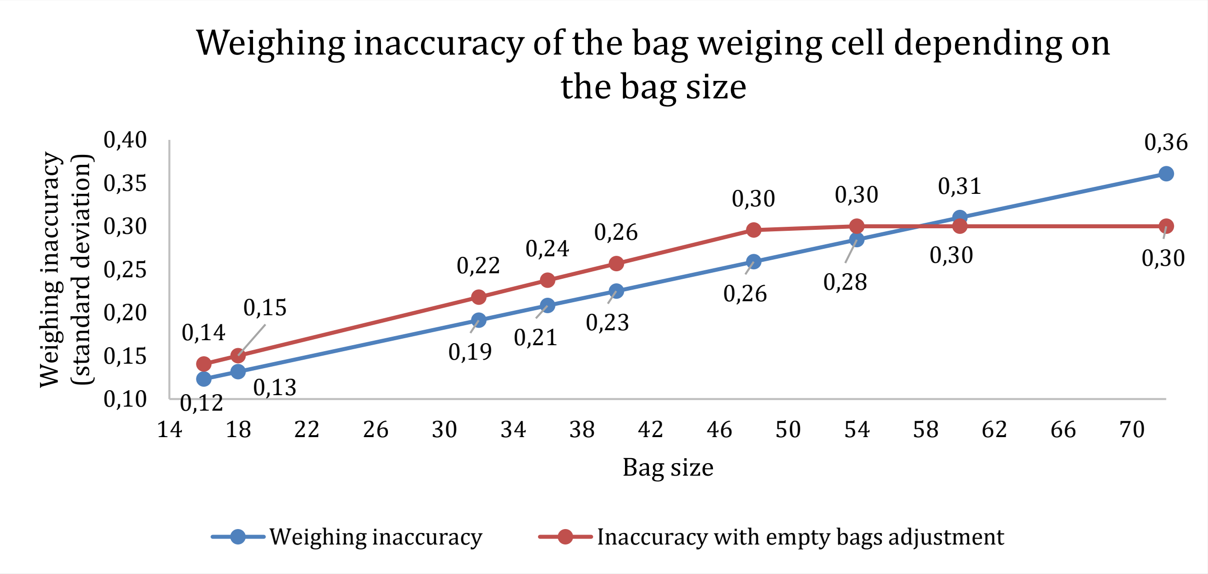

FIGURE 26: LINEAR CHANGE IN STANDARD DEVIATION OF THE BAG WEIGHING CELL BASED ON THE BAG SIZE.

Volume density distribution of coffee

The amount of coffee that can fill a cavity depends on the density of the coffee (more precisely, the volumetric mass density; also known as specific mass, of a substance is its mass per unit volume). With a relatively high volume density, more coffee can be sucked into the cavity, while the reverse is true with a low volume density. This causes weight variations of the pads based on their volume density. This stochasticity is not directly included in the model, since it is indirectly accounted for in the pad weight variation and the sine trend, as explained in Section 2.6.

This volume density varies per sample taken from each batch. In 2019, this volume density was normally distributed with a p-value of <0.005, a mean value of 716.7 and a standard deviation of 7.400 (see Figure 27). From this data, data points below 700 and above 740 are taken out of the sample, since they fall outside the internal norms and therefore represent unacceptable batches. The variation can be attributed to multiple causes, such as differences in humidity between batches, wear of grinding equipment and severity of burnt coffee. Based on the data, the standard deviation of the volume density is 1.033% of its norm value. Since the coffee gets mixed while it is transported, the density is expected to flow smoothly up and down. The variation in this volume density is likewise excluded from the model. It influences the variation in product carrier weight, which is part of the trend in product carrier weight (see further following sub-section "Trend in product carriers weight").

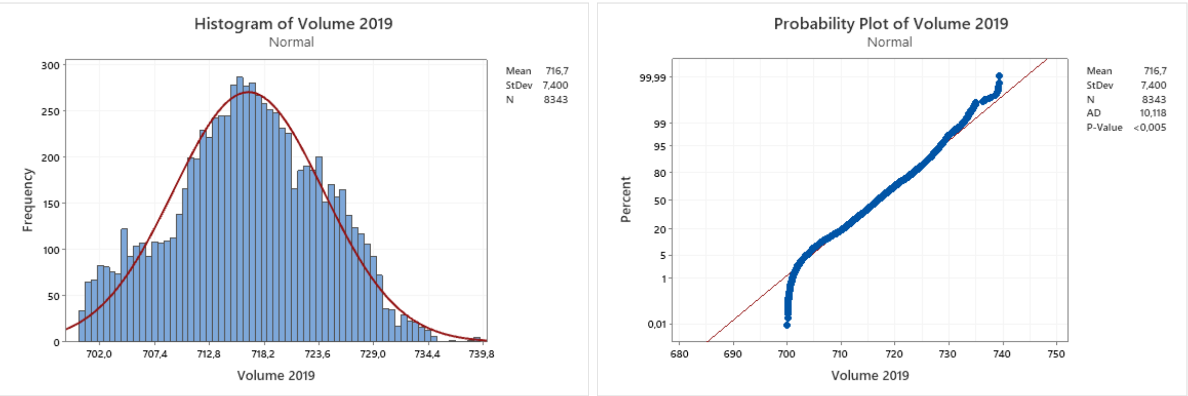

FIGURE 27: DISTRIBUTION OF VOLUME DENSITY WITHIN BAGS.

Weight adjustment inaccuracy

When the calculated average of the products carriers exceeds the set tolerances, the pad making machine receives a signal that is should adjust (or steer) the weight to the norm. This signal indicates the number of grams by which the sample is off multiplied by an adjustment coefficient. This steering coefficient is expressed in seconds of adjustment signal per gram offset from the target. The seconds are translated in the number of spindle rotations (see Figure 65). Ideally after adjustment the subsequent measurements of the 10 product carriers is exactly equal to the norm; however, the result of this adjustment also includes stochasticity (i.e. the average weight after steering is not exactly equal to the norm). It is not clear whether the variability in adjustment is caused by inaccurate adjustments to the machine or a variability between samples, used to calculate the average.
Because of this discrepancy, the translation between the weighing cell and the pad making machine is verified, this appears to be correct. Therefore, it is assumed in the model that the adjustment is correct too, such that discrepancies are caused by the variability in pad weight.

Weight adjustment delay

Adjustments in weight are made gradually instead of abruptly. This was tested by manually forcing the machine to adjust. However, this did not result in reliable data to find the length in time of the adjustment. Based on the actual observations and product specifications, it is assumed that the spindle adjusts with a constant speed of 1 second per gram of adjustment. Most lines produce x pads per minute, or 30 pads per second. Based on this knowledge, it is assumed that the adjustment delay to be gradually and the time it takes to adjust is based on the number of grams by which the product carrier weight is too high or too low. For example, if a product carrier is 2 grams too heavy, the adjustment takes $30\, pads * \frac{1 sec}{gram} * 2\, grams = 60\, pads$ to implement.

Trend in product carrier weights

The weights of subsequent product carriers are clearly not random, as can be seen in Figure 28 whereby the average of three product carriers per bar is shown with no steering activated. However, it is difficult to detect any trends from this picture.
Using several samples of individually weighed product carriers for periods of around half an hour, the trend is basically impossible to predict due to randomness. Based on Figure 29, we expect to find five periods within 2700 product carriers of 24 pads with an amplitude of 1.2 grams on a product carrier of 24 pads. Calculating this back to the granularity of a pad, results in a period[2] of $\frac{2\pi}{\frac{2700}{5} * 24} = 0.000484814$ and an amplitude of $\frac{1.2\, gram}{24\, pads} = 0.05\, grams\ per\ pad$. These values are used as indicator of the sine influence on pad weight.

[2] Formula for the period of a sine function is $Period\ = \frac{\pi}{k}$, where k is the number of pads

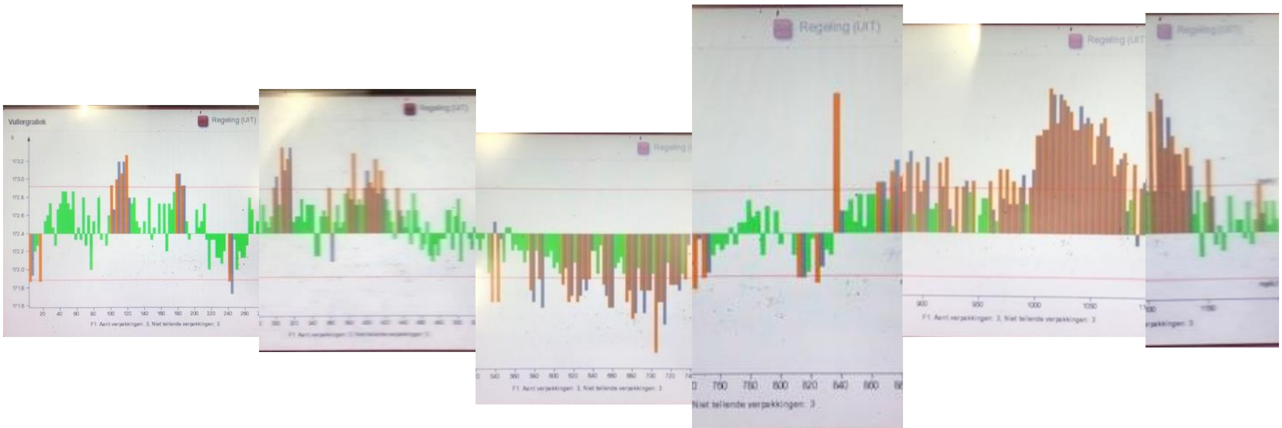

FIGURE 28: TREND OF PRODUCT CARRIERS PER AVERAGE OF THREE CONSECUTIVE PRODUCT CARRIERS (NOTE: THE Y-AXES IS ON THE SAME SCALE, THE X-AXES DIFFER SLIGHTLY).

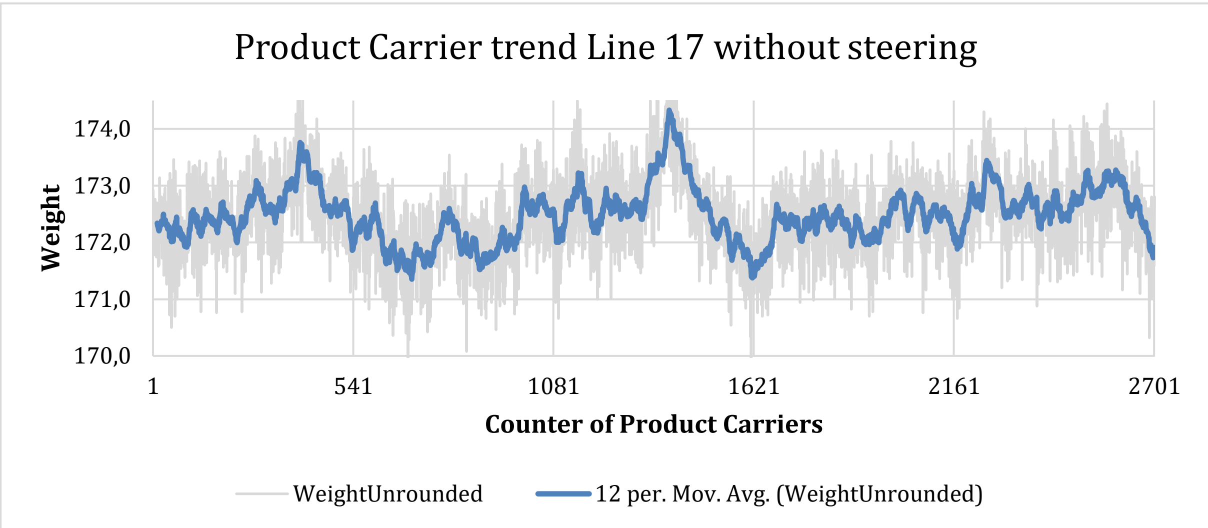

FIGURE 29: TREND WITHOUT STEERING OF LINE 17.

Discrepancy between pad weight of operator- and machine side of the dosing drum

One of the causes of variance between pads, is the difference in pad weights between the operator and the machine side of the dosing drum (see Figure 30). Among others, pollution in the dosing drum is one of the causes (Ten Berge, 2017). According to the data from mid-October 2020 to the beginning of January 2021, most of the time (83%), the difference lies between 0.02 and 0.12 grams on Line 17. Although there seems to be a sine function pattern in the data, this could be caused by the varying density of the coffee. Therefore, the difference between the operator and the machine side is assumed linear with a slope of 0.00000001852 grams per pad, making the cycle 0.10/0.00000001852 = 5.4 million pads. At a speed of 1,800 pads per minute, this represents 50 hours for one cycle. These assumptions are based on the data shown in Figure 31, since the difference varies continuously, the model is simplified to the real-world by assuming the numbers given above.
In the built model, the difference in the mean number of pads between the operator and the machine side increases by 0.000001333 with every pad made. When the differences reaches 0.12 grams, it is reset to 0.02 grams. Therefore, the assumed difference in dosing does not exceed 0.12 grams and remains at least 0.02 grams.

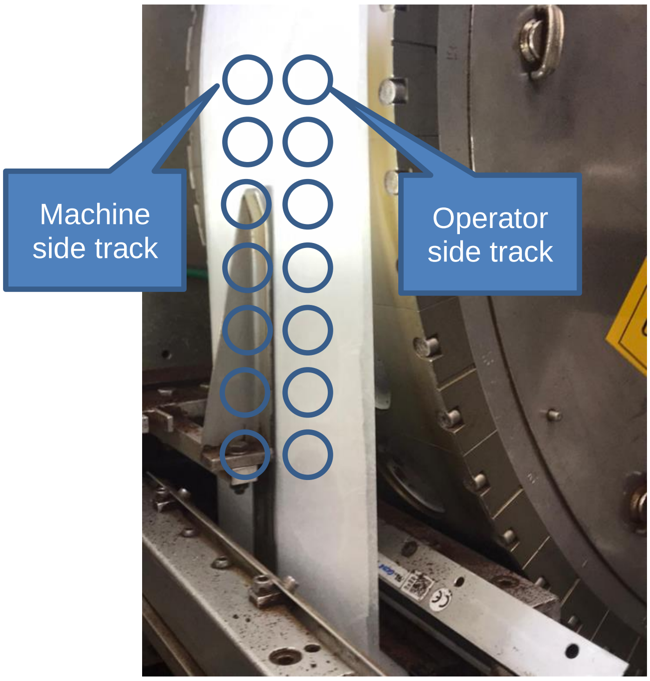

FIGURE 30: THE DOSING DRUM HAS TWO TRACKS WHERE PADS ARE MADE, THE MACHINE SIDE AND OPERATOR SIDE (CIRCLES ARE FOR THE INDICATION OF A TRACK OF PADS).

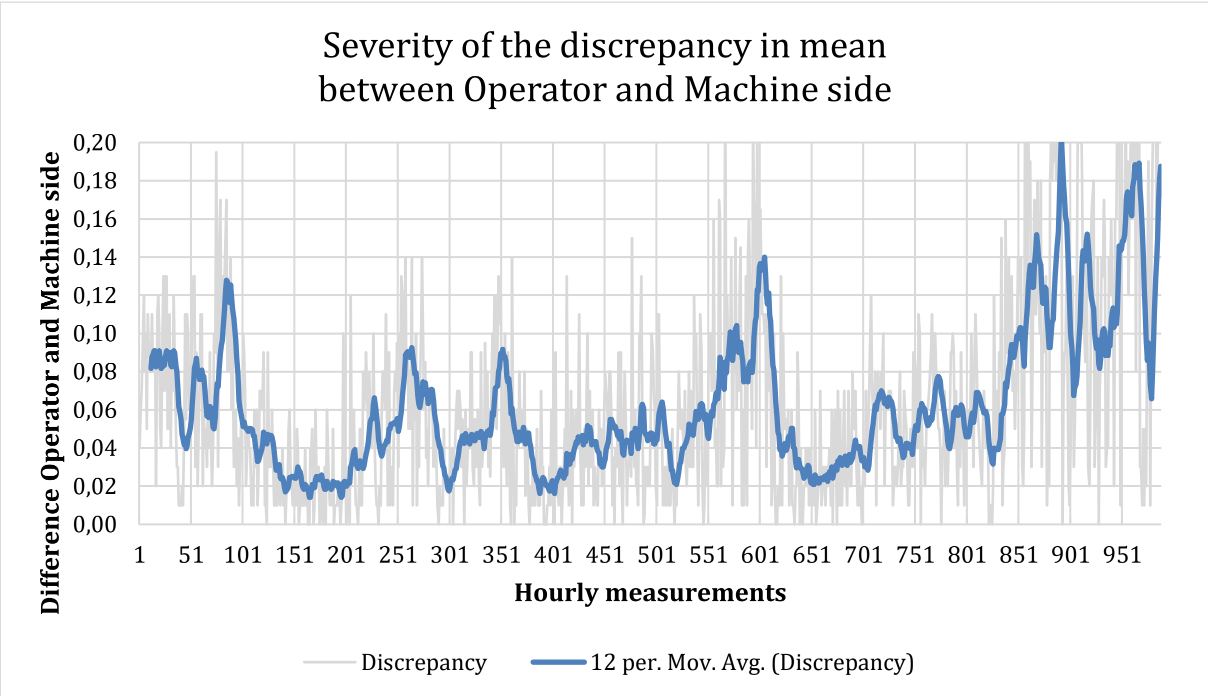

FIGURE 31: DIFFERENCE IN MEAN OF THE PADS BETWEEN OPERATOR AND MACHINE SIDES OF THE DOSING DRUM.

Weight disruption at machine start-up

With the initiation of a production line, the weights vary heavily due to a substantial change in the amount of coffee in the hopper. When the machine starts, the speed is low at the start and increases slowly to the normal speed. When the machine stops, coffee piles up in the hopper, and this heavy change causes a large increase in the product carrier weight after a start-up, which slowly returns to the norm again. The average weight of the product carriers before and after stopping the machine is analysed based on the average of the 20 product carriers before the spike. At the 14th product carrier after the start-up, a large and sudden increase in weight

occurs (see Figure 32). The average weight of decreases and falls below the norm at the 44th product carrier.
This machine start-up influence is divided into 31 phases (see Table 4), whereby each phase accounts for an increase in weight which is assumed to be fixed per pad. This assumption is made because only data on the granularity of the product carriers with 24 pads was available. For the model, it is calculated back to the granularity of a pad, resulting in the following (simplified) phases:

TABLE 4: CHANGE IN WEIGHT PER PAD PER PHASE DURING THE START-UP OF A PRODUCTION LINE.

Phase	Extra weight per pad	Number of pads in phase
1	0.1044	24
2	0.0463	24
3	0.0330	24
4	0.0262	24
..		
31	0.0001	24

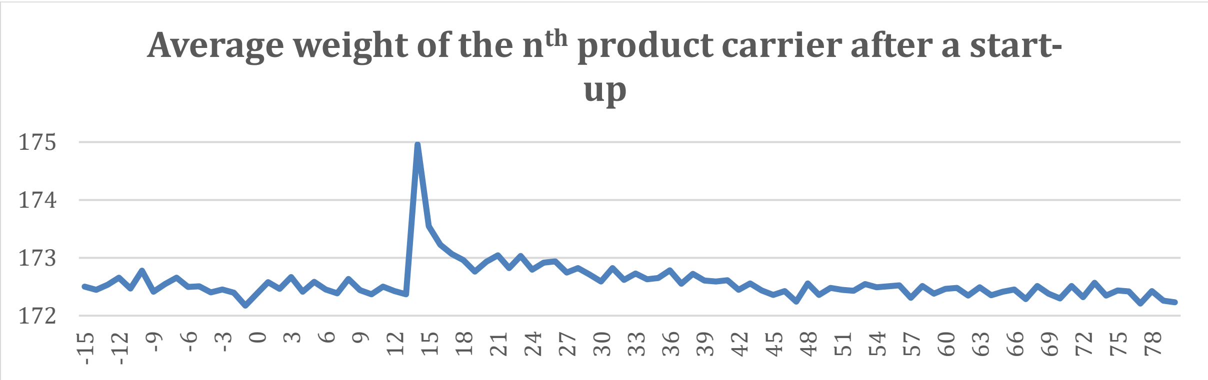

FIGURE 32: CHANGE IN WEIGHT AROUND THE START-UP OF A PRODUCTION LINE.

Occurrence of a production line initiation
Based on a weekend dataset (the weekend of 12 and 13 December 2020) at line 17, there were 80 start-ups over 73,532 product carriers. Assuming that the pad making machine produces x pads per minute, this translates into 4.9 start-ups per hour and once every 12.25 minutes, or, assuming x pads per minute and 24 pads per product carrier, once every 919 product carriers.

Effect of air humidity in the production hall on rejections

Air humidity is one possible cause of periodic fluctuations in the rejection rates noted in Section 1.4. From May to November 2019, the air humidity was measured multiple times a day. The average humidity per week is plotted in Figure 33. It shows a highly variable pattern that reaches from around 30% to 60% on a scale of 100%.
Although this could be a factor of influence, e.g. for the amount of moisture in the filter paper and product carriers, it does not seem to have a notable effect on rejection rates. A fitted regression analysis was conducted for the effect of air humidity on rejection rates. The R-squared measure for bags[3] is 26.4%, whereas that for the product carriers is 1.1% (see Figure 34). According to Theisens (2015), a good predictive model should have an R-squared

[3] The R-squared measure is the fraction of the variability in the data that is explained by the regression model. No regression model should be interpreted with an R-squared below 0.7 (Theisens, 2015).

measure of over 70%; therefore, it is concluded that air humidity has no substantial influence on rejection rates.

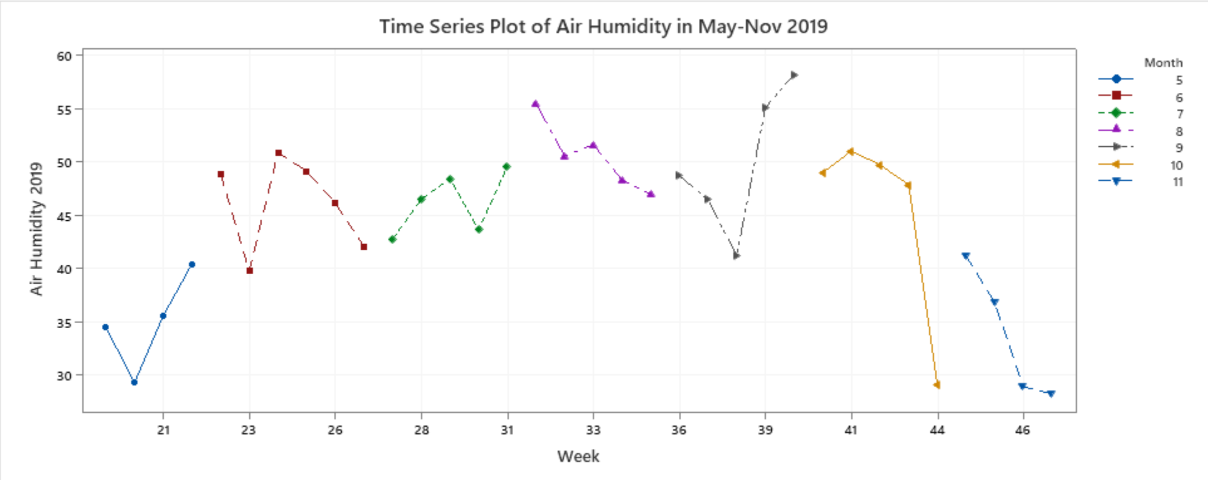

FIGURE 33: AIR HUMIDITY PER WEEK, GROUPED BY MONTH (AVERAGE OF MULTIPLE MEASUREMENTS PER WEEK).

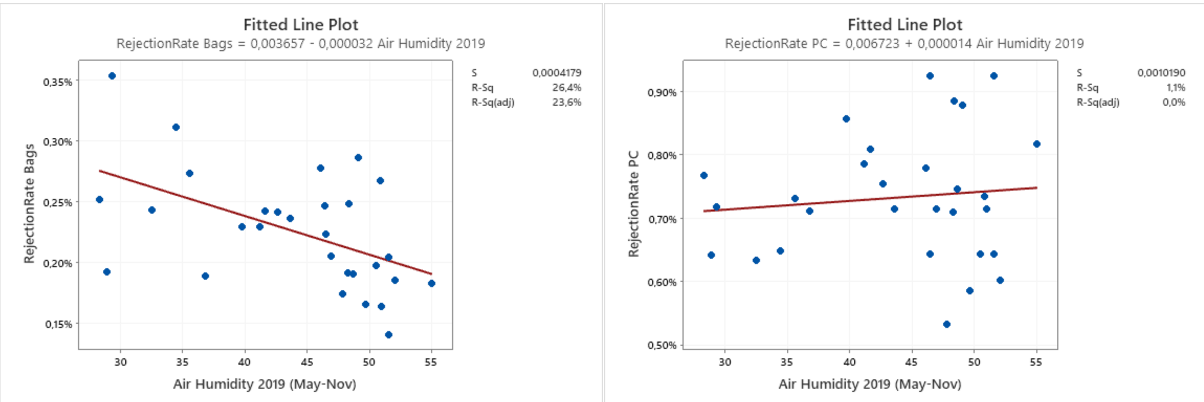

FIGURE 34: REGRESSION PLOT BETWEEN AIR HUMIDITY AND THE REJECTION RATE OF BAGS AND PRODUCT CARRIERS.

Conclusion

In this section, many sources of variation that are inherent to the process are discussed, like the variation of pad weight, variation of empty product carriers weight, the accuracy of the weighing cells and the variation in weight of empty bags. These sources for stochasticity are all implemented in the model built in this study later. Characteristics related to weight like the steering accuracy, steering delay, trend in pad weight, differences between operator and machine side, start-ups of a production line and the influence of air humidity on the process are discussed. Only some of these characteristics are implemented in the model built in this study later.

2.4 CONCLUSION ON THE CURRENT SYSTEM ANALYSIS

Within this section the current system and factors that could have any influence on the performance are described. First the root causes were defined, then mechanical factors were described to make sure they could be out of scope, sources for stochasticity and other characteristics of the behaviour of the system were described. With this information, there is a clear overview and understanding of crucial aspects of this process.

3. LITERATURE REVIEW

This chapter, answers the second research question, as to how the problem described in the previous chapter should be tackled based on the literature.

3.1 INTRODUCTION

Several strategies can be used to solve the problem at hand. One is to conduct research on the characteristics of the materials used and the factors that can influence the weight of these materials. Another strategy to solve this problem is to optimise the steering (adjustment) of the weights. Since this steering is an automated process, slight weight changes should be corrected within the automated feedback process. This automatic process consists of discrete events that impact the system.

3.2 POSSIBLE WAYS TO STUDY A SYSTEM

Law (2015) describes multiple ways to study a system (Figure 35). A system is defined to be a collection of entities, e.g., people or machines, that act and interact together toward the accomplishment of some logical end. In this section, the different ways are compared and the most appropriate approach is determined for the problem of interest.

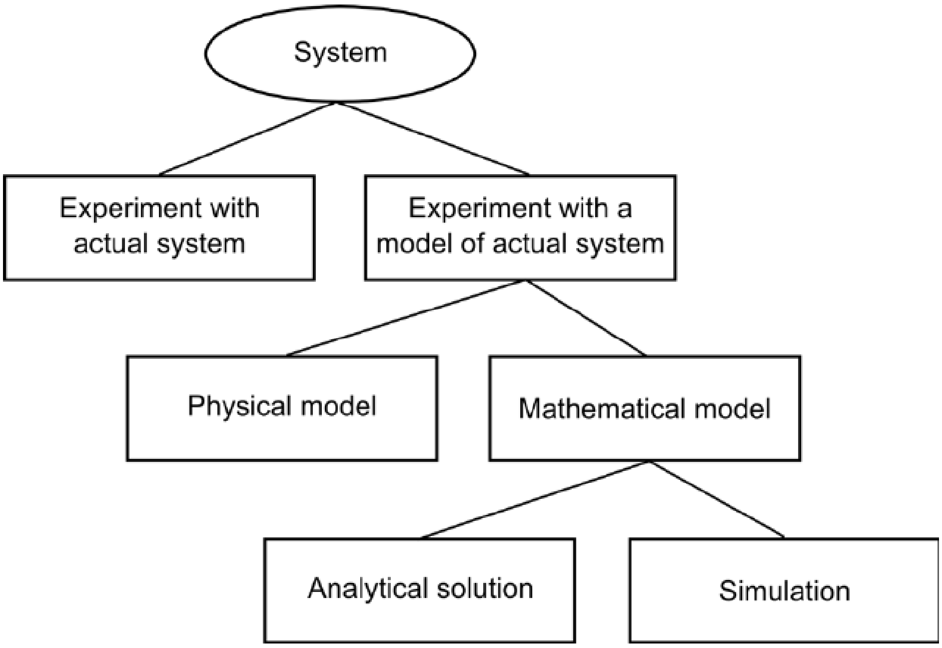

FIGURE 35: WAYS TO STUDY A SYSTEM (LAW, 2015).

Experiments with the actual system versus with a model of the system

According to Law (2015), if it is possible (and cost effective) to physically alter the system and then let it operate under the new conditions, it is probably desirable to do so. However, this is rarely feasible, because such an experiment would often be too costly or disruptive to the system.

Physical model versus mathematical model

Physical models, like a cockpit disconnected from the airplane to be used in pilot training, are not the typically kind of models of interest in operations research and systems analysis. Therefore, the vast majority of models built for operations are mathematical, representing a system in terms of logical and quantitative relationships that are then manipulated and changed so as to observed how the model reacts, and how the system would react.

Analytical solution versus simulation
Once a mathematical model is built, it must be examined to determine how it can be used to answer the questions of interest about the system it is supposed to represent. If the model is simple enough, it may be possible to work with its relationships and quantities to obtain an exact, analytical solution. A very simple example of a mathematical model is the familiar relation $d = rt$, where r is the rate of travel, t is the time spent traveling, and d is the distance travelled. In this example, if the distance to be travelled and the velocity are known , then the model to use is $t = d/r$ as the required time. This is a very simple, closed-form solution obtainable with a piece of paper and a pencil, but some analytical solutions can become extraordinarily complex, requiring vast computing resources. If an analytical solution to a mathematical model is available and computationally efficient, it is usually the preferred approach to studying the model rather than via a simulation. However, many systems are highly complex, such that any valid corresponding mathematical models are themselves complex, precluding any possibility of an analytical solution. In that case, the model must be studied by means of simulation.
For the analysed system in this research, it is not possible to have numerous thorough experiments on the actual system, since the quality norms are strict, and decreasing the capacity is not a possibility because then the demand cannot be met. A physical model is also not feasible, since there is no spare line to run these experiments on. The stochasticity in pad weight, product carrier weight and weighing inaccuracy can be captured in an analytical model. Some characteristics, however, cause an analytical model to be insufficient, including the queueing policy within lines and the effect of abrupt disturbances (i.e. hopper level drops, ceramic filter breaks, too many or too few pads) and the trend of the increasing standard deviation of pad weights. A simulation study provides more flexibility to assess how the system reacts to such policies and disturbances.
With this section, research question 2.1 “How can we model a system according to literature?” is answered, several options are mentioned and a simulation seems most appropriate for the faced problem.

Relevance of simulation
In the food and pharmaceutical industries, small products that need to meet high EU-regulations standards in terms of weight are made. Simulation makes it possible to reproduce processes virtually to study their behaviour, analyse the impact of possible changes and compare different design alternatives without the high costs of experimental studies (García *et al.* 2020). Since products should meet high standards in these aforementioned industries, assessing the impact of making changes to the system using a simulation does not jeopardise the product quality.

3.3 TYPES OF SIMULATION

There are several ways to simulate processes. Sachidananda et al. (2016) list four such approaches in the context of biopharmaceutical manufacturing, namely, mathematical programming, stochastic modelling, optimisation and discrete event simulation. This section presents examples of these methods and reflects on their effectiveness for the situations in which they were used.

Usage of a mathematical model for dynamic weighing

Yang et al. (2018) conducted a research on the precision weighing control of a dynamic backfilling weighing system in a coal mine. The dynamic nature of the weighing system is similar to the faced problem in this research. Within the process, the materials are conveyed by a spiral conveyor to a weighing hopper, and their materials weight is then measured by a weighing sensor equipped under the hopper. The real-time weight signal is sent to the weighing system. The weight measured by the weighing sensor is further increased after the remaining materials fall onto the hopper. When the materials in the air have all landed on the hopper, the actual weight is obtained. With the feeding process of extra materials, it is crucial to determine when to stop the spiral conveyor so as to obtain a precise weight value. A formula is used to represent the conveying capacity flow. The actual weight that ends up in the bag is a function of time, speed and other fixed parameters. The formula of the actual weight is a time-delayed, uncertain and nonlinear model. Yang et al. (2018) propose an adaptive iterative learning control of the weighing process. They optimise this adaptive iterative learning by dividing the weighing process into three stages. The weight added and detected in the rapid feeding stage is determined based on a formula. In the lower feeding stage, the weighing accuracy is improved by reducing the speed of the system. The third stage, the prediction feeding stage, estimates when the conveyor should stop so as to reach the target weight, which is basically is the sum of the weight already detected and the remaining materials that will fall onto the weighing hopper when the conveyor stops. The results show that the mathematical model improves the weighing accuracy as well as the feeding speed.
The mathematical model is suitable for solving the problem of Yang et al. (2018) for several reasons. First, this model does not take disruptions in the system into account (i.e. inaccuracies in the system are constant over time). Second, the relations between the characteristics of the system are understood to such a high level of detail that they can be represented in an analytical model. Yang et al. (2018) realised this by breaking the process down into multiple components that could be represented separately in an analytical model.

Usage of stochastic modelling to cope with variability

One of the most well-known techniques for stochastic modelling is monte carlo simulation, a mostly static model that is representative of a system at a particular time (Law, 2015).

Otsuka and Nagata (2018) used a monte carlo simulation for coping with dimensional irregularities in parts caused by machine errors. This is somewhat similar to filling of a product carrier based on several parts (the pads). The dimensions of each part are usually managed by conventional tolerances determined in the design stage. Tight tolerances values result in reduced performance variation along with an increase in the manufacturing cost. Otsuka & Nagata's (2018) research focuses on quality control in the design stage, i.e. researching the impact of the tolerances of parts on the performance of the final product. The authors assumed the dimensions of the parts are independent of one another and the expected dimensions of the final product and their standard deviation can be calculated by commonly known formulas of the mean and standard deviation of normally distributed parts. Otsuka & Nagata (2018) use a Monte Carlo method to solve the research question at hand. This method is applicable because the function of the length of all individual parts is linear and the parts dimensions are independent on each other, according to the research.

The monte carlo method is suitable to use for solving the problem of Otsuka and Nagata (2018) for several reasons. First, as Otsuka and Nagata (2018) note, the individual parts are linear and the dimensions of the parts are independent. Second, it is assumed that the constant variation over time is what makes it a static model (i.e., time does not play a role). Hence, there is no trend in the variation of the products and disruptions in the process are not taken into account.

Usage of optimisation by optimizing resource usage

Optimisation is a simulation methodology that aims to optimise processes without making fundamental changes to the system. For example, when capacity is lacking and a redesign of the process is not a possibility, the only option that remains is to improve the scheduling methodology used. Petrides and Siletti (2004) implemented such a solution in their study with a biopharmaceutical manufacturer. They attempted to improve the scheduling policy of batch processes to avoid having to invest in extra capacity. Using software, they simulated the effects of time-variable constraints and batch-to-batch variations while using resource constraints. Their experiments were defined by varying these constraints. The result of such a simulation is a schedule of batches that seem to be optimal for the tasks to be scheduled.
The optimisation methodology is suitable when the elements to be optimized (in this example, the batches) and resources available are known beforehand. The optimal sequence of a production plan can then be determined. This method is static and does not take disruptions in the process into account.

Usage of discete-event simulation (DES) for process control

Kern and Manness (1997) used a dynamic simulation to study a bottling line, in which a PID controller is used as tuning tool to stabilise the amount of liquid that ends up in a bottle. Just as with the faced problem, a certain level should be kept constant. The intent of their paper is to support the use of dynamic simulation as a means of gaining basic physical understanding and applying simple control techniques. One interesting characteristic of the sugar water bottling process is that it is a hybrid process involving continuous and discrete event process elements. Sugar water is fed continuously into the mix tank, and with the flow rate is controlled by a PID controller whose objective is to regulate the mix tank level. In contrast, the discharge from the mix tank is a pulsed on/off flow of sugar water per bottle and the sweetness of the liquid. This model can be seen as a discrete-event model, whereby the continuous flow is changing per delta time, and delta time is fixed. The event of filling a bottle can be seen as a disruption to the level of liquid in the mix tank, since it causes the level to drop abruptly. This is an example of a DES study, in which a continuous process needs to remain constant while being disrupted. Although no trends are mentioned, the controller should be able to correct for any that disrupt the process.
Antonelli et al. (2018) assess the performance of a manufacturing system using two simulation methods: system dynamics simulation (SDS) and DES. The preparation of input materials is studied with the help of SDS, while the production line is described with DES. System dynamics is a method to change elements of the system, such as a the location of a warehouse or the flow that determines the expected input or target output. Discrete event simulation is used to gain insights into the behaviour of a system and discover unexpected nonconformities by incorporating stochastic effects. In their case study, the authors describe the manufacturing of a product that consists of nine process steps. An SDS simulation is used to simulate inventories based on among others changing demand, unit costs and number of available workers. The simulated demand and inventories are inputs to the DES model. The behaviour of the production line is simulated by a DES, and several assigning strategies were simulated and analysed. In

this case study, DES is used to incorporate stochasticity into the model and consider the effect of different service disciplines at the queueing nodes.
Mathematical, stochastic and optimisation models are examples of static simulation models. Law (2015) describes a static simulation model as a representation of a system at a particular time, or one in which time simply plays no role. On the other hand, DES can be built as a dynamic simulation model that represents a system as it evolves over time.

3.4 LINK BETWEEN THE PROBLEM AND THE LITERATURE

In the central problem of this study, several elements motivate the use of a dynamic model instead of a static one, these elements are explained below.
The first element is that the product carriers that fill one bag are not independent of one another. In the event that the system deteriorates and the weight of the subsequently filled product carriers is slightly above the lower rejection limits, these filled product carriers could end up in the same bag, depending on the transport policy of sending product carriers to one or the other filling line.
The second element is that there is a trend present in the system. The standard deviation of pads increases since one side of the tube contaminates faster; therefore, the discrepancy between the pad weights between the two sides increases, which in turn increases the overall standard deviation of the pads. This trend should be simulated.
The third element is the fact that disruptions to the process occur. Product carriers can be damaged, affecting the estimation of the mean. Pads can be underfilled because the hopper level dropped abruptly, causing the system to erroneously adjust the pad weight upward. Ceramic filters can also break, causing 1 in 40 pads to be underfilled. The system does not automatically respond on these disruptions. A DES can be used to assess strategies that take these disruptions into account.
The fourth element is that there is a correlation between the weights of product carriers. Pad weights vary slowly, and subsequent product carriers can be either underfilled or overfilled. The transport policy influences which subsequent product carriers ends up in one bag.
Overall, these elements give ample reason to use a DES, which is able to incorporate all the elements in the system, whereas the other options are not (see Table 5).

TABLE 5: SUITABILITY OF SIMULATION APPROACH BY SYSTEM ELEMENT.

Problem element	**Mathematical modelling**	**Stochastic modelling**	**Optimisation**	**Discrete event simulation**
Stochasticity	○	●	●	●
Trend	-	○	○	●
Disruptions	-	○	○	●
Policies	-	-	-	●

- ● Can take element into account
- ○ Difficult to take element into account, but possible
- \- Unable to take element into account

3.5 STEPS IN CREATING A DISCRETE EVENT SIMULATION MODEL

Sachidananda et al. (2016) define six steps in the DES methodology, while Law (2015) describes the 10 steps of a simulation study (see Figure 36). Sachidananda et al.'s (2016) steps correspond to Law's 92015) first two steps. Law's (2015) further steps include validating the model, performing experiments and analysing the results. As these steps can better represent the whole process, these they are used as guidance for the study.

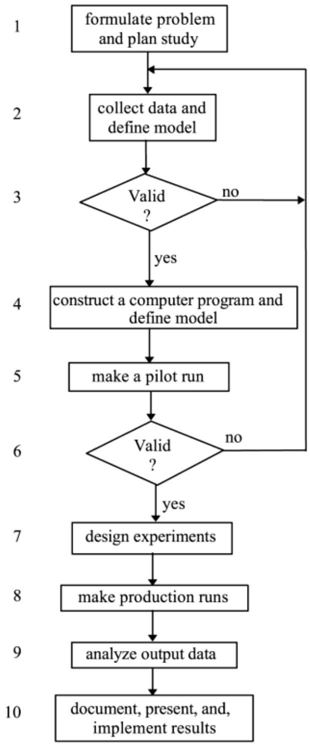

FIGURE 36: STEPS OF A SIMULATION STUDY.

3.6 PERFORMANCE MEASURES IN A SIMULATION STUDY

This section describes three different performance measures for a simulation study. To make sure results are reliable, the warm-up period, run length and number of replications should be statistically determined.

Warm-up period

According to Law (2015), if one is trying to determine the long-term or steady-state behaviour of a system, then it is generally advisable to specify a warm-up period for the simulation, that is, a point in simulated time when the statistical counters are reset (but not the state of the system). A warm-up period is thus required when the transient means converge toward the steady-state mean. However, if there are enough observations, the initial transient observations are "washed out" by the remaining steady state observations. In this research problem, the mean value of the pad weights can be set to the target weight, and no warmup period would be required. This is because i) the system starts in a steady state, ii) it only affects the first batch and iii) if many batches are simulated, the first batch will be washed out.
However, if we choose to start in a non-steady state, it takes one or several batches to bring the weight of the pads to the steady state. This should be determined by experiments on the model.

Run length

Our model is a non-terminating simulation, i.e. there is no natural event that specifies the length of a run. This length should be at least long enough to find statistically confident measurements of the objective used as output.

Replications

According to Law (2015) in order to generate independent replications, each replication should use separate sets of different random numbers and the same initial conditions. Each replication should also reset the statistical counters.
With this section, research question 2.3 “How can results of the system be verified and validated?” is answered, several options are mentioned and a simulation seems most appropriate for the faced problem.

3.7 CONCLUSION OF LITERATURE REVIEW

This chapter a review of the relevant literature for this research is provided. It started with an overview of possible methods to study a system. We then described several ways to simulate a system, and we linked the theory to the faced problem and assessed the fit of the possible solutions with the problem to make a decision. The decision was made to execute a discrete event simulation (DES) study to describe the system at JDE. This is mostly driven by the fact that the system that is looked at in this research is too complex for an analytical solution. Finally the steps needed to execute a DES were described and last the performance measures that are especially relevant for to this DES execution, which should be determined later on in this research.

4. THE SIMULATION MODEL

In this chapter, the first question to answer the third research question (see Section 1.5.3) is answered. In Section 4.1 the model is described in general and the assumptions in the model are listed. In Section 4.2 the inputs, characteristics, outputs and objectives for the simulation model are discussed. In Section 4.3, the verification of the model is described. In Section 4.4 the performance measures of the model (like the run length) are discussed. Finally, in Section 4.5 the model is validated.

4.1 GENERAL DESCRIPTION OF THE MODEL AND ASSUMPTIONS

The feedback loop system is simulated with Siemens Plant Simulation v.14. This section describes the simulation with which the problem is solved, including the inputs, outputs, assumptions, characteristics, verification and validation.

Selecting the simulation software

For selecting the simulation software, criteria from Tewoldeberhan et al. (2003) were used to assess a simulation software package. Tewolderberhan et al. (2003) defined criteria for assessing the performance on model development, input, output, and user criteria. Since the author of this research is familiar with Siemens Plant Simulation v.14, it is checked whether that software is sufficient. The criteria on which the software was assessed can be found in Appendix B: Selection criteria for simulation software selection. Based on the results in the appendix, we conclude that the Siemens Plant Simulation v.14 software provides all the features we use in this simulation study.

General description

The overall the model exists of five steps (see Figure 37).

- First, the pads are made and the product carriers are filled (nr 1 in Figure 37).
- Second, the weight of the product carriers is checked, and they are then either rejected or accepted. Furthermore, the check decides whether the system should make any adjustments or not (nr 2 in Figure 37).
- Third, the accepted product carriers are transported to either Line A or Line B (nr 3 in Figure 37).
- Fourth, the right number of product carriers is subsequently emptied into the bag, which is transported to the bag weighing cell (nr 4 in Figure 37).
- Finally, the full bags are weighed and subsequently rejected or accepted, nr 5 in Figure 37.

The simulated data is based on the granularity of a pad, so most aspects are also calculated to the granularity of the pads.

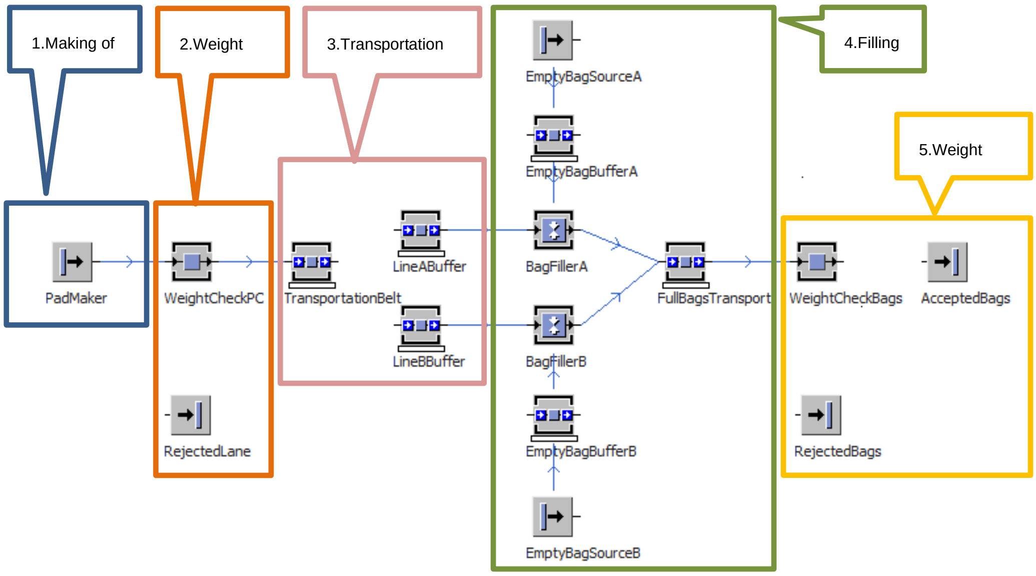

FIGURE 37: SCREENSHOT OF THE MODEL WITH DESCRIPTIONS OF THE STEPS IN THE PROCESS.

Assumptions

Some of the mentioned influences on variation in Chapter 2 are simplified in the simulation model. These assumptions are mentioned below.

Discrepancy between the operator and machine sides of the dosing drum
The discrepancy between the weights of pads from the operator and the machine side is assumed to increase at a constant rate. When this discrepancy is equal to or higher than 0.12 it resets to 0.02 again. In reality, the discrepancy changes at a less constant rate, and the difference can be higher than 0.12.

Sine function trend
The sine function trend is assumed based on a dataset of individual product carrier weights. The trend of the product carrier weights is divided by the number of pads, which yields the amplitude and period of the granularity of a pad. In practice, the amplitude and period of the sine function vary. Sometimes, a sine function is not detectable, and other times the period is lower or the amplitude higher. Since it is basically impossible to simulate such an uncertain trend, these assumptions for the trend are used as simplifications.

Accuracy of steering
The accuracy of steering cannot be accurately determined, since there is stochasticity both before and after the steering. Given that the translation from the weighing cell to the pad making machine is fully accurate, the steering is assumed fully accurate too. This is most probably a simplification, since it is plausible there is a form of imperfection in the steering.

Steering delay
The steering is assumed to have speed of 30 pads per gram and one gram per second. This implies that the steering most of the time is fully finished after filling one or two

product carriers. Though there are also indications that it takes longer. This should be taken into account when implementing the results.

Model based on Line 17
The model is based on Line 17, therefore some characteristics specific for a certain line are ignored. This slightly effects the validity for the bag sizes that are not produced on Line 17. This can be taken care of in the implementation phase, where settings can be adjusted to specific lines.

Linear inaccuracy of bag weighing cell
In the model, the inaccuracy of the bag weighing cell is assumed to increase linear with the number of pads that go in one bag.

4.2 INPUTS, CHARACTERISTICS, OUTPUT AND OBJECTIVES OF THE SIMULATION MODEL

This section, the inputs of the system, characteristics that are built in, outputs that are used and finally the objectives to base the performance on are described.

4.2.1 INPUTS

In this section, the used inputs are described. Several inputs are simplified, this is indicated in Table 6. All parameters, values and distributions are based on findings in Chapter 2.

Pad weight variations
The <u>mean weight</u> of the pads is the main input to the model, and it is assumed to be constant around the target weight. In reality, sometimes the mean of the pads can deviate from the specifications for several days or weeks due to incorrectly calibrated tare settings. This is simulated by varying the tare weight.
The <u>standard deviation</u> of the pad weights is set to an exact value such that the final standard deviation of pads is close to the found standard deviation 0.13 grams.
The <u>weight of the filter paper</u> is assumed to be constant.
In reality, the <u>discrepancy between the weight of the pads at the operator and machine side</u> of the dosing drum increases over time, until the dosing drum is cleaned. The speed of this trend is assumed to be constant over time and increases by 0.00001852 grams per pad.

Weight checks
The <u>weight limits</u> for both rejections and average calculations vary per bag size and experiment. In reality, these limits are based on a percentage of the target pad weight. In reality, this percentage can vary by decimal place. In the model, this is also a percentage that, has no limits on decimals, although the experiments are limited to varying one decimal place after the period.
The <u>probability of missing a pad</u> indicates how often a product carrier or bag is missing a pad.

Feedback loop
The feedback loop has multiple experimental variables, which are explained below.
The <u>sample size</u> determines how many product carriers are weighed to estimate the current average.

The lower and upper tolerances indicate when the feedback loop is activated. If the current average falls outside the upper or lower tolerance limits, the feedback loop is activated. These tolerances are expressed as a percentage of the target mean, again to one decimal place.
The steering factor is the severity of the adjustment. If this value equals 1, the weight is adjusted with the exact discrepancy between the measured and the target weight. With a value of 0.5, the weight is adjusted with half of the difference, and so on.
The feedback delay indicates how many product carriers are ignored after steering for calculating the current average weight of the product carriers.

Transport policy
The transport policy determines how many subsequent product carriers are send to one or the other bag filling line.

TABLE 6: INPUT VALUES FOR THE SIMULATION MODEL.

Model step	Input	Simplification of reality	Set value
1	Mean pad weight	Yes, assumed to vary around the target mean of 7.00 grams.	7.00
1	Initial standard deviation of pad weights	No	0.13
1	Weight of filter paper	Yes, assumed to be a constant weight without standard deviation	0.183
1	Difference between Operator and Machine side	Yes, assumed to be a constant trend that is automatically corrected	Trend of 1.852e-08 increase per pad
1	Probability of missing pads	Yes, estimated as a constant factor on the last pad made	0.1% probability of missing a pad, of which 80% occur in product carriers and 20% in bags.
2	Rejection limits product carriers	No	Varies
2	Average calculation limits product carriers	No	Varies
2	Sample size for average calculation	No	Varies
2	Lower and upper tolerance limits for when to steer	No	Varies
2	Steering factor	Slightly, the standard deviation of the effect of the adjustment is estimated.	Varies
2	Feedback delay	No	Varies
3	Transport policy	No	Either two or 10 consecutive product carriers are transported to the same bag filling line (depending on the production line)
5	Rejection limits bags	No	Varies
5	Average calculation limits bags	No	Varies

4.2.2 CHARACTERISTICS INCORPORATED INTO THE SIMULATION MODEL

Several characteristics that have an effect on the system are described, along with their behaviour and how they were implemented in the model. These are explained below and listed in Table 7.

Stochasticity of the empty product carrier weight

The weight of the empty product carriers is normally distributed and vary according to a certain standard deviation, these weights are independently generated. The details are based on the analysis described in Section 2.3.

Stochasticity weighing cell accuracy
The weights obtained by the weighing cells is also normally distributed and vary according to a certain standard deviation, these incorrections are independently generated and added to the detected weight of the product. The details are based on the analysis described in Section 2.3.

Rounding by the weighing cells
The weighing cells round the detected weights to an even number with two digits. Averages are calculated based on these rounded numbers.

Filler adjustments effects
When the feedback loop is activated, the weight is adjusted. The effect, however, is gradually implemented in the machine. In the simulation model, the adjustment starts when there is a delay of 12 product carriers or more, since these were already filled before the adjustment began. The pad weights gradually increase according to the speed of the spindle.

Sine function trend of the pad weights
The trend of the pad weights is simulated with a sine function that various every 24 (simulated) hours. A period is used that various according to a normal distribution with both a mean and standard deviation of 0.000484814 grams per pad and an amplitude that varies according to a normal distribution with a mean and standard deviation of 0.03 grams per pad.

TABLE 7: TABLE WITH CHARACTERISTICS USED AS INPUT IN THE SIMULATION MODEL.

Model step	Characteristic	Simplification of reality	Set value
1	Stochasticity of empty product carrier weight	No	Mean: 390.4 Standard deviation: 0.285
2	Stochasticity of accuracy of the weighing cell	No	Mean: 0 Standard deviation: 0.077
2	Rounding of weighing cell	No	Rounding on multiples of 0.02
2	Behaviour of filler steering effect	Yes	30 pads per gram (changes linear)
2	Sine function trend of pad weight	Yes, varies every 24 simulated hours	**Period:** Mean: 0.000484814 per pad Standard deviation: 0.000484814 per pad **Amplitude:** Mean: 0.03 grams Standard deviation: 0.03 grams

4.2.3 OUTPUTS OF THE SIMULATION MODEL
There are several outputs of the simulation model, these outputs give indications about the performance of the overall system. Not all of them are used as Key Performance Indicator to assess the performance of the model.

Total overfill
The total amount of overfilling is tracked through two objectives: pure overfilling and pure underfilling. This is the amount of coffee in a bag compared to the target amount. When

there is less coffee in the bag, the difference is known as underfill, while the reverse is true for an overfill.

Reworked coffee
The amount of reworking is based on the product carrier and bag rejections. The coffee from the pads in these rejected products are reworked.

Cost of reworked coffee
Rejecting a bag costs more than rejecting a product carrier. First, there are often more pads in a bag than in a product carrier; this factor is already included in the objective above. Second, more effort is spent on a bag than on a product carrier, such as in terms of transport. Third, when a bag is rejected, the empty bag is also rejected, which costs an extra amount of money. Therefore, the costs of rejecting a bag is assumed to be 62% higher than rejecting a product carrier, relative to the amount of coffee that is rejected. This percentage is based on the average costs per pad per material. The relative costs between filter paper costs and wrapping paper costs per pad results in the assumed extra costs of 62% for rejecting a bag. An overview of the costs is given in Table 8.

TABLE 8: MATERIAL COSTS PER PAD (FULL-YEAR DATA FROM 2019).

Material	Yearly expenses (€)	Pads produced / year	Costs per pad (€)	Costs per pad (%)
Box		x		
Filter paper				
Wrapping paper				
Coffee				
Total		**x**		**100%**

Falsely rejected product carriers and bags
The detected weight depends on the weight of a product carrier and the accuracy of the weighing cells. Therefore, a product could be rejected when it should actually be accepted. The number of incorrectly rejected product carriers and bags is tracked.

Distributions of pads, product carriers and bags
The mean and standard deviations of all pads, product carriers and bags is calculated at the end of a simulation run. Note that the rejected products are also included in this calculation.

4.2.4 OBJECTIVES

The main objective to optimise is the costs of rework, and this means decreasing the rejections rates of product carriers and bags. Reworking is costly because reworked coffee is devaluated by €x per kilogram, it requires labour, and it is disadvantageous to the quality of the product.
A secondary objective is the amount of overfilling. Every gram of extra coffee given to the customer comes at an additional cost, and underdosing is disadvantageous to the quality of the Senseo pads. Since the mean of the pad weights varies around the target mean, the total amount of overfilling is expected to be close to zero; therefore the combined amount of pure overfilling and pure underfilling is a better indicator of this objective. However, this is a secondary objective, which means that this objective will be optimised

by the model based on the costs of rework, when making a decision on the best possible values, this objective is taken into account.
Another objective is the probability that a bag with a missing pad is accepted. Internally, JDE has decided that this change may not exceed 1%.

4.2.5 OVERVIEW OF THE SIMULATION MODEL STRUCTURE

The simulation model is fed by inputs, the simulation model works based on the settings of these inputs and finally provides outputs with which the overall performance can be assessed. A visualization of the inputs, simulation and outputs is shown below in Figure 38.

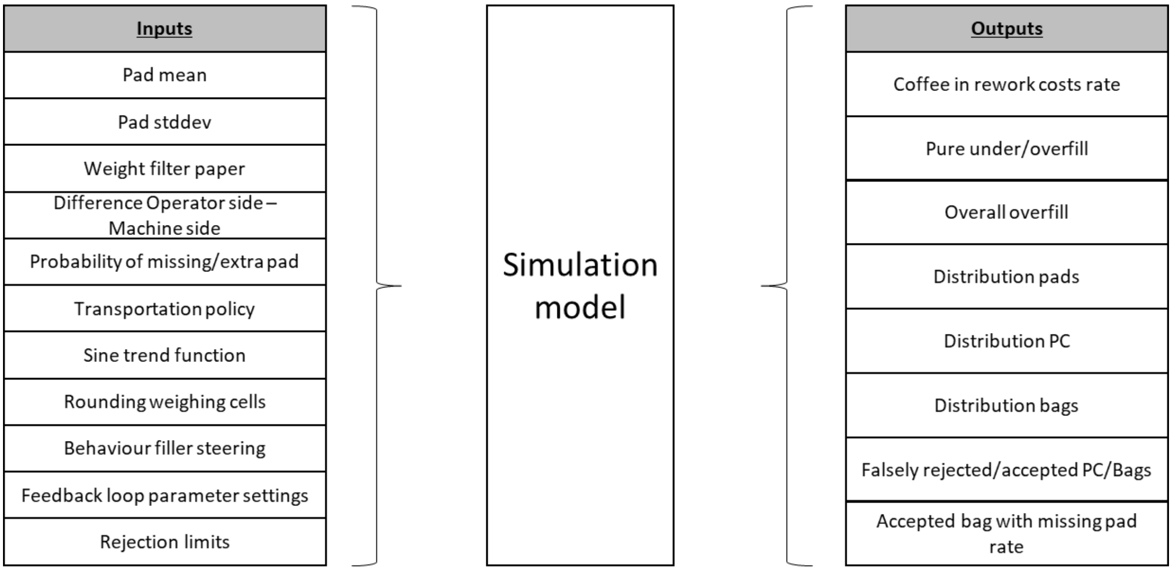

FIGURE 38: VISUALIZATION OF THE STRUCTURE OF THE SIMULATION MODEL.

4.3 VERIFICATION OF THE MODEL

In this section the verification of the model is described. The verification is related to whether the model does what it should do based on the built-in logic, e.g. like whether certain aspects are correctly summed up. Note that this should not be misinterpreted with validation, in validation it is checked whether the model is similar to what has been seen in reality.
Our approach to check whether the logic is correctly implemented in the model, all generated data was saved into data tables. There is a table with every pad generated, as well as, every product carrier filled and every bag that is filled with all their properties. The model is verified by cross-checking data points (for all tables containing the data points, see Appendix C. The data stored in the lists is presented in Table 9 by granularity.

Example: if the first two product carriers have a coffee weight of 101 and 102 grams, two product carriers go into one bag, then the first bag should have a weight of exactly 101+102=203 grams.

Weight checks
All combined weights should add up to the correct amount. For the pads list, this means that the weight of the pad should equal the total weight of the coffee and the filter paper. In the table, the values are rounded to two decimal places, since the filter paper weight is

0.183 grams, there could be a discrepancy of 0.1 grams between the total weight of a pad and the sum of the coffee and filter paper weights.
In the product carrier list, the link between individual pad weights and product carrier weights is first checked. The pads that fill one product carrier should be exactly equal to the indicated weights of the pads in the product carrier. Subsequently, the total weight of the pad, empty product carrier and weighing cell should add up to the detected weight rounded to the closest rounding number possible.
In the bags list, the weight of pure coffee in the product carriers that fill one bag should equal the coffee weight in that bag. The rounded bag weight should equal the sum of the coffee weight and the weighing inaccuracy, rounded to the closest possible number.

Rejected product carrier checks
The rejected products checked for whether they are correctly rejected by the model, based on the rejection limits. When a product carrier is rejected, it corresponding number should not be present in the bags list.

Transport policy
The logistics of product carrier transport is checked by tracking which product carriers end up in one bag in the bags list. If product carriers are transported to a bag filling line in twos, then two consecutive product carriers should end up in the same bag.

Steering delay
When the steering function is activated, the result of the steering should be delayed by 12 product carriers, and then the gradually implemented, spread over multiple product carriers. In the product carrier list, this is tracked by the mean pad weight at that moment, linked the sample size. This verifies that the change in the mean has been simulated correctly.

TABLE 9: LISTED SIMULATION DATA BY PRODUCT GRANULARITY.

Pads list	Product carrier list	Bag list
Weight of pad	Product carrier counter	Weight of coffee in bag
Amount of coffee in pad	Pads weight in product carrier	Weighing inaccuracy of weighing cell
Weight of filter paper	Weight of empty product carrier	Rounded bag weight
Counter of product carrier	Weighing inaccuracy of weighing cell	Overfilling
Side of the dosing drum on whichthe pad is made	Detected weight by the system	Underfilling
Value of the sine correction	Status (accepted or rejected)	Status (accepted or rejected)
	Just call indication (correct or incorrect status)	Just call indication (correct or incorrect status)
	Sample size	Number of product carriers in one bag
	Current average of samples	Bag number to calculate hourly averages
	Difference between the sample size and the nominal weight	Current hourly average
	Current mean pad weights on operator side	Missing pad in bag (binary value)
	Current mean pad weights on machine side	
	Weight of last pad	
	Missing pad at in product carrier (binary value)	
	Missing pad in bag (binary value)	

4.4 PERFORMANCE MEASURES OF THE MODEL

In this section the performance measures of the model is described. By statistically determining the warm-up period, run length and number of replications it is ensured that the found results are reliable.

Warm-up period

According to Law (2015), a warm-up period is required to make sure that the system is in a steady-state. In the modelled system, the mean pad weight decides whether the system is in a steady-state. If the mean varies around the targeted average value, all subsequent products (i.e.. product carriers and bags) also vary between their target values. In our simulation, this is the case from the beginning.

Two trends influence the mean weight of pads: the sine trend and the discrepancy in pad weight between the operator and the machine side of the dosing drum. Both factors are initially zero and they vary according to their respective patterns. Both trends having a value of zero simultaneously is a scenario that can occur when two cyclic functions vary over time, therefore it seems plausible the first bags made already have weight close to the target weight. Such that no warm-up period is required for this model. This is supported by comparing the average weight of bags in a batch. Figure 39 and Figure 40 below show the fluctuation in the batch average shown, while in Table 10 presents the exact 95% confidence interval. The fluctuation is caused by the sine function and randomness on the level of individual pad weight, the feedback loop ensures the average weight keeps close to the norm.

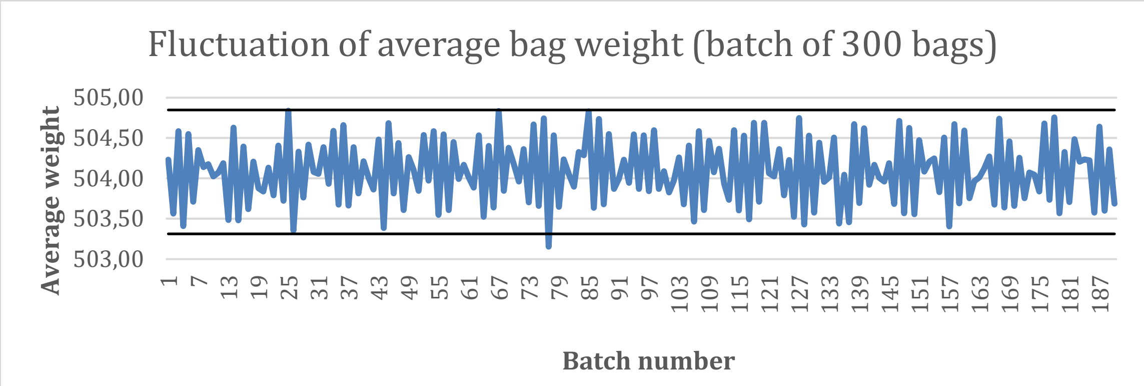

FIGURE 39: WEIGHT FLUCTUATION OF BAGS WITH 72 PADS, BASED ON BATCHES OF 300 BAGS.

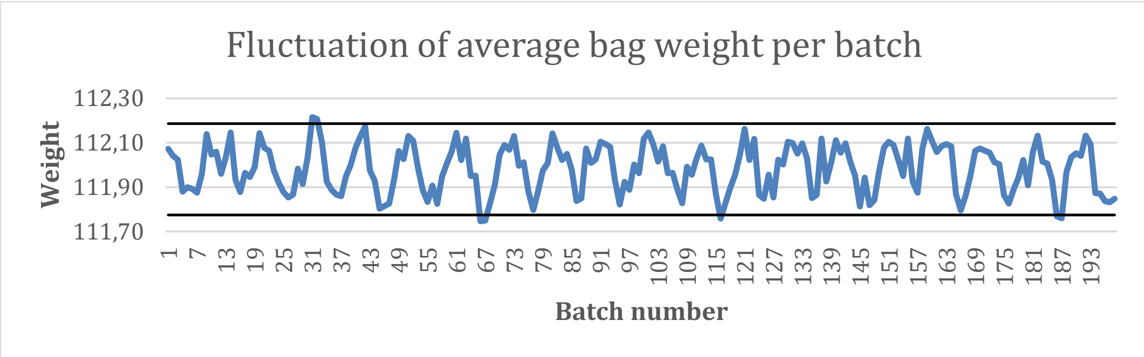

FIGURE 40: BAG WEIGHT FLUCTUATION OF BAGS WITH 16 PADS, BASED ON BATCHES OF 300 BAGS.

TABLE 10: BATCH STATISTICS FOR WARM-UP PERIOD DETERMINATION.

Bag size	Average	Standard deviation	95% Lower bound	95% Upper bound
72	504.09	0.396	503.31	504.85
16	111.98	0.106	111.77	112.19

Run Length and replications

The model represents a non-terminating system, since the system never stops by a natural event (Law, 2015). Therefore, there is no natural event that specifies the length of the run and the measure of performance for such a simulation is a steady state parameter. In our model, this parameter is the ‘Coffee in rework costs rate’. This parameter should be stable, a steady state can be reached by a small number of replications and a long run length or vice versa.

The bare minimum of the run length is decided by the largest cycle within the process. Again, these cycles are the sine function trend of the pad weight and the discrepancy in weight between the operator and machine sides of the dosing drum. The cycle of the discrepancy between sides is 48,000 pads, whereas the cycle for the sine function trend is 24,169 pads. For the smallest bag size of 16 pads, therefore, the run length should be at least 3000 bags, and for the largest bag size of 72 pads, this number should be 667 bags.

To determine the run length, a bag size of 72 pads is used, because it consists of the largest amount of pads per product carrier and three product carriers per bag. Rejecting such a bag has the greatest influence on the ‘Coffee in rework costs rate’ objective.

Therefore, the objective for a bag of 72 pads will have the slowest convergence rate compared to the other bag sizes.
To determine the best possible combination of run length and number of replications, ten different run lengths from 10 to 120 hours with incremental increases were analysed. The standard deviation of the Coffee in rework costs rate after n replications is plotted in Figure 41. At a run length of 10 hours, the standard deviation shows a sharp increasing trend, which suggests that the run length is not long enough to obtain a stable output. From 50 hours onward, the standard deviation remains fairly stable.

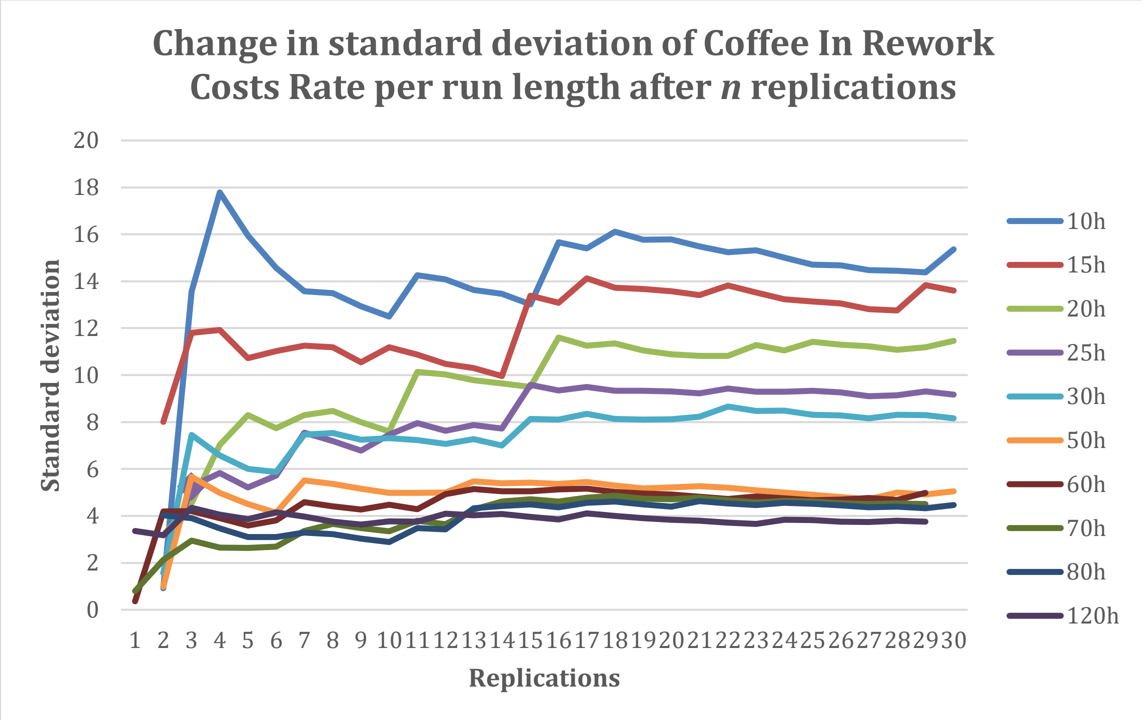

FIGURE 41: CHANGE IN STANDARD DEVIATION OVER REPLICATIONS PER RUN LENGTH.

For all run lengths, the number of replications based on the relative width of the confidence interval, and the relative error were calculated. The error in the found outcome is assessed, if the error is small enough, the outcome is highly reliable enough (Law, 2015) and therefore representative. The relative width should be lower than the relative error, one be sure the outcome sure falls within the limits of the relative error. The calculation of this so-called relative width is given in Equation 1. The relative error is calculated by the formula given in Equation 2. The observed error is calculated based on a t-value of 97.5% (1 – α/2) and n – 1 degrees of freedom. There is a sufficient number replications when the relative error is lower than the observed error, then the number of replications is enough. The relative error is set to 0.04762, based on the formula given in Equation 2 and a γ of 5%. Also, the number of required replications per run length was calculated. For a run length of 50 hours onward, fewer than 30 replication are enough. For a run length of 70 hours, 10 replications give a sufficient result, which is the most efficient balance computing wise between run length and replications in our analysis. Based on the results presented in Table 11, the number of replications is set to 10. Table 12 displays the results of the chi-square test, showing that the 10 replications give sufficient prove the output is normally distributed.

Equation 1: Relative error of the confidence interval y' compared to the average X in the equation.

$$\frac{t_{n-1,1-\alpha/2}\sqrt{S^2/n}}{\overline{X}} < \gamma'$$

Equation 2: Formula for the relative error.

$$\gamma' = \gamma/(1+\gamma)$$

TABLE 11: ERROR PER NUMBER OF REPLICATIONS FOR A RUN LENGTH OF 70 HOURS.

#Replications	Average costs	Average over replication	Variance over replications	T-value	ð	Y'	Sufficient?
1	57,26	57,26					
2	58,85	58,06	1,27	12,71	0,1745	0,04762	Not sufficient
3	53,74	56,62	6,85	4,30	0,1148	0,04762	Not sufficient
4	61,92	57,94	11,59	3,18	0,0935	0,04762	Not sufficient
5	58,44	58,04	8,74	2,78	0,0633	0,04762	Not sufficient
6	60,90	58,52	8,36	2,57	0,0518	0,04762	Not sufficient
7	55,28	58,06	8,46	2,45	0,0463	0,04762	Sufficient
8	51,35	57,22	12,88	2,36	0,0524	0,04762	Not sufficient
9	63,07	57,87	15,08	2,31	0,0516	0,04762	Not sufficient
10	57,49	57,83	13,42	2,26	0,0453	0,04762	Sufficient
11	59,34	57,97	12,28	2,23	0,0406	0,04762	Sufficient
12	50,58	57,35	15,71	2,20	0,0439	0,04762	Sufficient

TABLE 12: CHI-SQUARED TEST WITH 10 REPLICATIONS WITH A RUN LENGTH OF 70 HOURS.

Bin	Frequency	NormDistr	Difference	ExpectedValue	Error
55,1	2	0,22	0,22	2,2	0,03
58,8	4	0,60	0,38	3,8	0,02
62,5	3	0,90	0,30	3,0	0,00
66,2	1	0,99	0,09	0,9	0,01
				Total error	0,05
				Allowed Error	5,99
				Conclusion	Distribution accepted

Overall, with no warm-up period, a run length of 70 hours and 10 replications, the performance of the simulation model on 'Coffee in rework costs' is statistically significant.

4.5 VALIDATION OF THE MODEL

The model is validated in two ways. First, the interaction within the model is checked, see Section 4.5.1. This means the interaction between making product carriers and bags. This is done by using real-world data of individual product carrier weight. The results are expected to be highly similar. Second, data of one month for all bag sizes and all granularities were compared to the results of the simulated data, see Section 4.5.2. The results are compared based on their mean and their spread, based on box plots.

4.5.1 CHECKING THE INTERACTION WITHIN THE MODEL

The weights of individual product carriers and bags are logged to a server, and this data is used determine the standard deviation of both. The data points from the product carriers are used as input for the simulation model. With this input, the standard deviation of product carriers should be exactly the same in reality as in the model. The bag distribution given by the model, should be close to the distribution of the actual bags.

Table 13 lists the standard deviation of the product carriers and bags based on the individual measurements. The values are similar enough to conclude that the model works correctly.
The standard deviation of the product carriers is determined in exactly the same manner, beforehand by using the simulation model. This should be the case since the simulation model based the calculation on its predefined input.
The standard deviation of the bags differs 0.0045 between the real-world data and the simulated model. This slight difference may be caused, first, by inaccuracies in the data. The calculated standard deviation is not perfectly based on the bags filled by the product carriers used as input. This also explains the difference in the mean weights of the bags. The real-world dataset is adjusted based on the results of the simulation. Outliers that were 6.9 grams above the norm weight or 4.8 grams below the norm weight were deleted from the dataset, since these values are statistically <0.0% to occur.

TABLE 13: COMPARISON OF ACTUAL DATA AND SIMULATION MODEL.

	Standard deviation of product carriers	**Mean of product carriers**	**Standard deviation of bags**	**Mean of bags**
Individual measurements	0.7512	172.3871	1.2696	336.4849
Simulation results	0.7512	172.3889	1.2741	335.9967

Since the individual measurements and results of the simulation model are very similar, it may be concluded that the model works just as well as the actual system.

4.5.2 SPREAD OF DATA ON ALL THREE GRANULARITIES

To check the validity of the model, the results found in real-world data were compared with the results of the simulation model. This is done for three granularities – pad, product carriers and bags – to ensure that the translation of the input at one stage results in the correct output at the subsequent stage.
In reality, sudden fluctuations in the sine trend happen constantly (i.e. within an hour). In our simulation model, the sine function and tare settings are varied every 24 hour, such that the simulated results would have more extreme hourly averages than the hourly averages found in the actual data. While more extreme fluctuations can also happen in reality, they are overshadowed by the normal behaviour of the production line in any given hour. Therefore, the simulated data contains more extreme observations, which can have a profound influence on the usual parametric data analyses and, as a consequence, lead to erroneous conclusions (Carter et al., 2009). Because extreme values are overshadowed in real data and not in the simulated data, this statement of Carter et al. (2019) applies here too.
Due to the situation described above, the median and the spread of the real data are compared to the simulated results. For this comparison boxplots were used, since we are interested in whether the core of the simulated and the real-world data are similar. Depending on the objective, either the median, the spread or both were compared (see Table 14). The reason changes in the median were ignored is that the median should be close to the norm and if that is not the case, something structural is wrong in the production line, this is unrelated to the weight stabilization system. The boxplots are based on one month of real data and simulated data is based on 200,000 bags.

TABLE 14:RELEVANT COMPARISONS PER OBJECTIVE.

Granularity	Median	Spread
Weight of pads	No	Yes
Standard deviation of pads	Yes	Yes
Weight of product carriers	No	Yes
Standard deviation of product carriers	Yes	Yes
Rejection rate of product carriers	Yes	Yes
Weight of bags	No	Yes
Standard deviation of bags	Yes	Yes
Rejection rate of bags	Yes	Yes

Spread of pad weight

For the boxplot of pad weight, the median is expected to be close to the target weight of 7.183 grams (see the grey horizontal line in Figure 42). Since the real data is rounded to two decimals, it should be close to 7.18. In the real-world data, the median is a couple of centigrams higher or lower than the target value, which can be seen in Figure 42 where the lower bar represents the 25th percentile, the upper bar the 75th percentile and between these bare is the median. This shows that some production lines were constantly dosing too much or too little coffee in this particular month. In the simulated data, it is assumed that the average pad weight fluctuates around 7.00 grams; therefore, the median of the simulated data is always close to 7.18 grams. The pad weight for, for example, 32 or 54 pads is higher or lower than the expected mean. The discrepancy can be caused by biased weighing by the operator or the production line produced systematically lighter or heavier pads. Since the spreads of the real and simulated data are similar, the simulated pad weight seems to fluctuate in a similar manner as the real-world pad weight.

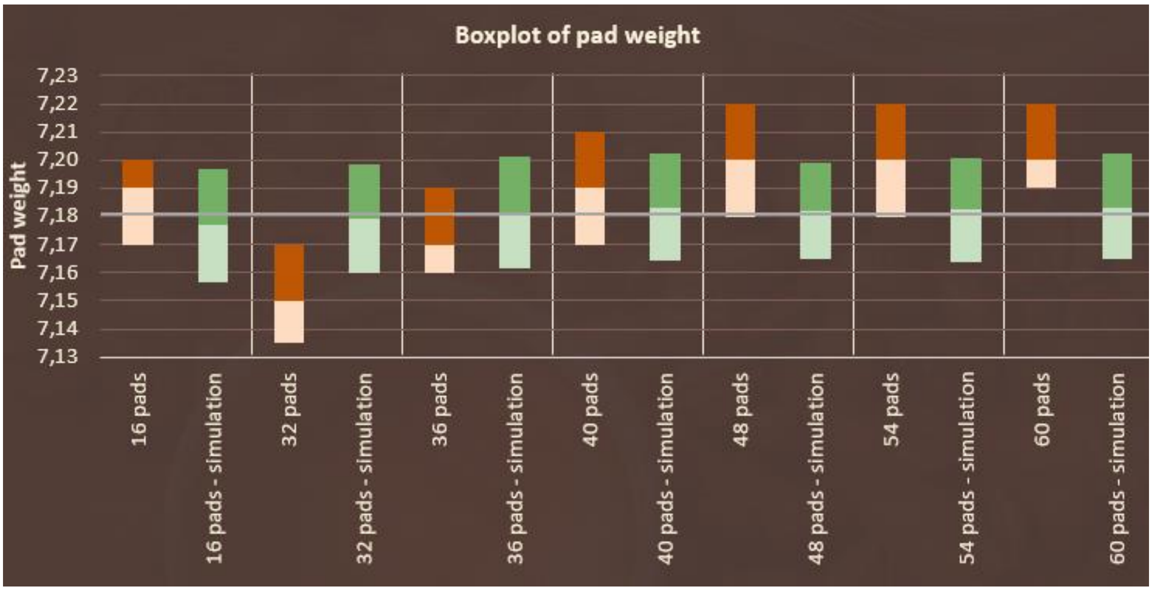

FIGURE 42: BOXPLOT OF PAD WEIGHT PER BAG SIZE (REAL VERSUS SIMULATED DATA).

Spread and median of the standard deviation of the pad weight

In most analysed data sets, the standard deviation of the pad weights varies at around 0.13 grams, as can be seen on the data for the bags of 40, 48 and 54 pads (see Figure 43). In the simulated data it is assumed that the standard deviation varies around 0.13 grams, although for some bag sizes, the standard deviation was higher in the particular month than was analysed. (Note that this is lower than the indicated standard deviation of 0.15 grams in Section 2.3, since the short-term standard deviation seems to be lower). The spread of the standard deviation seems to be similar in the simulated data and in reality. The spread is slightly smaller in the simulated data, because these values are based on figures with many decimal places; the real data is based on two decimals, and therefore this slightly smaller spread was expected. For bag sizes 16, 32, 36 and 60, the standard deviation of pad weight is higher, this is because this data is based on different production lines than Line 17. Overall, the standard deviation of the pad weight shows a similar pattern in both the simulation model and the actual data.

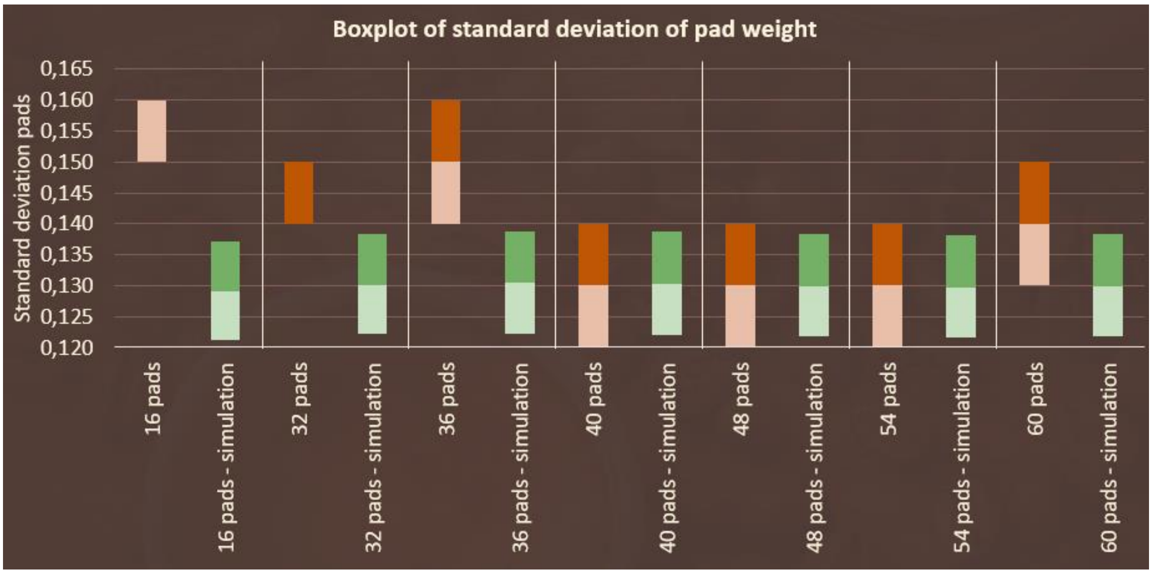

FIGURE 43: BOXPLOT OF STANDARD DEVIATION OF THE PAD WEIGHT PER BAG SIZE (REAL VERSUS SIMULATED DATA).

Spread of the product carrier weight

The spread of the product carrier weights in the simulated data is similar to that the real-world (see Figure 44). For product carriers with 20 and 24 pads. For product carriers with 16 pads, there was no data available, and for those with 18 pads, the actual spread is larger than the simulated one. Since the spreads for 20 and 24 pads are very similar, the simulated spread seems to be more accurate than the real-world data in that month.

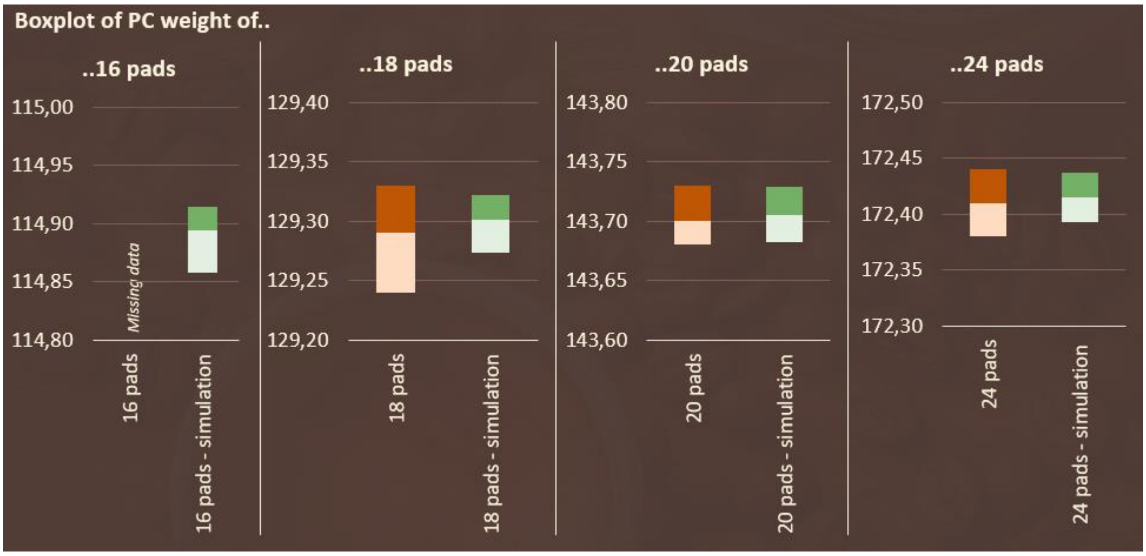

FIGURE 44: BOXPLOT OF PRODUCT CARRIER WEIGHT PER PRODUCT CARRIER SIZE (REAL VERSUS SIMULATED DATA).

Spread and median of the standard deviation of the product carrier weight

The standard deviation of the product carrier weights is consistently higher in the simulated data than the real-world data (see Figure 45). The standard deviation derived from the actual data is low compared to the theoretical standard deviations of the product carriers (based on a standard deviation of 0.1404 grams per pad calculated over several months). This theoretically calculated standard deviation excludes the standard deviations of the empty product carriers and any inaccuracies in the weighing cell. Therefore, it seems to be more plausible that the standard deviation should be higher in the long run. Since the median of the standard deviation of the product carrier with 24 pads is close to the real data value and higher than the theoretically expected standard deviation, it seems plausible that the actual standard deviation is often higher than the theoretical one. In conclusion, although the standard deviation is higher in the simulated model, the simulated values seem to be realistic as sources of stochasticity – such as the standard deviation of pad weights and of empty product carrier weights, as well as the inaccuracy of the weighing cell.

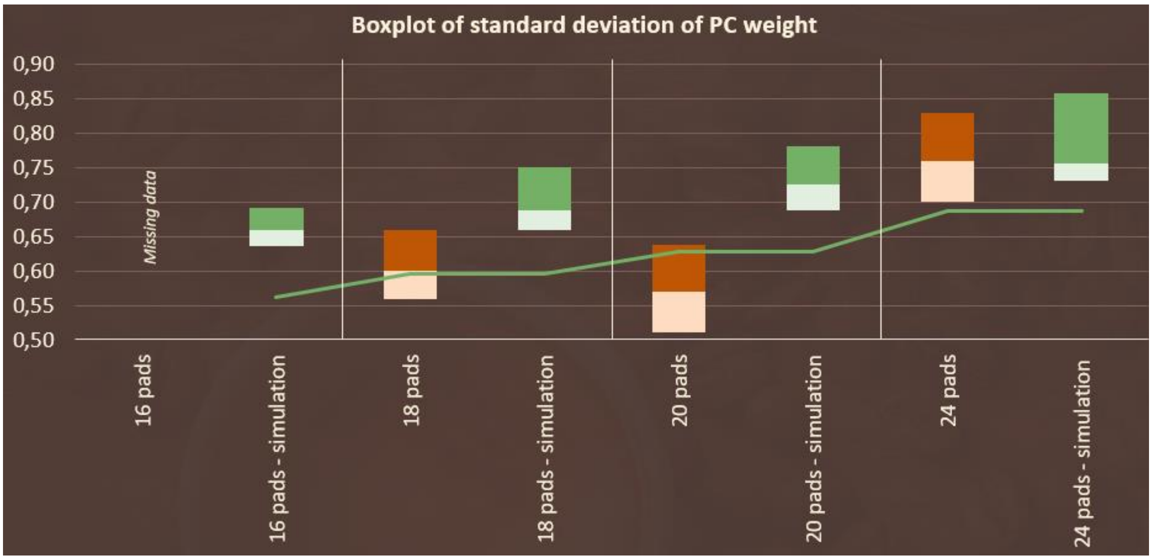

FIGURE 45: BOXPLOT OF PRODUCT CARRIER STANDARD DEVIATION PER BAG SIZE (REAL VERSUS SIMULATED DATA).

Spread and mean of the rejection rate of product carriers

The rejection rates of product carriers is difficult to compare, since this is influenced by the ratio of both missing and extra pads due to machine failures. In reality, this ratio varies, and in the simulation it is given as a constant factor. Therefore, the boxplots are not exactly the same (see Figure 46). Though, since the simulated median is both above and below the real median depending on the bag size, it is assumed the simulated rejection rate to be fairly similar to the real data.

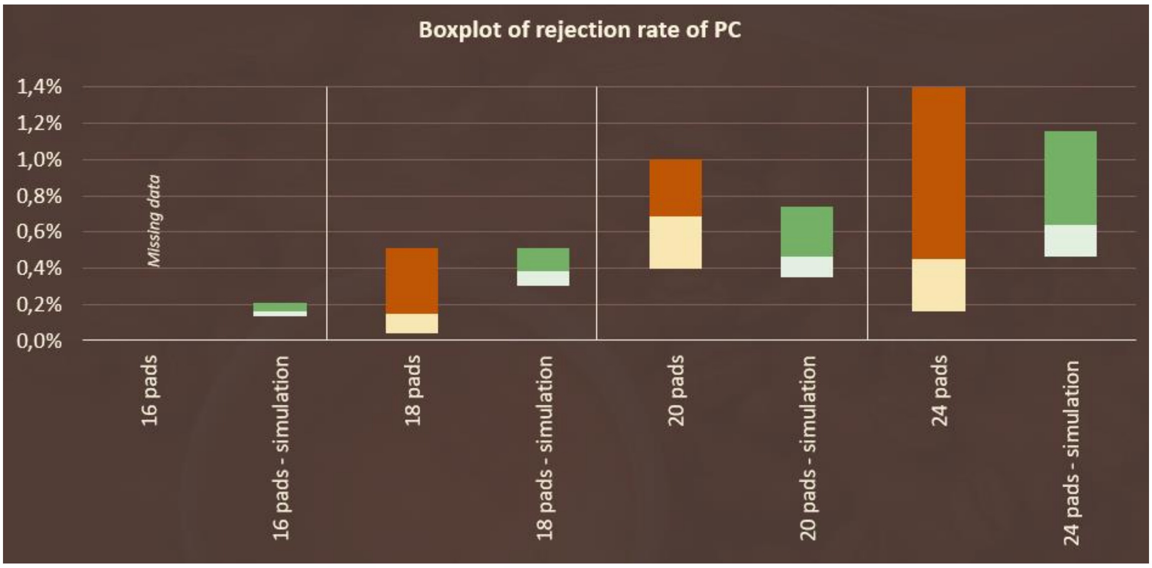

FIGURE 46: BOXPLOT OF REJECTION RATE OF PRODUCT CARRIERS PER BAG SIZE (REAL VERSUS SIMULATED DATA).

Spread of the bag weights

The simulated spread of the bag weights is not always similar to the spread observed in reality, as shown in Figure 47. For the bags with 32, 36, 48 and 60 pads, the two spreads are very similar. For bags with 16, 40 and 54 pads, the spread of the simulated data can either be larger, smaller. Since the spread can be either larger, smaller or similar under the same settings, it can be concluded that the data is so prone to randomness that the model seems to be fairly close to reality, although the simulated data does not fit perfectly.

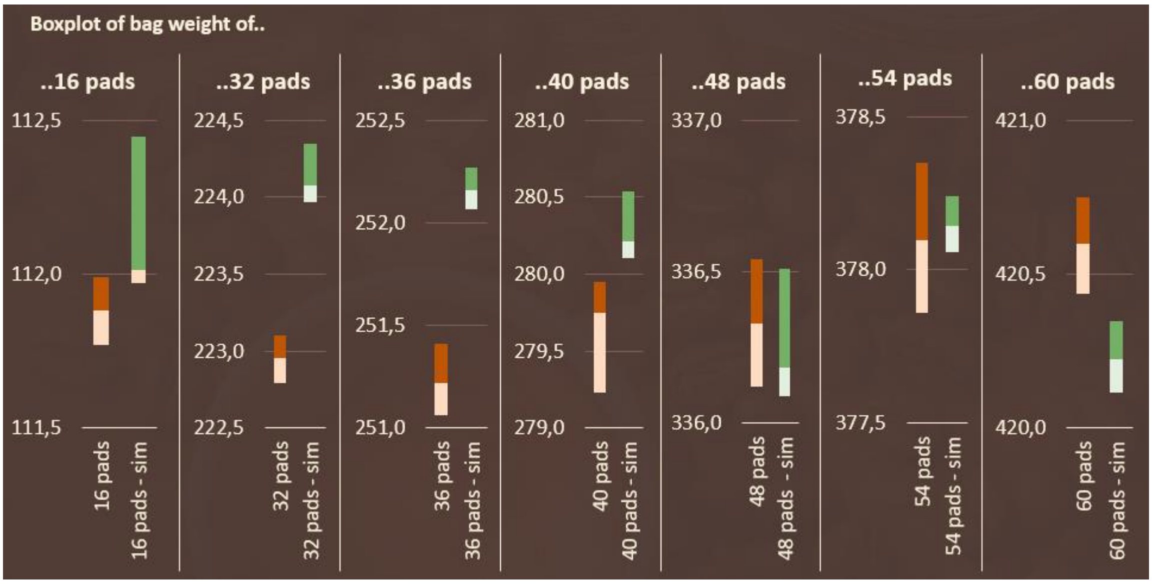

FIGURE 47: BOXPLOT OF BAG WEIGHT PER BAG SIZE (REAL VERSUS SIMULATED DATA).

Spread and median of the standard deviation of the bags weight
The simulated standard deviation of the bag weight is sometimes higher and sometimes lower than the data to which it is compared, as observed in Figure 48. With standard deviation both higher and lower, it is difficult to change the parameter settings such that all simulated data always perfectly fits to the real-world data. Furthermore, the expected theoretical standard deviation based on the standard deviation of pad weights is sometimes very close to the value found in the actual data. It could be the case that the line performed exceptionally well in the particular month in which the data was collected or that this line performs very well on average compared to Line 17, on which the model is based. Therefore, it is assumed that the model does fairly represent the real-world situation.

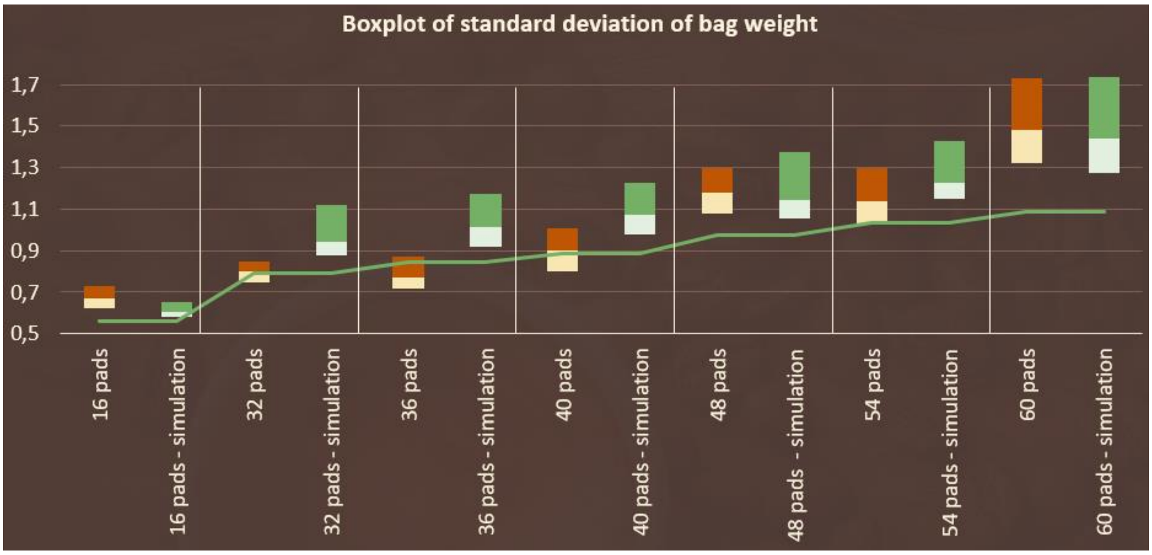

FIGURE 48: BOXPLOT OF STANDARD DEVIATION OF BAG WEIGHT (REAL VERSUS SIMULATED DATA).

Spread and mean of the rejection rate of bags

The rejection rate of bags is very similar for bags with 48 and 54 pads in terms of both its median and its spread (see Figure 49). For bags with 32 and 36 pads, the median is very similar as well, and the spread is smaller. For bags with 16, 40 and 60 pads, the rejection rates are lower than those seen in the actual data. Again, this can be explained by the ratio of missing and extra pads. Since this figure remains unknown, and the median is very similar for many bag sizes, it is assumed that the model represents the real-life situation fairly accurately.

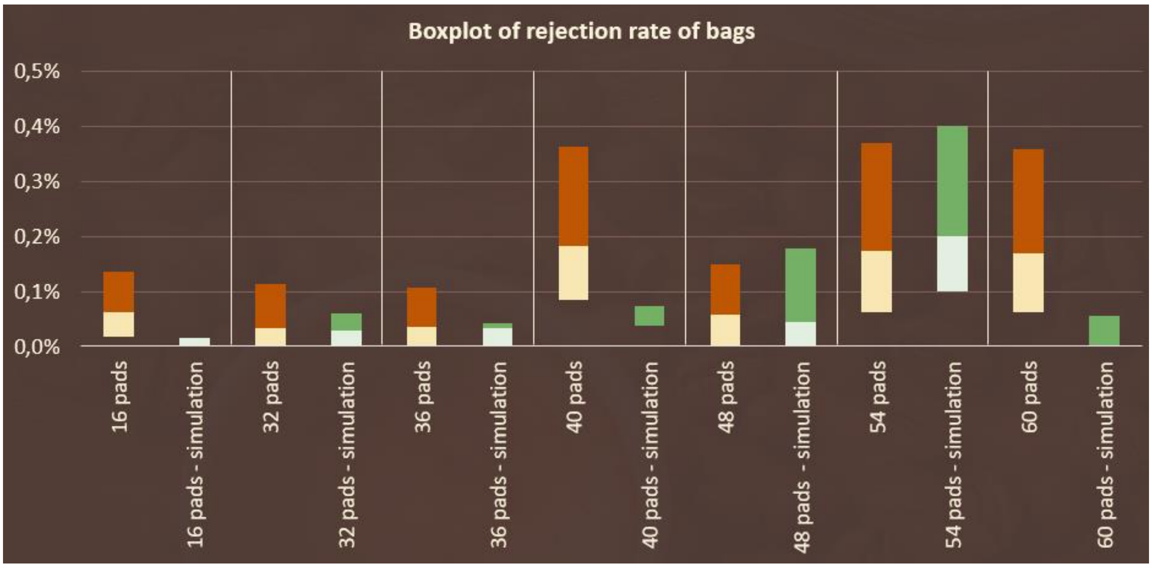

FIGURE 49: BOXPLOT OF REJECTION RATE OF BAGS PER BAG SIZE (REAL VERSUS SIMULATED DATA).

Conclusion of validation

Based on the Figure 42 to Figure 49 above, it can be concluded that the results of the simulation model does not fit the analysed real-world data perfectly. There are several reasons to be confident that the model adequately represents reality still. First, the real data will never be fully consistent. Since the production lines are prone to disruptions (such as operator interventions) that are not accounted for in the model there will be unexpected results that are difficult to model and that cannot be solved through the simulation. Second, the model does not take differences between lines into account. The model is based on findings from Line 17, which produces bags of 48 and 54 pads; therefore, the simulated data best fits the data about 48 and 54 pads, on other bag sizes the simulated data may fit less perfectly compared to the real data. Third, the model fits the data for the bag size of 48 pads very well. This is a strong indicator that it correctly represents a plausible real-world situation.

In conclusion, the model represents reality well enough to assume that any changes in the model have a similar effect in reality, which is the bottom line criterion of a model validation.

5. EXPERIMENTS

This chapter answers the third research questions (see Chapter 1.5.3) regarding the optimisation of the production system is answered.

First, the simulated current performance of the system is analysed in Section 5.1. Then we conduct experiments to find the best possible settings in Section 5.2. The experiments are conducted in three phases, every phase consist of multiple steps. In Phase A, the rejection limits are statistically calculated. In Phase B, the parameters for the feedback loop are optimized. In Phase C, the best possible rejection limits are found, while keeping constraints in mind.

The three phases are broken down in steps, listed below:

A) **Statistical calculation of rejection limits**
   1. Determine the maximum rejection limits for bags according to EU regulations
   2. Calculate the rejection limits for bags based statistically based on assumed numbers
   3. Determine the rejection limits for product carriers

B) **Determine the best feedback loop parameter combination**
   4. Run design of experiments with wide ranges
   5. Run design of experiments with marginal parameter changes until the best possible values have been found

C) **Identify the best possible rejection limits**
   6. Run design of experiments around rejection limits found in Phase A.

These parameter settings to be optimized are:
For the feedback loop:

- Sample size
- Tolerance
- Adjustment factor (or steering factor)
- Delay

For the rejection limits:

- Lower and upper rejection limits for the product carriers
- Lower and upper rejection limits for the bags

Note that in this chapter, the optimization for a bag with 48 pads is described for both rejection limits as parameters for the feedback loop. The experiments involve the process of packaging a bag with 48 pads, with two product carriers of 24 pads each. Best possible settings for other bag sizes are derived from the results for this bag with 48 pads. The bag size of 48 pads is chosen because i) the simulation is based on Line 17, which produces mainly bags with 48 pads, ii) a bag of 48 pads needs product carriers of 24 pads which is the largest size. Therefore the relation between product carrier weight and bag weight is maximum. iii) The validation is most reliable for a bag size of 48 pads.

When the best possible settings are found for a bag size of 48 pads, these settings are used as starting point for the design of experiments for a larger and smaller bag size. This continues, i.e. the best found settings for the bag size of 36 pads are the starting point of experiments for one bag size smaller which is 32 pads, et cetera.

5.1 CURRENT PERFORMANCE PER BAG SIZE

To effectively compare the results of the simulation model, first the current performance of the model is determined (see Table 15). This is done for all bag sizes, with the initial settings as they were before this research was conducted. In this table, there are three indicators,

i) the Coffee in rework costs rate (i.e. rework caused by rejected bags and product carriers)
ii) the overfill (i.e. the amount of extra coffee in a bag compared to the target weight)
iii) the probabilities that a bag is accepted with a missing or an extra pad in it.

For this research, the costs of rework are most important, the probabilities of accepting a bag with a missing pad is a constraint. The overfill and the probability of accepting a bag with an extra pad are inherently improved by the other constraints and therefore not used as objectives in the experiments.

The results in Table 15 are later compared to the ones obtained after optimising the parameter settings at the end of this chapter.

These parameter settings to be optimized are:

For the feedback loop:

- Sample size
- Tolerance
- Adjustment factor (or steering factor)
- Delay

For the rejection limits:

- Lower and upper rejection limits for the product carriers
- Lower and upper rejection limits for the bags

TABLE 15: SIMULATED PERFORMANCE PER BAG SIZE USING THE INITIAL PARAMETER SETTINGS.

Bag size	**Coffee in rework costs rate** (milligrams coffee per pad)	**Total overfilling** (grams)	**Rate of accepted bags with missing pad**	**Rate of accepted bags with extra pad**
16	134	-21,150		
18	35	18,354		
32	16	-29,271		
36	42	11,660		
40	69	55,511		
48	**140**	**65,925**		
54	124	14,683		
60	58	56,677		
72	114	56,767		

5.2 EXPERIMENTS

In this section, the experiments are conducted. There are three phases in which six steps are identified. The results of the experiments in these steps are explained in this section.

Phase A: Identifying the rejection limits based on a statistical analysis

In this step, the lower rejection limits (upper rejection limit is not relevant in European law) were first calculated based on the European laws on e-marks (related to the weight indicated on the product packaging). The rejection limits should at least fall within these limits. Then, the appropriate rejection limits for bags were calculated based on the standard deviation of pads and given the probability of accepting a bag with a missing pad is 1% maximum. Lastly, the appropriate rejection limits for product carriers are determined.

Step 1: Rejection limits based on European law
The numbers in Table 16 show the lower limits of the target weight based on the E-mark norms. In the end, the rejection limits should not be larger than these limits. In other words, the e-mark limits are lower bounds for the rejection limits in Step 2.

TABLE 16: E-MARK LIMITS PER BAG SIZE.

Bag size	Value on bag (grams)	E-mark norm (max. allowed weight off target weight)	E-mark limit (min. allowed absolute weight)	E-mark limit compared to target weight
16	111	4.5%	106.1	-5.9
18	125	4.5%	119.4	-6.6
32	222	9 grams	213.0	-11.0
36	250	9 grams	241.0	-11.0
40	277	9 grams	268.0	-12.0
48	333	3%	323.1	-12.9
54	375	3%	363.8	-14.2
60	416	3%	403.6	-16.4

Step 2: Statistically calculated limits for bags
In this step, the rejection limits for bags are calculated with a fixed mean and standard deviation per pad, assuming that all the pads are identical, independent and normally distributed. So no simulation was used in this step.

The trade-off here is to make the limits as high as possible to prevent rejections, while on the other hand prevent accepting a bag with a missing pad. To calculate the rejections rates, a mean pad weight of 7.183 grams including the filter paper is used, a pad mean of 7.00 grams excluding the filter paper and a standard deviation of 0.1401 grams (see Section 4.2). Together with the production engineer and quality specialist of JDE, it is determined that the probability of accepting a bag with a missing pad may be 1% at maximum. Based on the expected standard deviation per bag size (i.e. the standard deviation of the sum of individually distributed elements, determined by Equation 1.

EQUATION 1: STANDARD DEVIATION OF THE SUM OF NORMALLY DISTRIBUTED ELEMENTS

$$\sqrt{\sigma_a^2 + \sigma_b^2}$$

With these assumptions, the best possible rejection limits for bags are as follows (see Table 17). Note that all limits fall within the e-mark limits in Step 1.

TABLE 17: BEST POSSIBLE REJECTION LIMITS FOR BAGS (STATISTICALLY DETERMINED).

Bag size	Lower limit	Lower limit below the target weight (in grams)	Expected rejection rate (lower bound)	Probability of accepting a bag with missing pad
16	106.3	5.7	0.0000%	0.84%
18	120.4	5.6	0.0000%	0.78%
32	218.9	5.1	0.0000%	0.75%
36	247.0	5.0	0.0000%	0.80%
40	275.1	4.9	0.0000%	0.83%
48	331.3	4.7	0.0001%	0.84%
54	373.4	4.6	0.0004%	0.94%
60	415.6	4.4	0.0026%	0.80%
72	499.8	4.2	0.0211%	0.90%

It is clear that the statistically calculated rejection limits fall within the range of the maximum allowed limits according to EU regulations (E-mark limit). Figure 50 graphically shows this.

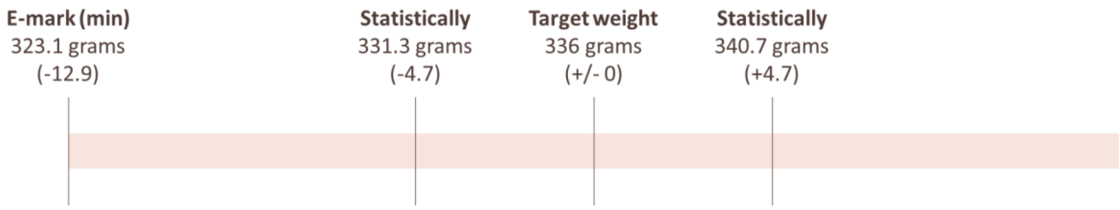

FIGURE 50: E-MARK LIMITS AND STATISTICALLY CALCULATED REJECTION LIMTS FOR BAGS FROM THE NORM VALUE (FOR BAG OF 48 PADS).

Step 3: Product carrier rejection limits

For product carriers, a trade-off between accepting a product carrier with a missing pad and the rejection rate is not so relevant. Since the bag that ends up with an extra or missing pad is probably rejected later on. Therefore, the rejection limits for product carriers may be as wide as we would like. Though, it should be taken into account that wide limits can result in greater fluctuations in bag weight; this point is considered further in the experiments when looking for the best possible rejection limits.

Since we will optimize the rejection limits for product carriers later on, they are set to +/- 3.5 grams of the target weight. Then, both the probability of rejecting a product carrier and the probability of accepting a product carrier with a missing pad are close to 0.0% (see Table 18).

TABLE 18: BEST POSSIBLE ESTIMATED REJECTION LIMITS FOR PRODUCT CARRIERS.

PC size	Lower limit	Lower limit off mean	Expected rejection rate lower bound	Probability of accepting a PC with missing pad
16	111.4	3.5	0.000000%	0.000000%
18	125.8	3.5	0.000000%	0.000000%
20	140.2	3.5	0.000001%	0.000001%
24	168.9	3.5	0.000018%	0.000018%

Phase B: Design of experiments to identify the best possible parameter settings

In this phase, we ran several design of experiments (DOE) to find the best possible parameter settings. First, a broad range is used to identify the most promising range of values. Minimal incremental changes are then used in subsequent DOEs to find the best possible settings.

Preliminary notes

At the beginning of this phase, the individual parameter settings were optimised while keeping the other parameters unchanged. Since this yielded worse results due to interaction between the parameters, the optimisation strategy was adapted to running DOEs. The results of optimising individual parameter settings can be found in Appendix E: One-by-one parameter optimisation. While running these experiments, it became clear that a delay of 12 product carriers was best possible. In order to save simulation time, we fixed this parameter in the remainder of the experiments.

Note that the experiments explained in this section are related to selecting the best possible parameters settings for a bag with 48 pads. The experiments for the other bag sizes are included in Appendix G: Results of experiments per bag size.

Explanation of the DOEs

We ran four DOEs, they are analysed in the remainder of this section and explained as follows.

- First, a short introduction of the DOE is given.
- Second, the DOE table with settings per parameter is shown.
- Third, a list with all the experiments resulting from the table in Step 2 is shown, with the corresponding results of each experiment.
- Fourth, the results are analysed by listing the observations made from the main effect plot and the interaction plot from the DOE.

The different parameters are repeated below, for a better understanding:
Sample size: the number of product carriers that is used to calculate the average weight of product carriers.

Tolerances: the maximum allowed discrepancy between the target weight and the average weight of product carriers. If the average weight exceeds the target weight by more than the tolerance, the feedback loop is activated.

Adjustment factor: the weight is corrected by the discrepancy between the target weight and the average weight of product carriers, multiplied by the adjustment factor.

Step 4: Run design of experiments with wide ranges

In this step, we run a DOE to determine what range of parameter settings seems most promising.

First round of DOE, with wide ranges

In this DOE, the sample size, tolerances and steering factors were changed with the high, medium and low settings, based on the bisection method (Wu, 2005). For the bisection method, three data points per parameter setting were defined to start with (low, medium and high). The low and high values are at least two increments away from the medium value. While Wu (2005) uses a numerical approach to determine the starting values, we indicate the plausible values by considering the status quo. Based on logical reasoning, the parameter settings were used, listed below in Table 19.

TABLE 19: PARAMETER SETTINGS FOR THE FIRST DOE.

	Parameters		
Level	**Sample size**	**Tolerance**	**Adjustment factor**
Low	3	0.2	0.5
Medium	6	0.5	0.8
High	12	0.8	1.2

The experiments following from the DOE mentioned above results in the performance on the 'Coffee in rework costs rate'. In this and upcoming DOEs, we will analyse the DOE by looking at i) the main effects plot and ii) the interaction plot between the settings of the parameters we are considering. The main effects plot can be seen in Figure 51, the interaction plot in Figure 52.

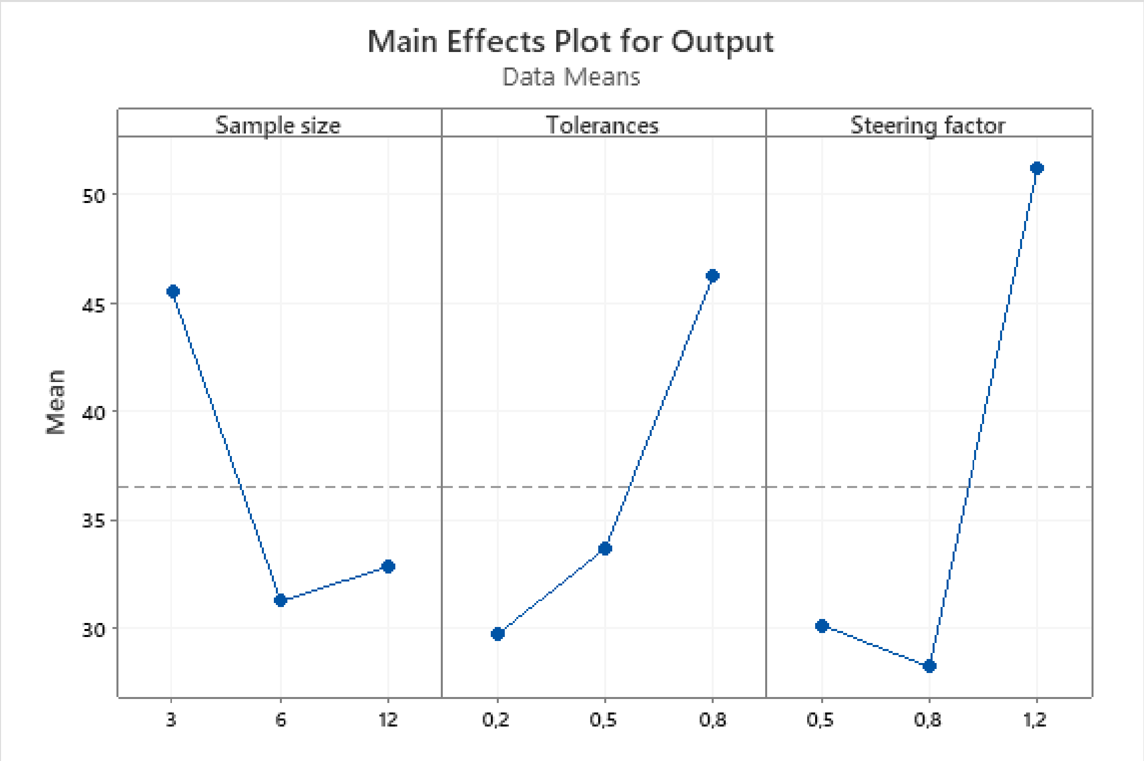

FIGURE 51: MAIN EFFECTS PLOT PER PARAMETER ON COFFEE IN REWORK COSTS RATE

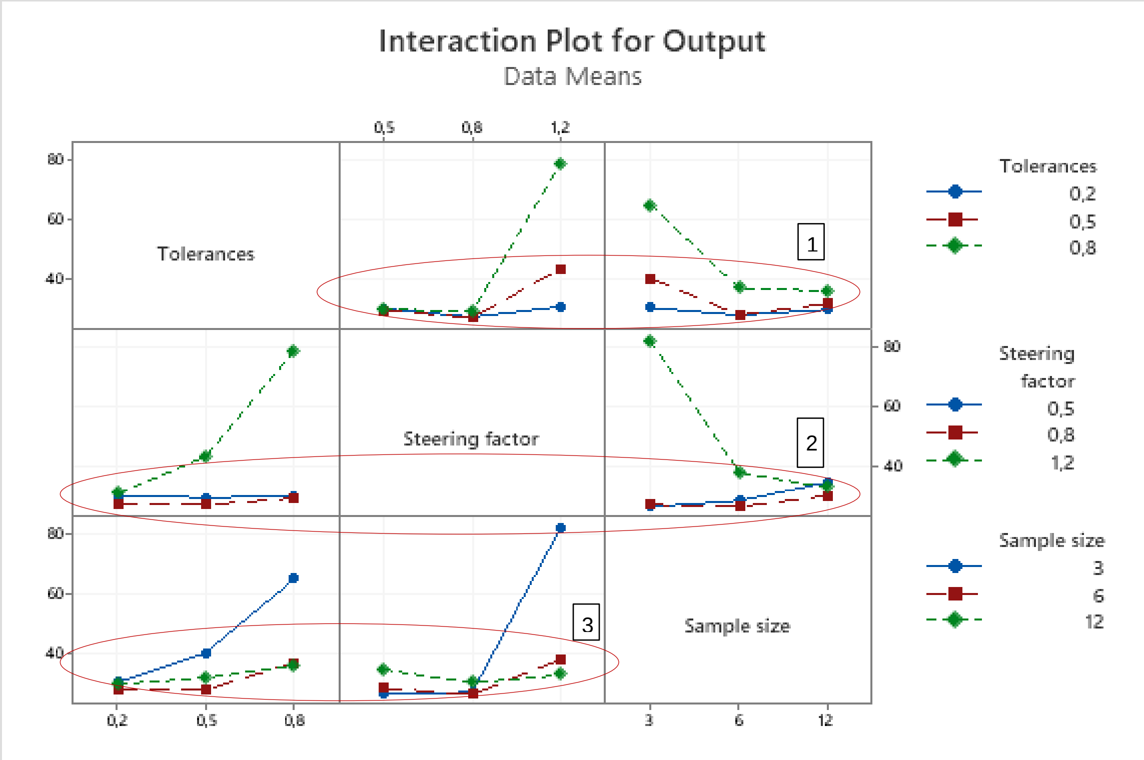

FIGURE 52: MAIN INTERACTION PLOT FOR PARAMETER SETTINGS ON COFFEE IN REWORK COSTS RATE.

Based on these plots, we can conclude that the best possible values lay most close to a sample size of 6 product carriers (see point 3 in Figure 52), a tolerance of 0.2 grams (see point 1 in Figure 52) and an adjustment factor of 0.8 grams (see point 2 in Figure 52).

Note that further main effects plot, interaction plots and tables with the experiments of this chapter are listed in Appendix F: Detailed figures regarding experiments

Step 5: Run design of experiments with marginal parameter changes
In this step, we ran multiple DOEs where parameters are marginally changed close to the indication of the best settings of the previous step.

Second round of DOE, with marginal ranges
Based on the DOE of the previous round, a DOE was defined as listed below in Table 20. So, the experiments are designed around a sample size of 6, around a tolerance of 0.2 and an adjustment factor around 0.8, these values follow from the first DOE.

TABLE 20: DOE SETTINGS PER PARAMETER FOR THE SECOND ROUND OF DOE.

	Parameters		
Level	**Sample size**	**Tolerance**	**Adjustment factor**
Low	5	0.1	0.7
Mid	6	0.2	0.8
High	7	0.3	0.9

Based on the results of the experiments of this second DOE, that were analysed using a main effects and interaction plot, the following parameter settings were selected for determining their potential, in the next DOE:

- A sample size of 5, 6 and 7 product carriers;
- A tolerance of 0.1 and 0.3 grams;
- An adjustment factor of 0.8 and 0.9 grams.

Third round of DOE, with marginal ranges
Based on the DOEs of the second round, another DOE is formulated as listed below in Table 21. The sample size varies around 6 product carriers again, the tolerance changes between 0.1 and 0.3 grams and the adjustment factor varies between 0.8 and 0.9 grams.

TABLE 21: SETTINGS PER PARAMETER FOR THE THIRD ROUND OF DOES.

	Parameters		
Level	**Sample size**	**Tolerance**	**Adjustment factor**
Low	5	0.1	
Medium	6		0.8
High	7	0.3	0.9

Based on the results of the experiments of this third DOE, that were analysed using a main effects and interaction plot, the following parameter settings were selected for determining their potential, in the next DOE:

- A sample size of 4 and 5 product carriers;
- A tolerance of 0.1 and 0.2 grams;
- An adjustment factor of 0.9 and 1.0 grams.

Fourth round of DOE, with marginal ranges
Based on the DOEs of the third round, we devised the fourth DOE as listed below in Table 22. The sample size varies at 4 and 5 product carriers, the tolerance on 0.1 and 0.2 grams and the adjustment factor on 0.9 and 1.0 grams.

TABLE 22: DOE SETTINGS PER PARAMETER FOR THE FOURTH ROUND OF DOE.

	Parameters		
Level	**Sample size**	**Tolerance**	**Adjustment factor**
Low	4	0.1	0.9
Medium	5	0.2	1.0

This DOE results in four experiments, these experiments with their outcome are listed in Table 23. As can be seen from this table, the best possible settings are:

- A sample size of 5 product carriers;
- A tolerance of 0.1 grams;
- An adjustment factor of 0.9 grams.

These settings results in a ‘Coffee in rework costs rate’ of 23.29 milligram per pad. These settings are used in the next phase, where the rejection limits are set to the best possible values within the constraints given.

TABLE 23: LIST OF EXPERIMENTS IN THE FOURTH DOE; (WITH HIGH, MEDIUM AND LOW PARAMETER SETTINGS).

Experiment	Sample size	Tolerance	Adjustment factor	Coffee in rework costs rate
1	4	0.1	0.9	23.37
2	4	0.2	1.0	24.11
3	**5**	**0.1**	**0.9**	**23.29**
4	5	0.2	1.0	24.35

Phase C: Design of experiments around the best possible rejection limits

In this phase, the rejection limits were optimised, to ensure that the probability of accepting a bag with a missing pad (also known as the 'missing pad rate') is no greater than 1.0% and secondarily that the 'Coffee in rework costs rate' is minimised.
In these experiments, the best possible parameter settings from Phase B are used. As a starting point, the calculated theoretical rejection limits were used. The rejection limits for product carriers and bags were varied in two DOEs.
With the parameter settings found in Phase B, no product carriers with a missing pad were accepted, and 2.49% of the bags with a missing pad were accepted. Since the internal norm is set to 1% (by JDE), the rejection limits should be widened.
Step 6: Run design of experiments around rejection limits found in Phase A
In this step, the rejection rates for product carriers and bags are varied while the parameters for the feedback loop remain constant. This step is finished when we found settings where the probability of accepting a bag with a missing pad is less than 1%.
First round of DOE, for rejection limit optimisation
In the first round of experiments, the ideal range of settings was identified. Therefore, tight, wide and plausible limits were used, to find out which limits made most sense. Table 24 presents the DOE, and Table 33 displays all the resulting experiments from the DOE; note that the experiments that are deemed sufficient are marked grey in Table 33.

TABLE 24: SETTINGS FOR THE INDICATION OF THE REJECTION LIMITS.

DOE	**Rejection limit PC** (+/- grams from nominal weight)	**Rejection limit bag** (+/- grams from nominal weight)
1	3.3	4.3
2	3.5	4.5
3	3.7	4.7

Based on the results of the experiments of the first DOE on rejection limits, the following rejection limits were selected for the next DOE, mostly driven by decreasing the probability that a bag with a missing pad is rejected:

- Product carrier rejection limits of 3.3 and 3.4 grams;
- Bag rejection limits of 4.4 and 4.5 grams.

Second round of DOE, for rejection limit optimisation
Based on the outcomes of the previous DOE, the DOE shown in Table 25 was devised. The experiments were designed with the rejection limits for the product carriers of 3.3 and 3.4 grams and the rejection limits for the bags of 4.4 and 4.5 grams.

TABLE 25: SETTINGS FOR OBTAINING THE BEST POSSIBLE REJECTION LIMITS.

DOE	**Rejection limit PC** (+/- grams from nominal weight)	**Rejection limit bag** (+/- grams from nominal weight)
1	3.3	4.4
2	3.4	4.5

This DOE results in four experiments, these experiments with their outcome are listed in Table 26. As can be seen, there is one option, for the first time, where the probability of accepting a bag with a missing pad is below 1%. Then, as can be seen from this table, the best possible rejection limits are:

- 3.3 grams for product carriers;
- 4.4 grams for bags.

These rejection limits result in a 'Coffee rework costs rate' of 26.34 milligram per pad and a missing pad rate of 0.6%.

TABLE 26: EXPERIMENTS FROM SECOND DOE FOR BEST POSSIBLE REJECTION LIMITS.

Experiment	**PC**	**Bag**	**Coffee in rework costs rate**	**Missing pad rate**
1	**3.3**	**4.4**	**26.34**	**0.6%**
2	3.3	4.5	25.35	1.1%
3	3.4	4.4	25.82	1.4%
4	3.4	4.5	24.89	1.9%

Conclusion of experiments

At the end of these experiments, the overall objective 'Coffee in rework costs rate' is decreased by 81%, from 139.9 to 26.34 milligram per pad. After the Phase A in which the rejection limits were statistically calculated, the Coffee in rework costs rate decreased by 52%. Then in Phase B in which the parameter settings were improved, the Coffee in rework costs rate were decreased by 65%. Then in Phase C in which the rejection limits were set in such a way that it met the constraint of having at most 1% probability of accepting a missing pad increased by 'Coffee in rework costs rate' by 13%, because of tighter rejection limits. See Figure 53 for the Coffee in rework costs rate per phase and see Table 27 for the listed best parameter settings and rejection limits after the experiments.

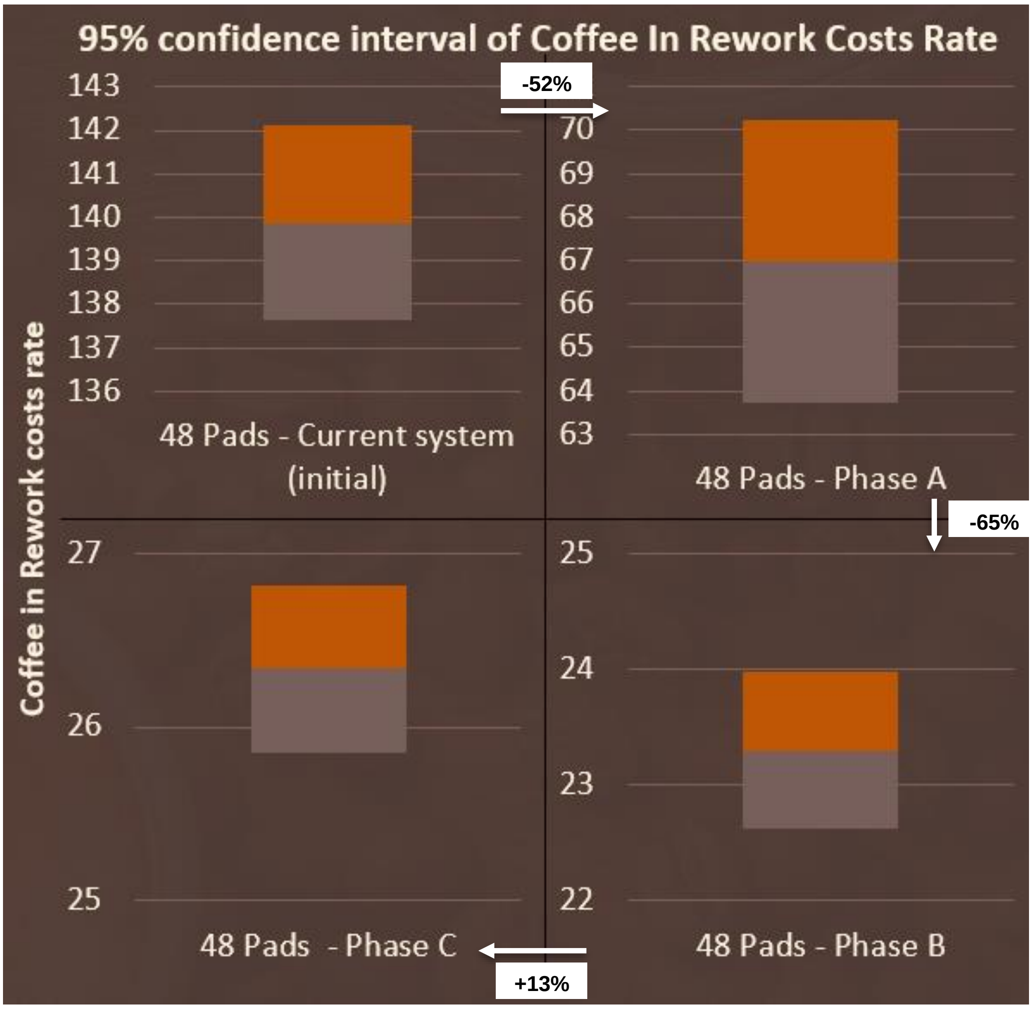

FIGURE 53: REWORK IN COSTS RATE AFTER EVERY PHASE OF EXPERIMENTS

TABLE 27: TABLE WITH BEST POSSIBLE PARAMETER SETTINGS OBTAINED AND REJECTION LIMITS FOR THE PRODUCTION OF BAGS WITH 48 PADS.

Parameter	Best possible setting
Sample size	5
Delay	12
Tolerance	0.1
Steering factor	0.9
Product carrier rejection limits	+/- 3.3 grams
Bag rejection limits	+/- 4.4 grams

5.3 SENSITIVITY ANALYSIS

In this section, the last part of the third research question is answered, see Section 1.5.3. With the sensitivity analyses the impact of variations in parameter settings, the variation of the tare, the transportation policy and the allowed probability of accepting a bag with a missing pad are analysed.

With the analysis on parameter settings, the most critically factors for the results were found. With the analysis on tare, the impact of correcting a tare regularly on the amount of rejections and the overfill (see Section 1.4.3) was analysed

Since the transportation policies could differ per line (see Section 2.1), we ran a sensitivity analysis on the other transportation policy.

Sensitivity analysis on parameter settings
When JDE wants to implement the results, it is interesting to know the impact of changing a parameter compared to the best possible settings. To give JDE an idea about what parameters have most impact on the cost of rework. Therefore, we ran experiments where one parameter was changed at a time compared to the best possible settings defined earlier.

The parameters were varied by two incremental values below and above the best possilbe found setting (sample size and steering factor). The tolerance and delay are already as low as possible, so these parameters are increased with three incremental values. This results in variations as follows:

- sample size to 3, 4, 6 and 7 product carriers;
- tolerances to 0.2, 0.3 and 0.4 grams;
- steering factor to 0.7, 0.8, 1.0 and 1.1 grams;
- delay to 13 and 14 product carriers.

The main effects of the different parameter settings are shown in Figure 54. An extensive list of experiments and their results can be found in Appendix F: Detailed figures regarding experiments.

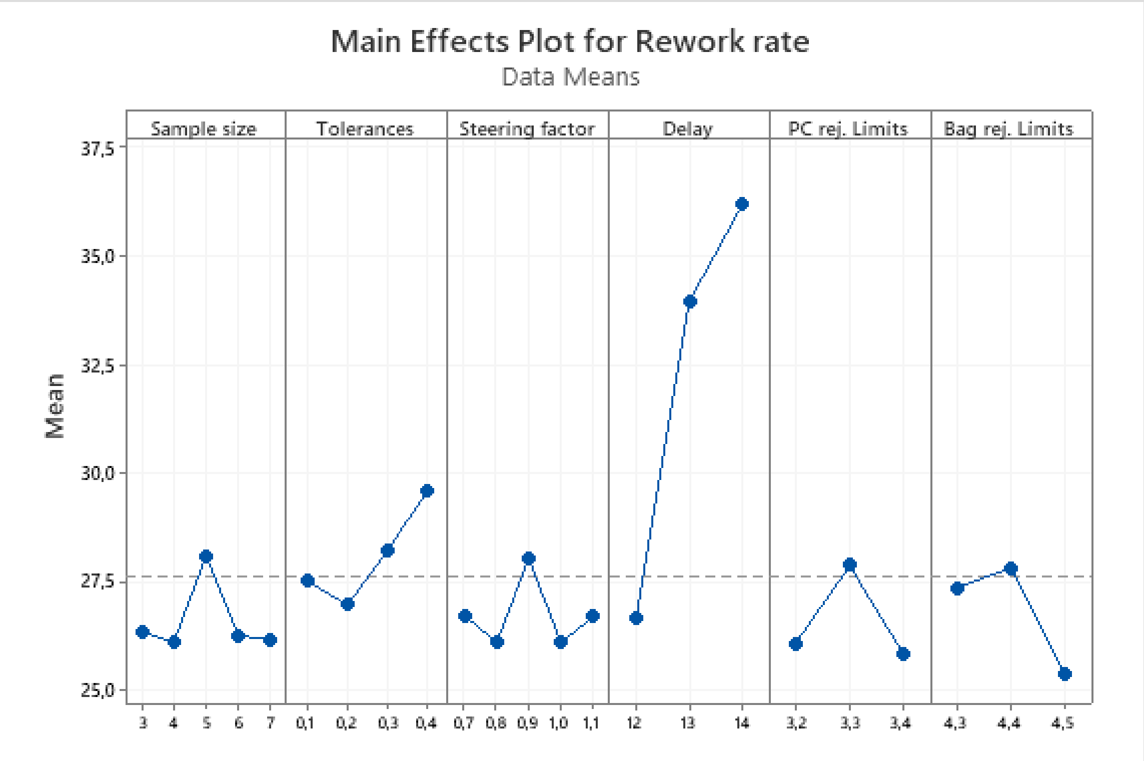

FIGURE 54: INTERACTION PLOT OF PARAMETERS WHEN CHANGING ONE FACTOR AT A TIME

Interestingly, many experiments show results that are very close to the near-best found reworking costs of 26.34, it shows that most small changes will barely affect the results. It is also interesting that with this sensitivity analysis, even better results than the found best found setting in the latter Section were found (experiments 3, 4 and 9). The impact of the settings are as follows:

- Sample size could be increased, with only a minor increase in Coffee in rework costs rate;
- Tolerances can be increased, but every increase causes and increase in Coffee in rework costs;
- Adjustment factor could be decreased, with only a minor increase in Coffee in rework costs rate;
- Delay has a very large impact on the Coffee in rework costs rate. It should be kept minimal;
- Product carrier rejection limits can easily be varied without much impact;
- Bag rejection limits have a high impact on the Coffee in rework costs rate. The best balance between wide rejection limits and the probability of accepting a bag with missing pads is up to JDE.

Sensitivity analysis on tare optimization

For this analysis, the tare (the weight of an empty product carrier) was held fully constant over the simulation run. In practice, a slight variation always exists. Though, currently the tare is checked only occasionally when a problem at the production lines occurs and the tare setting could be the problem. Checking whether the tare is correct more regularly could impact the number of rejections. Overall, a full constant and correct tare could result in a reworking costs rate decrease of 3.3% (see Figure 55). This is only a minor change, so this gives barely reason to increase the frequency of checking whether the tare is correct. However, the reduces by 72% when having a constant tare. Since overfill and underfill seems to balance out currently (see Section 1.4.3) the savings are minimal. When only looking at the overfill, which is 26.000 kg per year and the costs of coffee are €xper kilo, the savings could add up to around €x per year when the tare is corrected frequently.

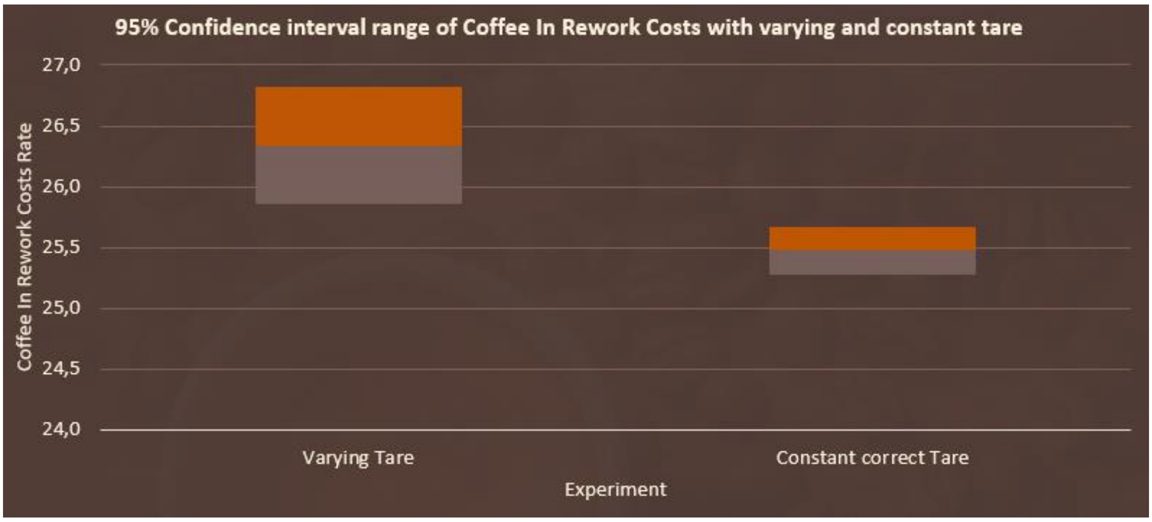

FIGURE 55: IMPACT OF TARE VARIATION ON COFFEE IN REWORK COSTS RATE.

Sensitivity analysis on transport policy

Since there are lines with a transport policy where two subsequent product carriers go to the same bag filling line, then two consecutive product carriers go to the other bag filling line, and lines where 10 subsequent product carriers go to the same line. To assess the impact of these differences, an experiment with a transport policy of two and 10 subsequent product carriers was ran. As can be seen in Figure 56, there is barely any impact noticeable. Therefore, the results are reliable for production lines with varying transport policies. For this experiment, the best possible settings found in Chapter 5.2 were used.

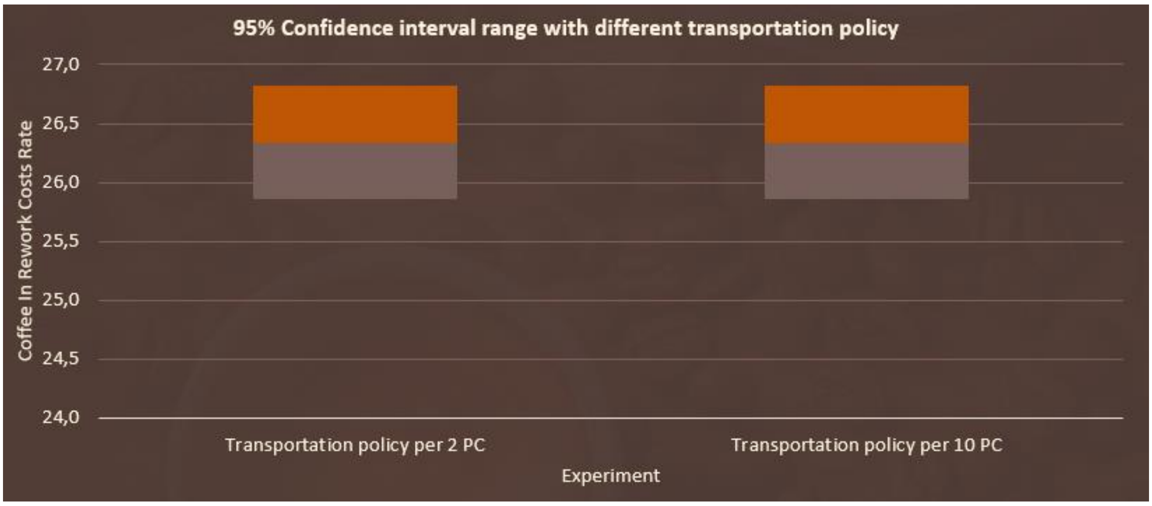

FIGURE 56: IMPACT OF CHANGED TRANSPORT POLICY ON THE REWORKING COSTS RATE.

Sensitivity analysis on acceptable probability of accepting a bag with missing pad and the rejection rate of bags

JDE could decide to accept less or more bags that accept a missing pad. Accepting less bags with missing pads results in more rejected bags. When increasing the rejection limits, the rejection rate drops exponentially and the probability of accepting a bag with a missing pad increases exponentially, as can be seen in Figure 57.

For example, increasing the rejection limit from 4.5 to 5 increases the probability of accepting a bag with a missing pad with 413% and it decreases the rejection rate with 27%. Given the costs of rejecting (see Section 1.4.3), a decrease in rejection rate from 0.11% to 0.08% results in approximately results in a yearly cost saving of €x (given the weight rejections are 30% of all rejections). It's up to JDE whether these cost savings way up against the increased probability of accepting a bag with a missing pad.

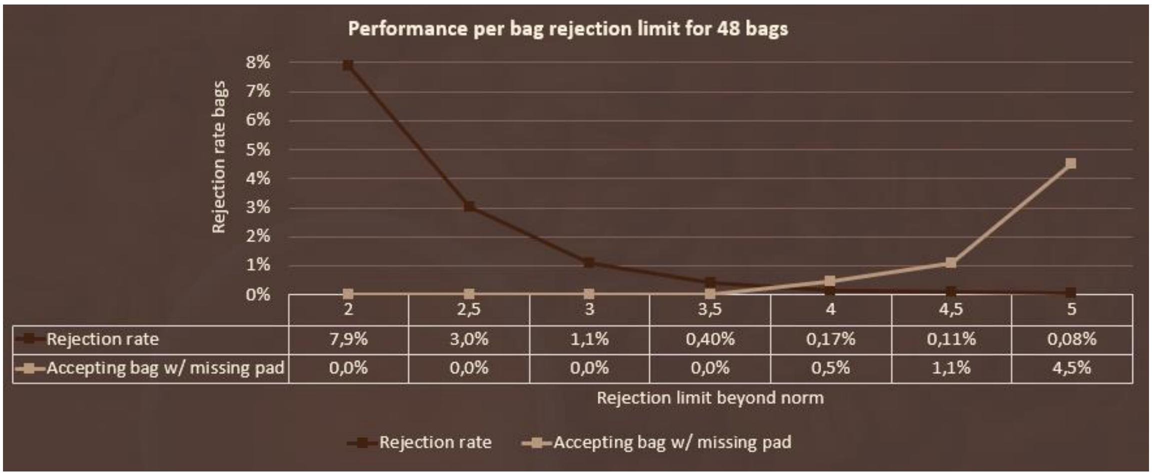

FIGURE 57: CHANGING REJECTION RATE AND PROBAILITY OF ACCEPTING A BAG WITH MISSING PAD UNDER VARYING REJECTION LIMITS

5.4 LIST OF BEST POSSIBLE SETTINGS PER BAG SIZE

To find the best possible settings for the other bag sizes, we started from the settings for one bag size larger or smaller. A DOE was executed around the best possible parameter settings of that smaller or bigger bag size, if necessary, a second round of DOE was ran. The best possible values from the second DOE are assumed to be best possible (and no further analyses were conducted with respect to time constraints). With these best possible parameter settings, a DOE is was run with rejection limits above, around, or below the theoretical limits. The combination that results in the lowest reworking costs objective and a probability of accepting a bag with a missing pad below 1% is considered the best possible set of values. Table 28 below presents the best possible settings per bag size.

TABLE 28: BEST POSSIBLE SETTINGS PER BAG SIZE.

	Sample size	**Delay**	**Tolerance**	**Adjustment factor**	**PC rej. limits (+/- grams)**	**Bag rej. limits (+/- grams)**
16	6	12	0.1	0.7	3.4	4.9
18	4	12	0.1	0.7	3.4	4.9
32	3	12	0.1	0.7	3.4	4.9
36	5	12	0.1	0.7	3.4	4.6
40	5	12	0.1	0.8	3.3	4.5
48	5	12	0.1	0.8	3.3	4.4
54	5	12	0.1	0.7	3.4	4.2
60	5	12	0.1	0.8	3.6	3.9
72	5	12	0.1	0.9	3.6	3.9

In general, the sample size is decreased to 3 to 6 product carriers, which means that 3 to 6 product carriers make up for the inaccuracy of the weighing cell and the stochasticity in product carrier weight. It is unexpected that the sample size for a bag of 16 pads is larger than the others, although the difference when slightly changing the sample size is minor The delay is set as low as possible, which is plausible because of the assumed speed of adjusting the weight. The tolerance is set as low as possible too, that seems logical because the trend in the simulation model is quite constant and the weight adjusting is assumed correct. Then it is expected that a quick steering is preferred. The adjustment factor is 0.7 to 0.9, which is expected. Since there is a trend in the model, the weight could decrease without the adjustment, therefore it is expected that the adjustment factor is slightly below 1.0. The rejection limits for product carriers increased when the product carriers increased as well, since it slightly decreased the amount of rejections. The bag rejection rates become smaller when the bag size increases. That is as expected since the standard deviation of larger bag sizes is higher too. Therefore, the probability of accepting a bag with a missing pad increases too when the rejection limits are not changed.

The rejection rates for product carrier are decreases for all bag sizes, as shown in Figure 58. The weighted average decrease is 62%, based on the share of product carriers filled per bag size compared to all product carriers filled. Detailed results of the performance per bag size is shown in Appendix H: list of results in the initial and best possible situation per bag size.

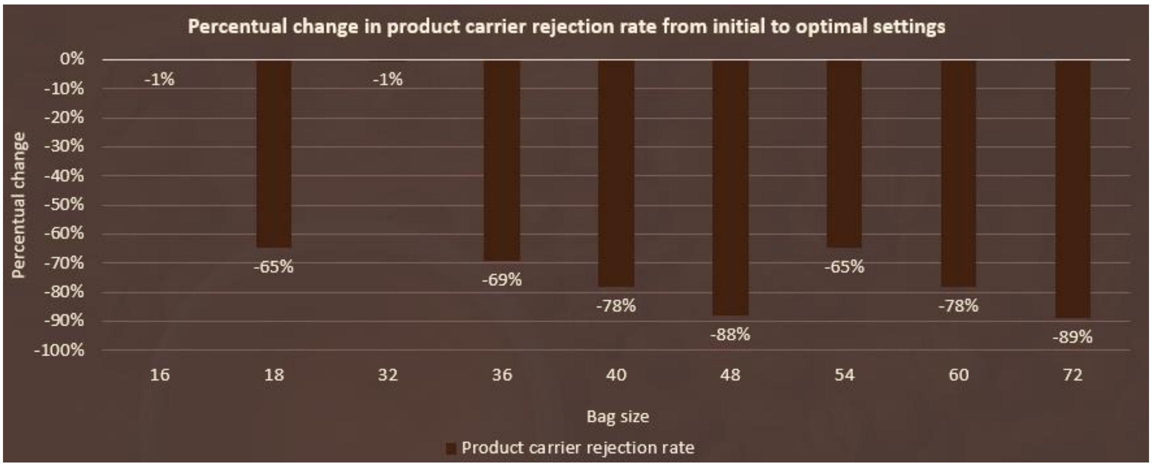

FIGURE 58: PERCENTUAL CHANGE IN PRODUCT CARRIER REJECTION RATE FROM INITIAL TO BEST POSSIBLE FOUND PERFORMANCE

The rejection rate for bags are sometimes decreased and sometimes increased, see Figure 59. Especially for bag sizes of 60 and 72 pads, the increase is substantial. This is caused by the fact that the initial rejection limits were very wide. The weighted average increase is 192%, based on the share of a bag size compared to all bags made in 2019.

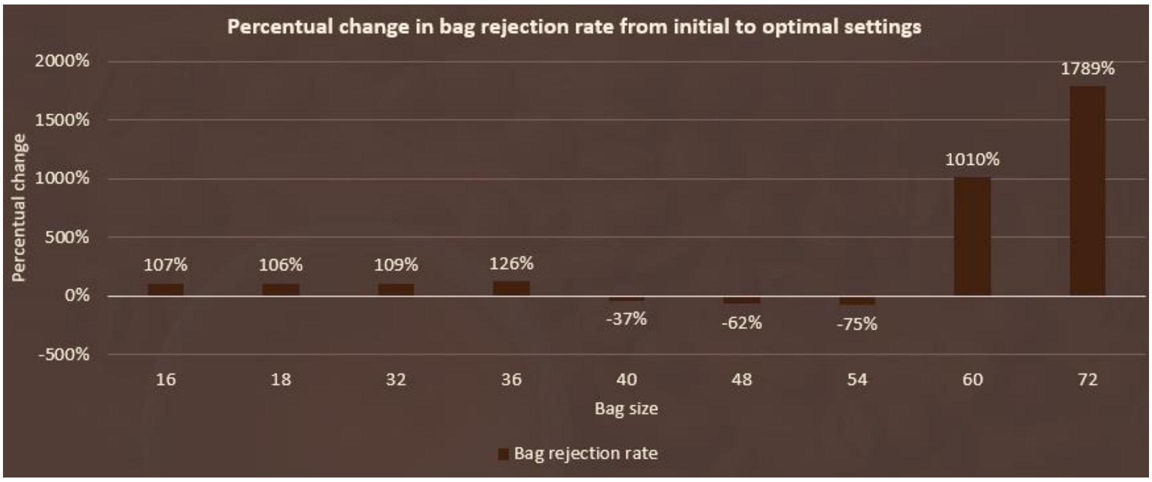

FIGURE 59: PERCENTUAL CHANGE IN BAG REJECTION REATE FROM INITIAL TO BEST POSSIBLE FOUND PERFORMANCE

5.5 CONTROLLING THE DETERIORATION OF THE PRODUCTION PROCESS

This section the fourth and final research question was answered, regarding the continuous control of the system to prevent unnoticed flaws during production.

Within this process, two events; were aimed to be prevented; rejections and systematic overfills. Rejections apply to both product carriers and bags. Systematic overfills apply to the hourly average of the final product, which should be exactly equal to the target weight. In this section, the possible role of Statistical Process Control to contribute to the mentioned objectives (see Section 1.5) by defining them as Key performance indicators (KPIs) is discussed.

Statistical Process Control (SPC) was introduced by Walter Shewhart in 1924. Shewhart used simple control charts for early detection of process variation. SPC helps to detect special cause variation, considering the variation that cannot be explained by common causes alone. In other words, the system is working beyond the limits.

Types of control charts

According to Theisens (2015), there are seven common types of control charts (see Figure 60). The most suitable chart to apply on our process depends on the type of data to analyse or control. Roughly, there are three charts that are suitable for continuous data and four charts suitable for attributive data.

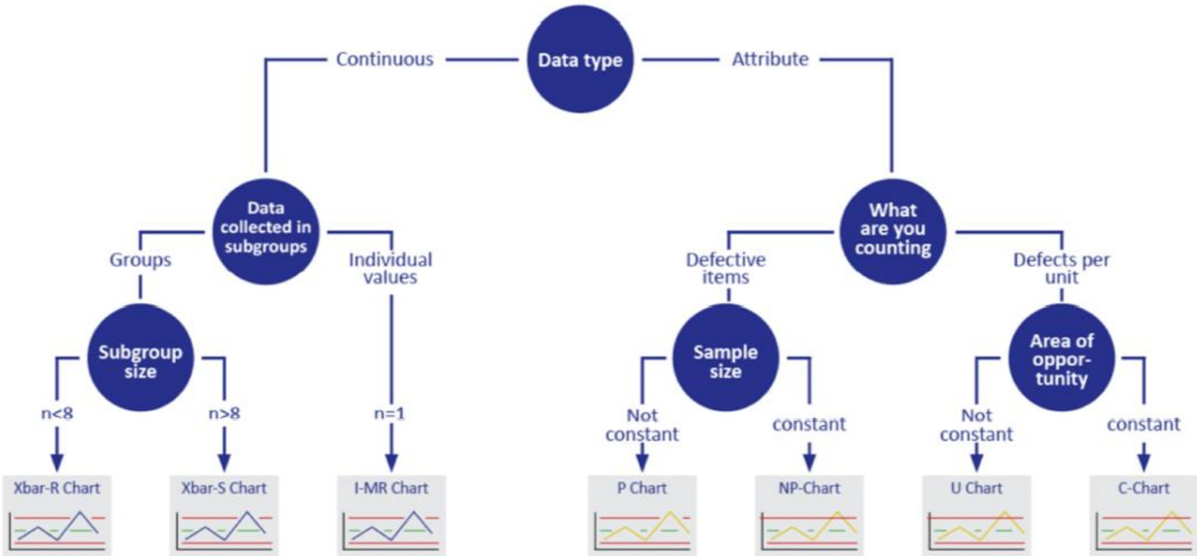

FIGURE 60: TYPES OF CONTROL CHARTS (THEISENS, 2015).

Control chart for Key performance indicators

The two Key Performance Indicators (KPI) that can and need to be tracked are i) the rejection rates of the product carriers and bags and ii) the hourly average weight of the bags. With the first KPI, JDE can track when the system is deteriorating and therefore performing worse than usual. Detecting issues fast can prevent rejections to occur. With the second KPI, JDE can track whether the tare is set accurately (the tare is the average weight of product carriers, which is subtracted while weighing the full product carriers). When a more accurate tare is set, the overfill can be decreased saving coffee and the coffee in rework costs rate could potentially be decreased by 3.3% (see section 0).

KPI to control rejection rates

The first KPI, rejection rates, is based on attributive data. Rejected items are counted and based on the total production within a time interval, the rejection rate is calculated. Since the total production (so sample size) varies every hour, a P-Chart would be suitable to use (see Figure 60 for the logic flow). The control limits in a P-chart vary according to the sample size. The lower and upper control limits are calculated by the formulas below. The rejection rate p represents the average rejection rate over a period of time, this period can be longer time and is an indication of the common rejection rate.

EQUATION 2: FORMULA FOR CALCULATING THE LOWER CONTROL LIMIT.

$$LCL_i = p - 3 * \sqrt{\frac{p(1-p)}{n_i}}$$

EQUATION 3: FORMULA FOR CALCULATING THE UPPER CONTROL LIMIT.

$$UCL_i = p + 3 * \sqrt{\frac{p(1-p)}{n_i}}$$

EQUATION 4: FORMULA FOR CALCULATING THE REJECTION RATE.

$$p = rejection\ rate = \frac{number\ of\ rejected\ items}{number\ of\ items\ made}$$
$$n_i = number\ of\ items\ made\ in\ time\ interval\ i$$

KPI to control overfill

The second KPI, hourly overfill, is based on continuous data. Every hour, one data point is added. Although these are actually based on many measurements, the data is available in hourly averages, every data point in a control chart is based on one hourly average and so one observation (n=1). Since there is always a natural fluctuation in individual weight, averages are suitable to track the performance. Therefore, an I-MR chart (Individual / Moving-Average chart) is suitable to track the performance on overfill. The control limits are normally based on rejection limits, though since observations are averages, JDE should define control limits based on for them acceptable variation.

Implementation

It would be ideal that every production line has the same control limits. Though, since the performances can vary per production line, it could be wise to use suitable limits per line first. Then, the aim is to make sure every line performs in such a manner that the control limits can be as low as possible. Since operators can change settings on the production line and take action to bring the processes back in control, it would be beneficial to give them access to the control charts and train them to take appropriate action when key performance indicators perform beyond control limits.

Tracking the performance on the KPIs mentioned can help to solve issues causing rejections and can help to prevent overfill. Control limits should be determined and for a successful implementation, operators could be trained to use the control charts.

5.6 REDESIGN OF THE WEIGHING PROCESS

One of the major sources for stochasticity is the variety in weight of empty product carriers. In this section possible ways to reduce this variety are discussed and the impact of reducing that variety is analysed.

Ways to reduce the variety on empty product carriers

Two ways to decrease the impact of the weight variation of product carriers were identified. First, a new set of product carriers can be bought that are made of material that is less prone to variation. Second, another weighing cell can be installed in the machine, then first the empty product carrier is weighed, then the product carrier is filled, then the full product carrier is weighed. The costs of these options were not further researched, though it is plausible that the first option, replacing the product carriers will be the cheaper option and adding a weighing cell to the production line will be more costly.

Potential impact of a redesign

The potential impact of a redesign is assessed by comparing the coffee in rework costs rate under the best possible settings with product carrier weight variation with the coffee in rework costs rate under the best possible settings, but with sample sizes of 1, 2, 3, 4, 5 and 6 and no weight variation of product carriers. This implies that the option to reduce the variety on weight of product carriers is so successful that the variation is fully diminished. If this is the case, the coffee in rework costs rate is decreased by 4.4%, see Figure 61. Based on the costs of rejecting product carriers, the potential benefit is €x per year. Given there are 8450 product carriers which costs €x each, an investment of over €x is needed for new product carriers. The investment for a new weighing cell is expected to be even higher. It seems not plausible that such an investment in new product carriers or another weighing cell is worth it.

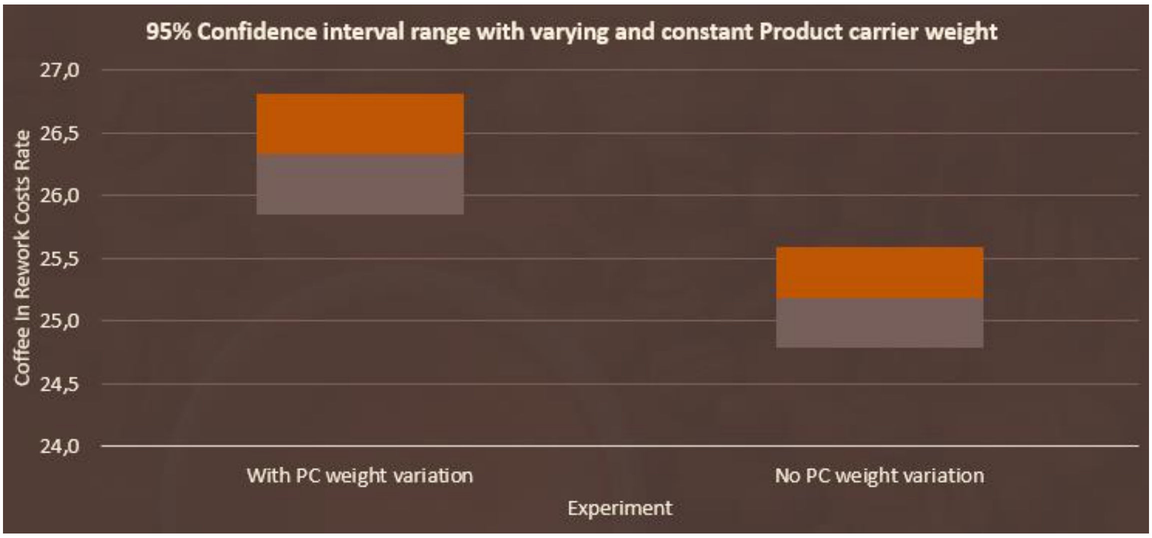

FIGURE 61: EFFECT OF HAVING NO WEIGHT VARIATION ON EMPTY PRODUCT CARRIERS.

5.7 IMPLEMENTATION PLAN

The best found parameter settings for the feedback loop, the best found rejection limits and the control charts can lead to significant less rejections. The rejection limits have most effect on the rejections, parameter settings have a lot of effect too. The effect of the control charts is more insecure. It depends on the mechanical deteriorations which are not researched, and it depends on the varying tare. A constant tare can mainly have a large effect on the underfill and overfill.

To seize the potential of the found assumptions, JDE has to implement the findings. These findings can be implemented in four phases, driven by the imperfections of the model compared to reality. The phases are as follows:

> *Phase 1:* Change the parameter settings, but use higher values than the recommended settings; consult the results of the sensitivity analysis and the assumptions described when choosing the values. Monitor the results.

Phase 2: Set the parameter settings to the recommended values gradually and monitor the effects on the system. Start with changing the parameters that have the least impact on the results as seen in the sensitivity analysis.

Phase 3: Change the rejection limits to the best possible limits obtained and monitor the rejections.

Phase 4: Implement the settings to other lines and bag sizes while monitoring the results.

Phase 5: Implement the control charts, starting at one line. Monitor results and implement at other lines too.

Every phase counters the assumptions and imperfections of the model.

In the first phase, the parameters for a bag of 48 pads are slightly changed. When slightly changing the parameters the effects will be less severe. With this slow change, especially the assumptions about the accuracy and speed of adjusting the weight and the assumption about the trend can be tested.

In the second phase, the parameters can be set close to or exactly on the recommended values. Again, in this phase the assumptions about adjusting the weight and the trend are assessed on accurateness. After this phase, the weight should be as stable as possible.

In the third phase, the rejection limits are changed. It could be the case that there are more abrupt fluctuations in reality than simulated. Then, the weight of bags vary more in reality. So when changing the rejection limits, the rejections should be monitored. If the rejection rate is too high according to the process engineer of JDE, the limits can be widened.

In the fourth and last phase, the best possible settings can be implemented to other lines and other bag sizes too. The lessons learned from the previous phases should be taken into account. Subtle differences per line (e.g. a less stable hopper level) could cause slightly other best possible parameter settings or rejection limits.

In the fifth phase, the control charts can be introduced. Since limits in the control chart can vary between lines and bag sizes, it is recommended to implement a control chart at one line first. Then, after monitoring control charts can be designed for all bag sizes and production lines.

6. CONCLUSIONS & RECOMMENDATIONS

In this chapter, the main findings of our research are summarised and the main research question is answered. The conclusion of this research is formulated, recommendations that follow from the findings and limitations of this research are formulated.

6.1 RESEARCH CONCLUSION

The current process of producing Senseo pads in the JDE production facility in Utrecht results in more rejections of product carriers (semi-batches) and bags (final products) than desired. Currently, the average rejection rate of product carriers is x% and the average rejection rate of bags is x%. To keep rejection rates as low as possible two possible actions can be taken: i) optimise the rejection limits and ii) optimise the feedback system built into the production line to keep the weight of the pads (and therefore of the product carriers and bags) as stable as possible. Both actions were analysed to answer the research question, which is formulated as follows:

"How can JDE decrease the rejection rates within the process by at least 20%?"

To answer this question, a simulation model to represent the production line was built. For the model, all notable causes of variation were identified and implemented, as well as, the logic of processes observed in reality.
To identify the best possible rejection limits and parameter settings, several design of experiments were ran, first, to optimise the parameter settings, then to optimise the rejection limits. Two objectives were taken into account to make decisions, i) the 'Coffee in reworks costs rate' which represents the average milligram of coffee that is reworked and the 'missing pad rate' which represents the probability that a bag is accepted while missing one pad.
After optimising the rejection limits for product carriers and bags, as well as the parameter settings for the feedback loop to produce a bag with 48 pads, the system performance improved compared to the initial and best possible simulated results as follows. The product carrier rejection rate decreased from x% to x% (-88%) and the bags rejection rate from x% to x% (-62%). The reworking costs rate decreased from 139.9 to 26.34 (-81%) and the probability of accepting a bag with a missing pad dropped from x% to x% (-34%). Overall, the weighted average product carrier rejection rate decreased by 62% and the weighted average bag rejection rate increased by 192%, though the weighted average total rework rate decreased by 35%.

6.2 RECOMMENDATIONS, FURTHER RESEARCH AND LIMITATIONS

Recommendations for dealing with the assumptions made in this research and how to implement the results are described below, separated in short- and mid-long term recommendations.

Recommendations

Short term

Following the optimised rejection limits and parameter settings, we recommend to implementing these findings on the factory floor on the short term. However, assumptions were made that require caution when implementing the recommendations. These assumptions may cause the following effects: i) the steering factor steers is assumed to be fully correct (i.e. the exact amount of weight adjusted). If this is not the actual case, the steering factor should probably be lower than suggested. ii) The steering is assumed to

happen with the speed of 30 pads per gram (i.e. if the machine steers 0.5 gram, it takes 15 pads) and the steering goes linear. If the actual steering takes longer, the delay should be higher than suggested. iii) A varying sine function in the model was used, while this sine function is continuous, abrupt changes in weight could occur more frequently. If the actual weight changes are more abrupt, the tolerance should probably be higher than suggested.
Besides these assumptions, the sensitivity analysis in Section 5.2 show that several parameters have a large impact, while some others have a minor impact on the reworking costs rate and the probability of accepting a bag with a missing pad. These sensitivities should be taken into account when implementing the solution.
Based on the assumptions, it is recommended to implement the new settings in phases on Line 17, since the model and data are mostly based on findings from this line and for a bag size of 48 pads. The phases are described below, in each phase it is up to the process engineer at JDE to assess when, how and whether to proceed to the next phase.

Phase 1: Change the parameter settings, but use higher values than the recommended settings; consult the results of the sensitivity analysis and the assumptions described when choosing the values. Monitor the results.
Phase 2: Set the parameter settings to the recommended values gradually and monitor the effects on the system. Start with changing the parameters that have the least impact on the results as seen in the sensitivity analysis.
Phase 3: Change the rejection limits to the best possible limits obtained and monitor the rejections.
Phase 4: Implement the settings to other lines and bag sizes while monitoring the results.
Phase 5: Implement the control charts, starting at one line. Monitor results and implement at other lines too.

Mid-long term
While this research was conducted, a production engineer at JDE also examined the mechanical details of the system. Since many rejections were caused by mechanical rather than process issues, diving further into these mechanical problems and analysing the ratio between the two types of issues can also result in substantial savings.
To prevent producing while the system is performing badly, statistical process control (SPC) charts should be made in such a way that they could be updated and used quickly. It is recommended to use these SPC charts frequently to act upon sudden changes quickly.

Further research

There are several further research options.

Seasonality in the rejection rates
There are indications that seasonality plays a role in the number of rejections that occur. It could be interesting to further research whether this is the case, what the severity is and how JDE should act upon changing external conditions.

Effect of a higher target weight
This research was focused on making sure the weight of pads was as close to 7.00 grams as possible. It could also be possible that aiming at a slightly higher weight (e.g. 7.05 grams), results in less rejections and a slight increase in overfill. This benefits of this strategy could be further researched.

Machine start-up
The weight just after a start-up cause a spike in weight for several product carriers. It could be further researched how this spike could be prevented or how the weight stabilisation system is able to detect this flaw and ignore it by not triggering the steering.

Steering based on slope of the sine trend
It seems reasonable that with a sine trend, under- or oversteering are both most accurate depending on the direction of the weight at the moment of steering. E.g., if the weight is increasing while the steering is implemented, the steering factor should probably be higher than 1, opposite, if the weight is decreasing already while the steering is implemented, the steering factor should probably be lower than 1. The possible effect of such a variable steering factor could be further researched.

Use of Statistical Process Control (SPC) Charts
The optimal usage of SPC charts should be determined, probably by trial and error. The frequency of using them depends on the fluctuations of the system, the effort required to update and control the charts and the possible benefits. I would recommend to update and use them biweekly first, then adapt the frequency based on the observations.

Limitations to the research

There are several limitations in this research, besides the assumptions made.

Local vs. Global optimum
During the experimenting to identify the best possible solution, i) the bisection method was used to narrow the range of possible solutions. One of the risks of using this methods is that we may have discarded the more extreme values in the first round of DOEs, around which the parameter settings were optimised. ii) DOEs were executed for the parameter settings first, then for the rejection limits. Iterating between optimising the parameters and the rejection limits more often could result in better results. Therefore, a risk remains that a local optimum was found, instead of a global one.

Expressing multiple objectives in Euros
In this research, the optimised objective is based on the reworking costs rate. It could be interesting to take more objectives into account and express all of them in Euros, to further optimize the parameter settings and the rejection limits. Objectives that could be considered are, among others, the amount of work for operators, the impact on the environment, the possible wear of the system when the machine steers and the overfilling.

Stochasticity in weight of filter paper
The possible stochasticity of the weight of filter paper is not directly included in the model, since there were no resources available to measure this. Though, it is indirectly included in the standard deviation of pads.

Effect of air humidity on the weight of product carriers and filter paper
The possible effect of air humidity on the weight of product carriers, the weight of filter paper and the density of the coffee were not measured because of a lack of resources. This is one of the possible explanations for the seasonal trend in rejections. This effect is ignored in this research.

6.3 CONTRIBUTION TO LITERATURE AND PRACTICE

In this section the contribution of this research to both practice as science is discussed.

First it is worth to mention that the conducted research is very specific, it is conducted in the food and beverages industry on a production line that was specifically designed for JDE. This makes it impossible to apply findings one on one to another situation. Though, there are interesting findings to deal with stochasticity, trends and disruptions in a food and beverage production line.

No literature was found so specific on how to deal with stochasticity and trends in product weight, as this research. This research provides a proof of method to use discrete-event simulation to deal with stochasticity, trends and disruptions in order to minimize the rejections on a food production line.

Companies that face similar challenges at their production lines can be inspired by this research to use a discrete-event simulation. Conducting a similar study will give them insights in the relation between stochasticity, weight disruptions and rejection limits, in order to prevent waste. When these challenges are addressed, companies should be aware that probably the rejection rates have the most influence on the rejection rates.

In general, it was found that stochasticity in the system, in this research mostly caused by variations in pad and product carrier weight, can be dealt with by measuring several consecutive products and base the performance on its average.
When having a trend like the sine function in this research, quick steering is preferred and measuring the new performance of the system after adjusting the weight should be done as quickly as possible.

In practice, for JDE, this research will contribute to having less rejections and so less rework. This will be beneficial for the amount of waste of packaging material and coffee. JDE already started the implementation of the recommendations, based on the results of this research. When all phases of the implementation are finished, the actual impact will become clear.

We hope these insights can be used in other production environments where the varying weight of a product is monitored and adjusted accordingly as well.

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APPENDIX A: SYSTEM INFLUENCES ON WEIGHT STABILIZATION

This section, aims to minimize influences of the weight by the machine itself, like an imperfect dosing drum or unstable hopper level. This should reduce the variation for which the feedback loop has to compensate. So it has the purpose to make sure instant improvements can be made, not to simulate any of these influences. With this section the first part of answering research questions 1.4 in Section 1.5 is provided.
Several characteristics or settings of the machine can also have an impact on the stability of the pad weight:

- Hopper level of the coffee supply
- Agitator speed within the hopper
- Vacuum suction of coffee into the tube
- Spindle for weight adjustment

Hopper level

The more stable the coffee level in the hopper, the more constant the pad weights. Figure 62 compares the hopper levels and averages of three consecutive product carriers. Based on the judgment of the production engineer at JDE, the hopper level is considered constant, and a direct relation between the varying hopper level and average weights is therefore not substantial. This comes with the sidenote that this applies when the production line is running, with the start-up of the machine a peak in hopper level causes weight variation that is explained in section 2.3.
In the machine, the speed of the screw that supplies the coffee is controlled by a PID controller to keep the hopper level constant. Because of this research, we changed the settings of this PID such that the hopper level becomes more constant. The PID controller previously adjusted the level of coffee to 485mm (i.e. the distance between the PID controller and the coffee), when the coffee level drops below or rises above 55% of the target level, the coffee supply speeds up or stops, respectively. This results in fluctuations in the hopper level. The target level is changed to 457.5mm (i.e. the aimed level of coffee in the hopper is higher), which results in fewer accelerations and stops of the screw and therefore a more constant coffee supply. This is a side benefit of this research for stabilizing the weights. However, this factor is excluded from the simulation model, since it is inherently included in the trend of the pad weights.

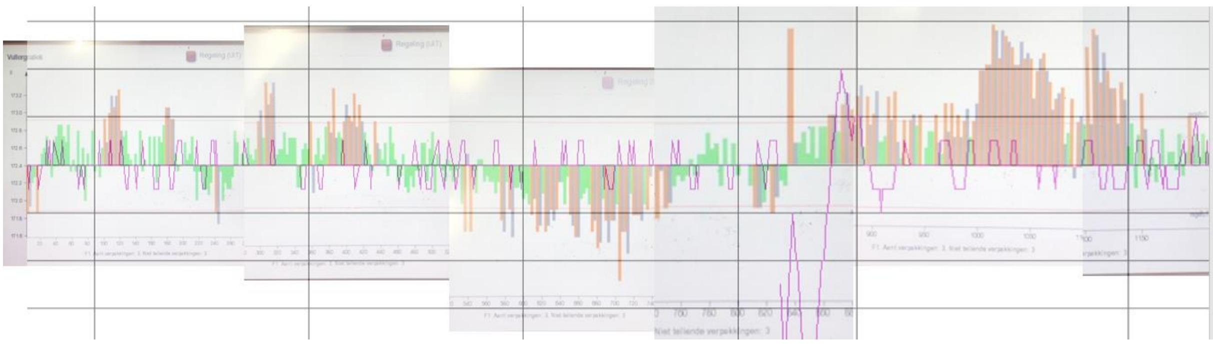


FIGURE 62: AVERAGE OF 10 (GREEN AND ORANGE) OR 25 (GREY) PRODUCT CARRIERS AND HOPPER LEVEL (LINE 17, 24-11-2020).

Agitator speed within the hopper

The agitator mixes the coffee in the hopper to prevent clumping. The rotation frequency of this agitator is set to 500 Hz at default. During tests, the speed of this agitator is varied from 100 to 500 Hz by steps of 100 Hz. Figure 63 shows that differences between frequencies have no substantial influence on the distribution of the product carrier weight. Therefore, this setting is kept constant at the default level. This factor is further excluded in this research, since it is inherently included in the pad weight distribution.

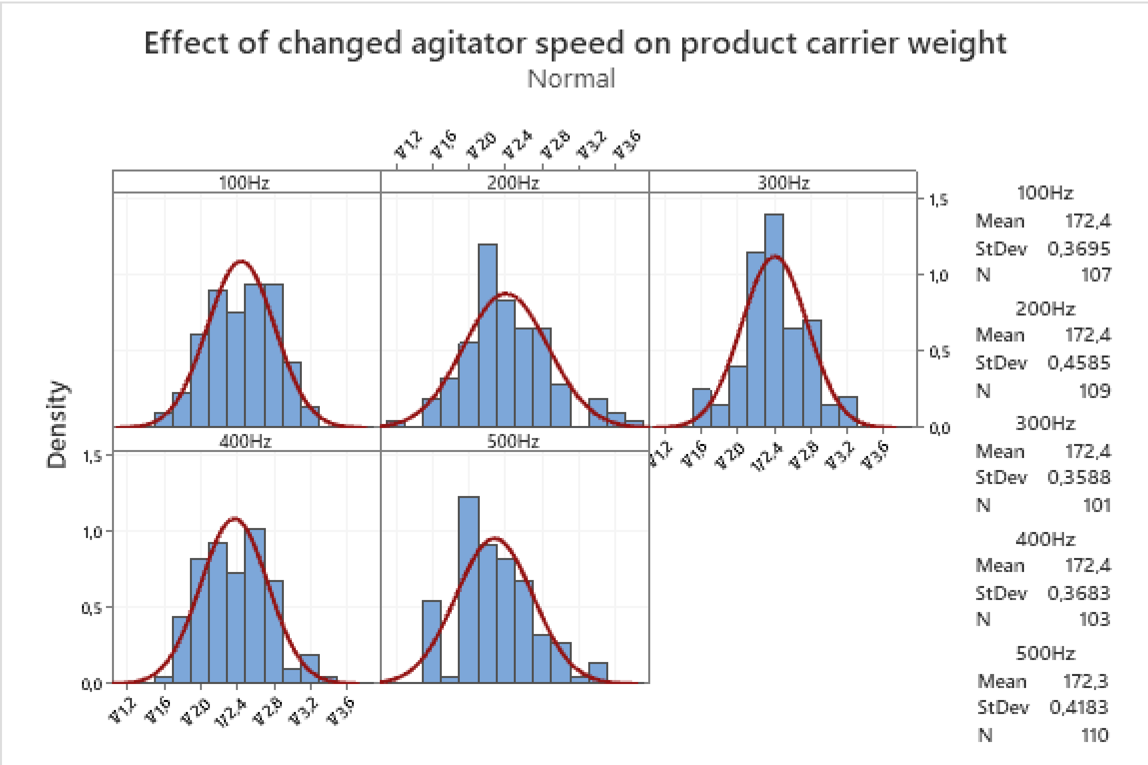


FIGURE 63: AVERAGE OF 10 OR 25 PRODUCT CARRIERS WITH VARYING AGITATOR SPEED.

Vacuum suction of coffee into the tube

The coffee is vacuum sucked from the hopper into a piston in the dosing drum. Since it is not possible to measure the vacuum power, simple tests were executed to assess the impact of changing flows. The flow of the vacuum was varied to assess the impact on the pad weight. Just before the spike in Figure 64 (left) , the flow was manually increased from the default 80 to 40 litre/minute. In Figure 64 (right), the vacuum was manually dropped from the default 80 to 120 litre/minute. The effect of this vacuum power is not researched further, nor is it modelled in the simulation study, due to three reasons. First, in both experiments, a spike in weight is detected, due to the change in vacuum power, although this spike is corrected by the model very quickly and accurately. Second, based on the expert judgement of a process engineer at JDE, we assessed that a drop or spike of 40 litre/minute is unlikely to happen. The third reason to exclude this factor from the simulation model, is that a slight variation in vacuum suction power is inherently included in the standard deviation of the pad weight as well as the trend that is described later in Section 0. As the correction is very accurate, a large drop or spike is unlikely to happen, and the variation is indirectly accounted for in the model.

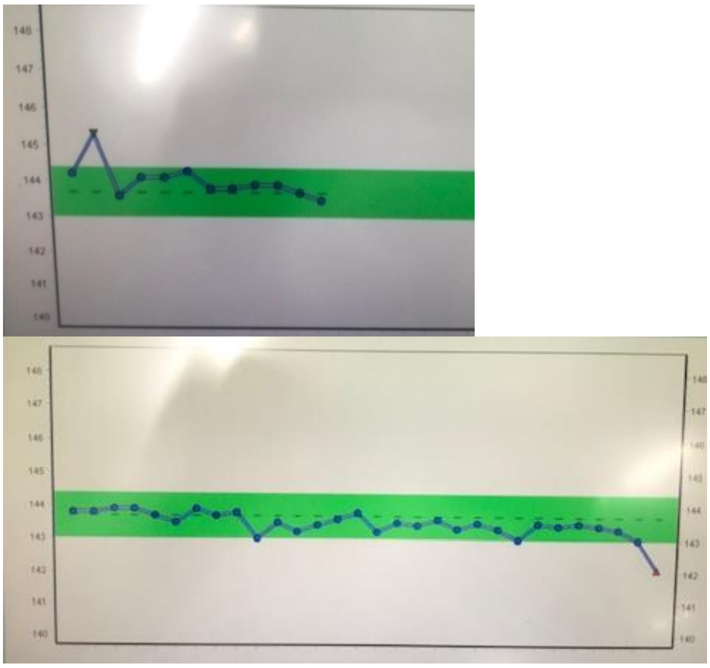


FIGURE 64: AVERAGE WEIGHT OF THE PRODUCT CARRIERS, WHICH IS INFLUENCED BY CHANGING THE VACUUM PRESSURE FROM 80 TO 120 LITRE/MINUTE (LEFT) AND 80 TO 40 LITRE/MINUTE (RIGHT) (PHOTOS TAKEN FROM THE DASHBOARD AT THE PRODUCTION LINE, SCREENSHOT WAS NOT POSSIBLE).

Spindle for weight adjustment

The weight is adjusted mechanically by a spindle that rotates a cam, resulting in a variation in the of the cavity depth (see Figure 65). The product carrier weighing cell obtains an average; if the average falls outside of the tolerance range, a signal is given to the pad making machine. The pad making machine adjusts the weight by decreasing or increasing the depth of the cavity, by turning the spindle.

x

FIGURE 65: PAD FILLING FROM COFFEE SUPPLY UP TO THE CAVITY (ADAPTED FROM[4]).

[4] From research R. Ten Berge (2017)

Rounding of weighing cells

The weighing cells (i.e. for both product carriers and bags) round their detected values on an even number with two digits, i.e. multiples of 0.02. The used averages are based on these values and also rounded in the same way.

Conclusion

With this section, the first part of the answer to research question 1.3 “What factors influence the process of weighing and can be changed”, is given. In this section possible causes by imperfections in the production line are discussed. All possible causes, the hopper level, speed of the agitator and the fluctuation of vacuum power are all negligible. The aim was to check whether they could be improved instantly, which is not the case.

APPENDIX B: SELECTION CRITERIA FOR SIMULATION SOFTWARE SELECTION

The criteria are scored from 1 to 5, where 5 indicates “Excellent”, 4 indicates “Good”, 3 indicates “Sufficient”, 2 indicates “Insufficient” and 1 indicates “The feature doesn’t exist”. The criteria in bold are selected as being the most important criteria for this research. Since all bold criteria are scored 4 or 5, Siemens Plant Simulation v.14 is sufficient to use.

Below in the tables, the score per criterium for Siemens Plant Simulation v.14 are shown.

Table: Model development and input category Criteria

Criteria	Weight
Graphical model building	**4**
Merging models	2
Conditional routing	4
Statistical distribution	**5**
Queuing policies	**5**
Reuse of user defined modules	5
Built-in functions	3
Link to other languages	2
Coding tools and utilities	3
Input from text files	**4**
Input from database	5
Input from spreadsheets	**5**
Automatic data collection	**5**
Batch input mode	4
Interactive input mode	4

Table: Output category criteria

Criteria	Weight
Standard report generation	**5**
Report customization	2
Integration with statistical packages	2
Integration with other simulation packages	1
Feature for exporting data to database	3
Feature for exporting data to spreadsheets	**5**
Feature for exporting data to text files or word processors	4
Optimization	2
Output analysis feature	**4**
Business graphics	3

Criteria	**Weight**
Cost	**5**
Connectivity with internet	2
Package interoperability	2
Package link to different animation packages	1
Package has open source code	3
Package application area	4
Flow oriented modeling approach	4
High level architecture	5
Capability for continuous simulation	2
Simulation strategy	4

APPENDIX C: DATA TABLES OF THE SIMULATION MODEL

	integer 0	real 1	real 2	real 3	integer 4	string 5	real 6
string	PadNum	PadWeight	CoffeeWeightPad	FilterPaperWeightPad	ProductCarrierNum	PadSide	SinusCorrection
1	1	7.13	6.94	0.18	1	OS	0.00
2	2	7.47	7.29	0.18	1	OS	0.00
3	3	7.30	7.12	0.18	1	OS	0.00
4	4	7.28	7.10	0.18	1	OS	0.00
5	5	7.07	6.89	0.18	1	OS	0.00
6	6	7.16	6.98	0.18	1	OS	0.00
7	7	7.08	[illegible]	[illegible]	1	OS	0.00
8	8	7.48	7.30	[illegible]	1	OS	0.00
9	9	7.50	7.31	[illegible]	1	OS	0.00
10	10	7.43	7.25	[illegible]	1	MS	0.00
11	11	7.29	7.11	0.18	1	MS	0.00
12	12	7.07	6.89	0.18	1	MS	0.00
13	13	7.23	7.04	0.18	1	MS	0.00
14	14	7.30	7.12	0.18	1	MS	0.00
15	15	6.99	6.81	0.18	1	MS	0.00
16	16	7.21	7.03	0.18	1	MS	0.00
17	17	7.33	7.14	0.18	1	MS	0.00
18	18	7.33	7.15	0.18	1	MS	0.00
19	19	7.16	6.98	0.18	2	OS	0.00

Pad weight of
first full product

FIGURE 66: LIST OF GENERATED PADS (1/2)

	integer 0	real 1	real 2	real 3	integer 4	string 5	real 6
string	PadNum	PadWeight	CoffeeWeightPad	FilterPaperWeightPad	ProductCarrierNum	PadSide	SinusCorrection
18	18	7.33	7.15	0.18	1	MS	0.00
19	19	7.16	6.98	0.18	2	OS	0.00
20	20	7.20	7.01	0.18	2	OS	0.00
21	21	7.46	7.27	0.18	2	OS	0.00
22	22	6.91	6.73	0.18	2	OS	0.00
23	23	6.99	6.81	[illegible]	2	OS	0.00
24	24	7.18	7.00	[illegible]	2	OS	0.00
25	25	7.14	6.96	[illegible]	2	OS	0.00
26	26	7.22	7.03	[illegible]	2	OS	0.00
27	27	7.11	6.92	0.18	2	OS	0.00
28	28	7.25	7.07	0.18	2	MS	0.00
29	29	7.20	7.01	0.18	2	MS	0.00
30	30	7.67	7.49	0.18	2	MS	0.00
31	31	7.06	6.88	0.18	2	MS	0.00
32	32	7.28	7.09	0.18	2	MS	0.00
33	33	7.14	6.95	0.18	2	MS	0.00
34	34	7.18	6.99	0.18	2	MS	0.00
35	35	7.28	7.10	0.18	2	MS	0.00
36	36	7.14	6.96	0.18	2	MS	0.00
37	37	7.07	6.88	0.18	3	OS	0.00

Pad weight of
second full

FIGURE 67: LIST OF GENERATED PADS (2/2)

	integer 0	real 1	real 2	real 3	real 4	string 5	string 6	integer 7
string	PCNum	PadsWeight	ProductCarrierWeight	WeighingInaccuracy	DetectedWeight	Status	JustlyCall	SampleSizeNumber
1	1	130.657486	390.567464	0.062873	130.880000	Accepted	TP	1
2	2	129.551840	390.722515	0.038346	129.920000	Accepted	TP	2
3	3	129.280021	390.632470	-0.139559	129.3[illegible]000	Accepted	TP	3
4	4	130.296421	390.510325	-0.141968	130[illegible]00	Accepted	TP	4
5	5	129.335245	390.176213	0.057621	12[illegible]	Accepted	TP	5
6	6	128.503582	390.071156	-0.091351	[illegible]	ccepted	TP	6
7	7	130.202602	390.240952	-0.077891	[illegible]	ccepted	TP	7
8	8	129.242689	390.638157	-0.065796	[illegible]	ccepted	TP	8
9	9	130.161381	390.683870	0.060657	[illegible]	ccepted	TP	9
10	10	129.031167	390.351721	-0.022150	[illegible]	ccepted	TP	10
11	11	130.347145	390.808663	-0.135215	130.620000	Accepted	TP	1
12	12	130.624655	390.344974	-0.036164	130.540000	Accepted	TP	2
13	13	129.496666	390.766633	0.038013	129.900000	Accepted	TP	3
14	14	129.565293	390.948311	-0.033820	130.080000	Accepted	TP	4
15	15	129.258146	389.913082	0.003382	128.780000	Accepted	TP	5
16	16	129.406701	390.918735	-0.036741	129.880000	Accepted	TP	6
17	17	127.847427	390.424238	0.143194	128.020000	Accepted	TP	7
18	18	129.399779	390.297569	-0.054961	129.240000	Accepted	TP	8
19	19	130.235302	390.151082	0.023251	130.000000	Accepted	TP	9
20	20	129.683799	390.282180	0.017242	129.580000	Accepted	TP	10

Weights of first two full product

FIGURE 68: LIST OF PRODUCT CARRIERS (1/2)

	integer 0	real 8	real 9	real 10	real 11	real 12	integer 13	integer 14
string	PCNum	SampleSizeCurrentAverage	DiffSampleAverageNominalW...	CurrentPadsMeanOS	CurrentPadsMeanMS	WeightLastPad	MissingPadPC	MissingPadBag
1	1	130.880000	1.580000	7.000000	7.000000	7.145033	0	0
2	2	130.400000	1.100000	7.000000	7.000000	6.961095	0	0
3	3	130.060000	0.760000	7.000000	7.000000	6.860906	0	0
4	4	130.110000	0.810000	7.000000	7.000000	7.325235	0	0
5	5	129.920000	0.620000	7.000000	7.000000	6.683187	0	0
6	6	129.613300	0.313300	7.000000	7.000000	6.877776	0	0
7	7	129.662800	0.362800	7.000000	7.000000	7.103940	0	0
8	8	129.632500	0.332500	7.000000	7.000000	7.046172	0	0
9	9	129.728900	0.428900	7.000000	7.000000	6.897500	0	0
10	10	129.652000	0.352000	7.000000	7.000000	6.958142	0	0
11	11	130.620000	1.320000	7.000000	7.000000	7.050666	0	0
12	12	130.580000	1.280000	7.000000	7.000000	7.072560	0	0
13	13	130.353300	1.053300	7.000000	7.000000	7.303857	0	0
14	14	130.285000	0.985000	7.000000	7.000000	6.856742	0	0
15	15	129.984000	0.684000	7.000000	7.000000	6.993171	0	0
16	16	129.966700	0.666700	7.000000	7.000000	6.995297	0	0
17	17	129.688600	0.388600	7.000000	7.000000	6.796051	0	0
18	18	129.632500	0.332500	7.000000	7.000000	7.061782	0	0
19	19	129.673300	0.373300	7.000000	7.000000	6.835025	0	0
20	20	129.664000	0.364000	7.000000	7.000000	7.273186	0	0

FIGURE 69: LIST OF PRODUCT CARRIERS (2/2)

	integer 0	real 1	real 2	real 3	real 4	string 5	string 6	integer 7
string	BagNum	BagCoffeeWeight	BagWeighingInaccuracy	BagWeightRounded	Overfill	Status	BagJustlyCall	PCNum1
1	1	253.62	-0.11	253.52	1.62	Accepted	TP	1
2	2	252.99	-0.43	252.5[illegible]	0.99	Accepted	TP	3
3	3	251.25	-0.15	251[illegible]	-0.75	Accepted	TP	5
4	4	252.86	0.43	25[illegible]	0.86	Accepted	TP	7
5	5	252.60	0.85	[illegible]	.60	Accepted	TP	9
6	6	254.38	-0.26	[illegible]	.38	Accepted	TP	11
7	7	252.47	0.41	[illegible]	.47	Accepted	TP	13
8	8	252.08	0.76	[illegible]	.08	Accepted	TP	15
9	9	250.66	-0.55	[illegible]	1.34	Accepted	TP	17
10	10	253.33	0.32	253.66	1.33	Accepted	TP	19

Weight of first full bag

FIGURE 70: LIST OF BAGS (1/2)

	integer 0	string 6	integer 7	integer 8	integer 9	integer 10	real 11	integer 12
string	BagNum	BagJustlyCall	PCNum1	PCNum2	PCNum3	BagSampleSizeNumber	BagSampleSizeCurrentAverage	MissingPads
1	1	TP	1	2		1	253.52	0
2	2	TP	3	[illegible]		2	253.04	0
3	3	TP	5	[illegible]		3	252.39	0
4	4	TP	7	[illegible]		4	252.62	0
5	5	TP	9	[illegible]		5	252.78	0
6	6	TP	11	[illegible]		6	253.01	0
7	7	TP	13	[illegible]		7	252.99	0
8	8	TP	15	[illegible]		8	252.97	0
9	9	TP	17	[illegible]		9	252.65	0
10	10	TP	19	20		10	252.75	0

First bag is filled by first

FIGURE 71: LIST OF BAGS (2/2)

	integer 0	real 1	real 2	real 3	real 4	string 5	string 6	integer 7
string	PCNum	PadsWeight	ProductCarrierWeight	WeighingInaccuracy	DetectedWeight	Status	JustlyCall	SampleSizeNumber
386	386	129.032224	390.005423	0.077753	128.720000	Accepted	TP	6
387	387	129.161496	390.185694	-0.080127	128.860000	Accepted	TP	7
388	388	122.285317	390.086647	-0.020430	121.960000	Rejected	TN	8
389	389	129.367869	390.434089	0.049831	129.460000	Acc[illegible]ted	TP	9
390	390	130.545918	390.293596	0.079589	130.520000	A[illegible]d	TP	10

FIGURE 72: LIST OF PRODUCT CARRIERS WITH ONE REJECTION

The 338th product carrier

The 338th product carrier

	integer 0	string 6	integer 7	integer 8	integer 9	integer 10	real 11
string	BagNum	BagJustlyCall	PCNum1	PCNum2	PCNum3	BagSampleSizeNumber	BagSampleSizeCurrentAverage
192	192	TP	383	384		192	252.34
193	193	TP	385	386		193	252.33
194	194	TP	387	389		194	252.33
195	195	TP	390	391		195	252.34
196	196	TP	392	393		196	252.34
197	197	TP	394	395		197	252.34

FIGURE 73: LIST OF BAGS WITH INDICATION OF PRODUCT CARRIERS THAT GO IN ONE BAG

APPENDIX D: AGGREGATED DATA OF BAGS WITH 48 PADS

APPENDIX E: ONE-BY-ONE PARAMETER OPTIMISATION

Determining the best possible sample size

The sample size is the number of product carriers that is measured to determine the average weight of product carriers at that moment in time. The minimum sample size is 1 and there is no maximum, currently the default is set at 10 product carriers. We ran experiments in extremes and in between at first, namely sample sizes of 1, 5, 10 and 20. From these four settings, a sample size of 5 product carriers resulted in the lowest Coffee In Coffee in rework costs rate. A second round of experiments was ran with sample sizes of 2, 3, 4, 5, 6 and 7.

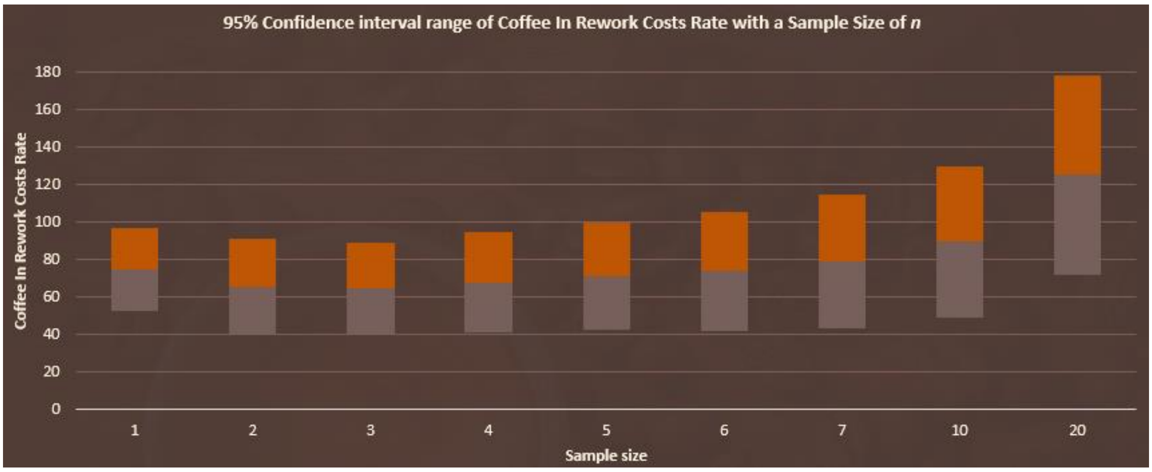


FIGURE 74: 95% CONFIDENCE INTERVAL BOXPLOT OF THE EFFECT OF SAMPLE SIZES ON THE COFFEE IN REWORK COSTS RATE.

Determining the best possible delay

The delay is the number of product carriers that the weighing cells does not take into account for calculating the average of product carriers at that moment in time. This delay is activated after the machine steered the weight. The minimum value is 12, since there are product carriers that are between the machine and the weighing machine where the steering had no effect yet. The effect of steering takes 30 pads per gram the weight is higher than the norm weight product carriers depending on the product carrier size, for the bag size of 48 pads with product carriers of 24 pads, this will not be more than 3 product carriers. We ran experiments at:

1. 12 (The effect of the steering is included in the new sample size)
2. 13 (The effect of the steering is often slightly included in the new sample size)
3. 14 (The effect of the steering is often slightly included in the new sample size)
4. 15 (The effect of the steering is already finished)

After these experiments, a delay of 12 product carriers resulted in the lowest coffee in rework costs rate. Since the coffee in rework costs rate increases when the delay increases, no further experiments were needed.

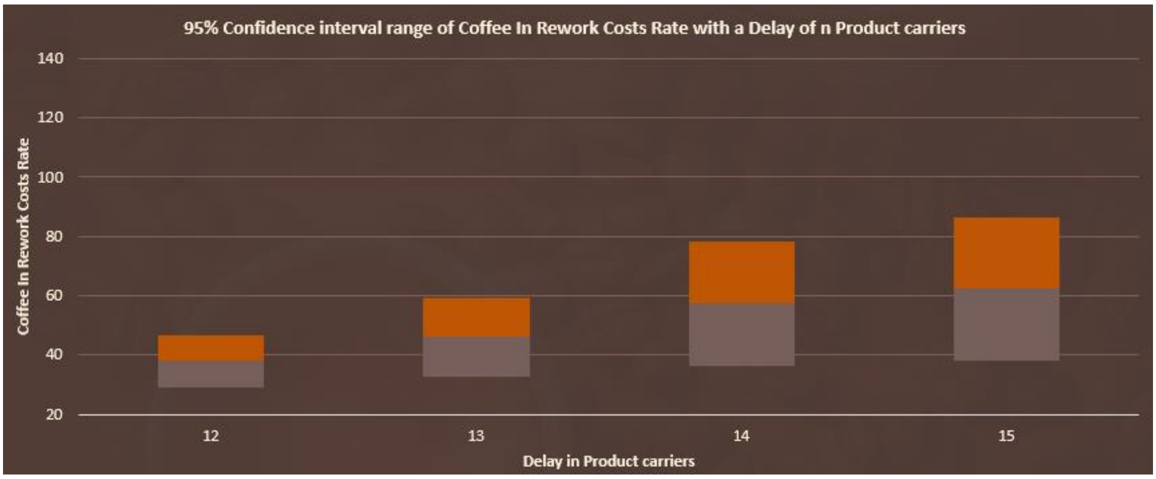


FIGURE 75: 95% CONFIDENCE INTERVAL BOXPLOT OF THE EFFECT OF DELAY IN PRODUCT CARRIERS ON THE COFFEE IN REWORK COSTS RATE.

Determining the best possible tolerances

The tolerance determines at what average of product carriers, the steering mechanism is activated. This is expressed in a percentage of the nominal weight of the filled product carriers, minus the tare of the product carrier itself. By default, this tolerance is determined on 0.5. We can ran experiments with 0.2, 0.4, 0.6 and 0.8 lower and upper tolerances. Based on the results shown in Figure 76, the setting of tolerances does not seem to influence the objective Coffee In Rework Costs Rate significantly. Though, a higher tolerance value seems to be better than a lower one.

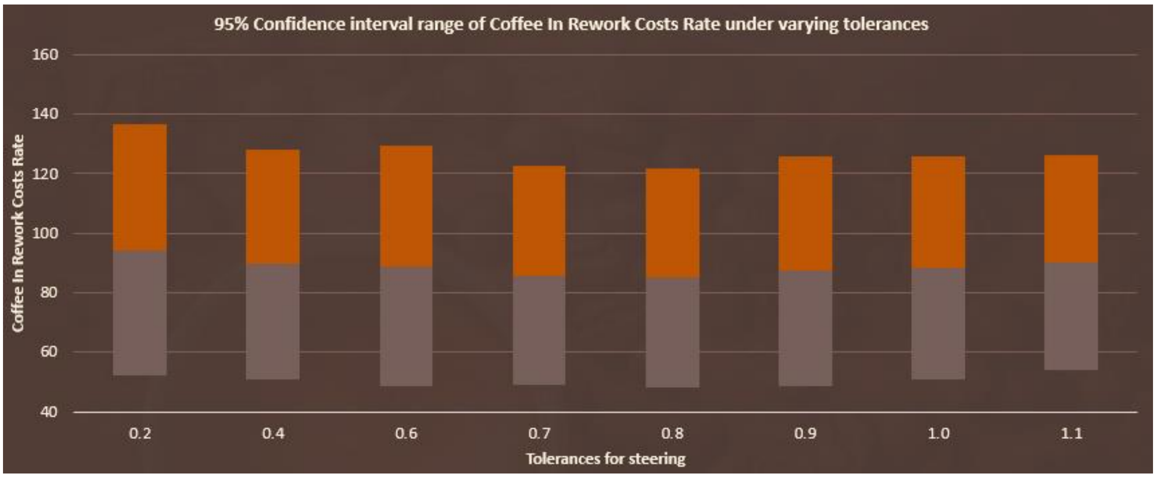


FIGURE 76: 95% CONFIDENCE INTERVAL BOXPLOT OF THE EFFECT OF TOLERANCES ON THE COFFEE IN REWORK COSTS RATE.

Determining the best possible pulse factor

The steering factor determines the severity of steering, when the steering mechanism is triggered. Currently, this factor is set at 50% at default. We ran experiments with extreme values, namely at 50%, 80%, 100%, 120% and 150%. We choose 4 experiments that are mirrored compared to the expected value of 100%, since assume that the curve of the best possible value is an upward opening parabola.

After the first round of experiments, a steering factor of 0.8 seems to be the best possible, based on the objective Coffee In Rework Costs Rate. In a second round of experiments, a steering factor of 0.7 and 0.9 is examined too.

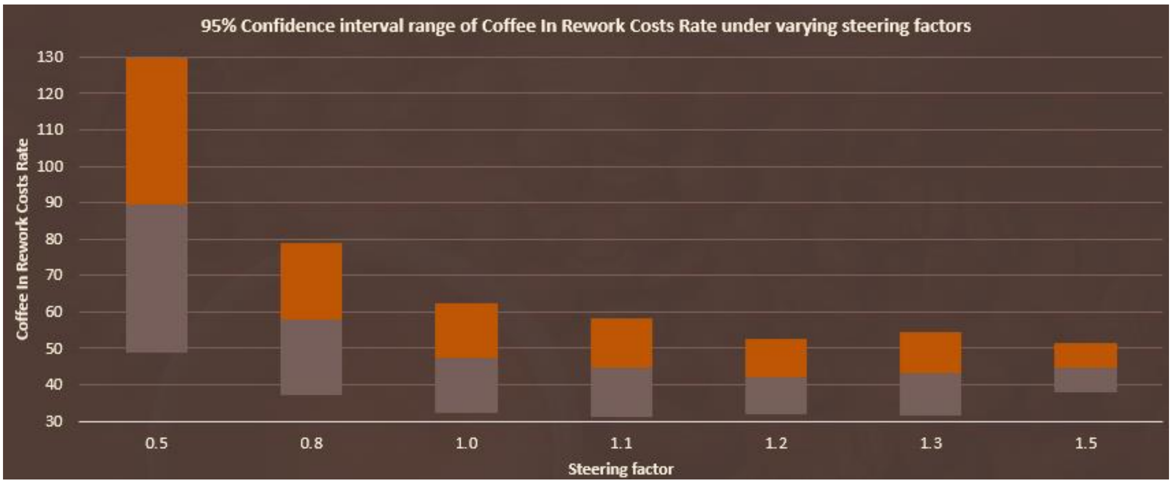


FIGURE 77 95% CONFIDENCE INTERVAL BOXPLOT OF THE EFFECT OF THE STEERING FACTOR ON THE COFFEE IN REWORK COSTS RATE.

Step 3: Design of Experiments around the best possible values

For the DOE, we used the two settings with the minimal Coffee In Rework Costs Rate per parameter. For example, the minimum costs rate were realized with a sample size of 2 and the then minimum costs with a sample size of 3.
Given the best possible values, we run a DOE around these best possible values.

Experiment	Delay	Sample size	Tolerances	Steering factor
1	12	2	0.8	1.2
2	12	2	0.8	1.3
3	12	2	0.8	1.2
4	12	2	0.9	1.3
5	12	2	0.9	1.2
6	12	2	0.9	1.3
7	12	3	0.8	1.2
8	12	3	0.8	1.3
9	12	3	0.8	1.2
10	12	3	0.9	1.3
11	12	3	0.9	1.2
12	12	3	0.9	1.3
13	13	2	0.8	1.2
14	13	2	0.8	1.3
15	13	2	0.8	1.2
16	13	2	0.9	1.3
17	13	2	0.9	1.2
18	13	2	0.9	1.3
19	13	3	0.8	1.2
20	13	3	0.8	1.3
21	13	3	0.8	1.2
22	13	3	0.9	1.3

23	13	3	0.9	1.2
24	13	3	0.9	1.3

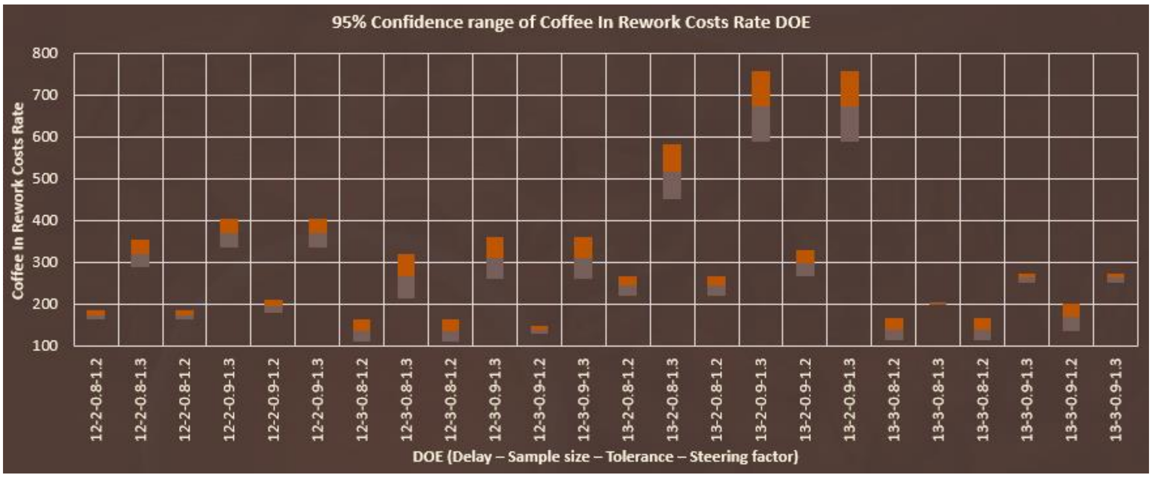


FIGURE 78: RESULTS OF DOE.

The first notable thing of this DOE is that the objective increased, compared to the experiments of the one-by-one parameter variations. This implies that the combination of the best possible settings does result in suboptimal results. We can conclude that the one-by-one parameter optimizations were local optima and we need another approach to find the global optima.

To find these global optima, we first looked at the main effects of the parameters to see if we can fix some of the parameters, see Figure 79. This figures implies that we should decrease the Delay, though the Delay cannot be lower than 12, therefore we are able to leave out this parameter in the next round of experiments. It also implies that we should increase the Sample size, decrease the tolerances and decrease the steering factor. These outputs are used to design a new DOE.

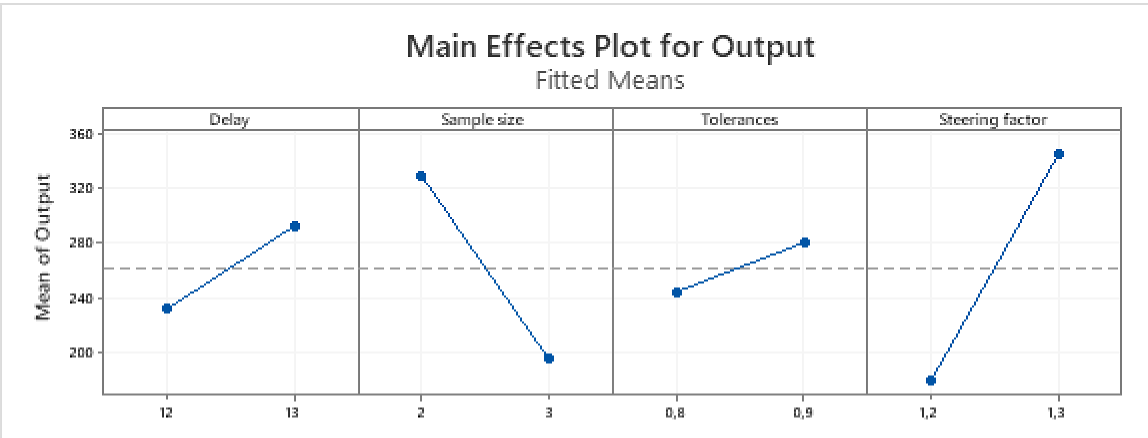


FIGURE 79: MAIN EFFECTS OF PARAMETERS WITH TWO SETTINGS PER PARAMETER.

APPENDIX F: DETAILED FIGURES REGARDING EXPERIMENTS

Step 1: European law

According to European law, the weight of a product may vary from the value declared on the bag within certain limits. According to Council Directive 76/211/EEC, the weights should meet the following requirements:

- 1.1 the actual contents should not be less, on average per hour , than the nominal quantity ;
- 1.2 the proportion of pre-packages with a negative error greater than the tolerable negative error presented in Figure 80 should not exceed 2.5% of the packages produced per hour
- 1.3 no pre-package should have a negative error greater than twice the tolerable negative error given in the table in Figure 80.

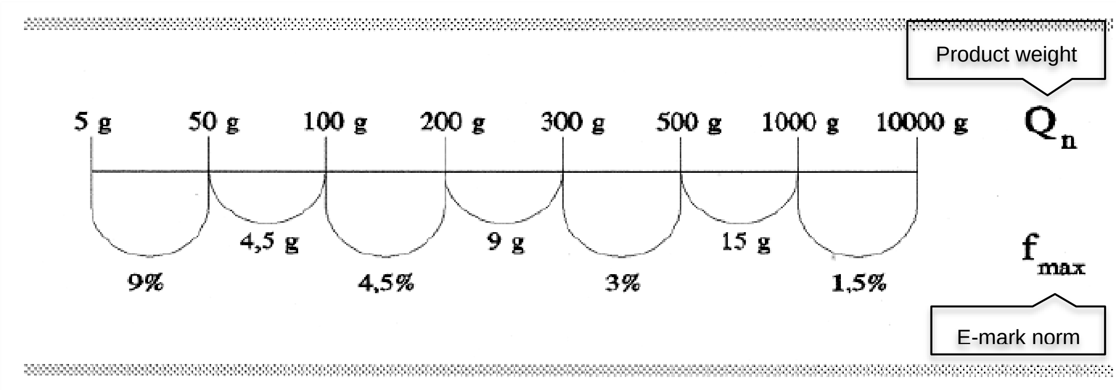


FIGURE 80: E-MARK LIMITS PER WEIGHT RANGE.

TABLE 29: LIST OF EXPERIMENTS IN THE FIRST DOE, WITH A HIGH, MID AND LOW PARAMETER SETTING.

Experiment	Sample size	Tolerance	Adjustment factor	Coffee in rework costs rate
1	3	0.2	0.5	26.57
2	3	0.2	0.8	26.14
3	3	0.2	1.2	25.71
4	3	0.5	0.5	26.44
5	3	0.5	0.8	25.20
6	3	0.5	1.2	26.30
7	3	0.8	0.5	26.21
8	3	0.8	0.8	25.30
9	3	0.8	1.2	26.39
10	6	0.2	0.5	26.34
11	6	0.2	0.8	25.61

12	6	0.2	1.2	25.64
13	6	0.5	0.5	26.67
14	6	0.5	0.8	26.48
15	6	0.5	1.2	25.88
16	6	0.8	0.5	26.66
17	6	0.8	0.8	25.69
18	6	0.8	1.2	25.94
19	12	0.2	0.5	26.59
20	12	0.2	0.8	26.53
21	12	0.2	1.2	26.75
22	12	0.5	0.5	26.00
23	12	0.5	0.8	25.91
24	12	0.5	1.2	26.46
25	12	0.8	0.5	26.41
26	12	0.8	0.8	25.59
27	12	0.8	1.2	25.66

TABLE 30: EXPERIMENTS IN THE SECOND DOE.

Experiment	**Sample size**	**Tolerance**	**Adjustment factor**	**Coffee in rework costs rate**
1	5	0.1	0.8	23.58
2	5	0.1	0.9	23.29
3	5	0.3	0.8	24.40
4	5	0.3	0.9	24.43
5	6	0.1	0.8	23.82
6	6	0.1	0.9	23.63
7	6	0.3	0.8	24.23
8	6	0.3	0.9	24.39
9	7	0.1	0.8	23.86
10	7	0.1	0.9	23.65
11	7	0.3	0.8	24.32
12	7	0.3	0.9	24.39

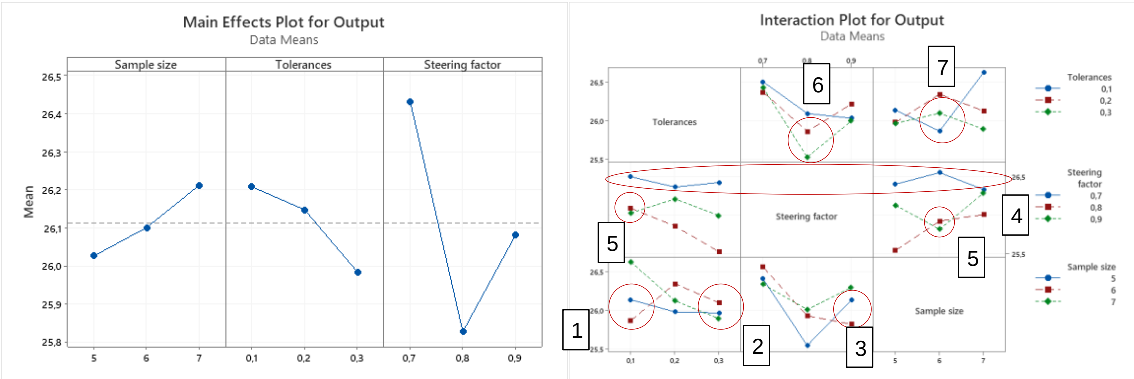


FIGURE 81: MAIN EFFECTS PLOT AND AND INTERACTION PLOTOF SECOND DOE PER PARAMETER.

TABLE 31: LIST OF EXPERIMENTS IN THE THIRD DOE (WITH A HIGH, MEDIUM AND LOW PARAMETER SETTING).

Experiment	Sample size	Tolerance	Adjustment factor	Coffee in rework costs rate
1	3	0.2	0.5	23.58
2	3	0.2	0.8	**23.29**
3	3	0.2	1.2	24.40
4	3	0.5	0.5	24.43
5	3	0.5	0.8	23.82
6	3	0.5	1.2	23.63
7	3	0.8	0.5	24.23
8	3	0.8	0.8	24.39
9	3	0.8	1.2	23.86
10	6	0.2	0.5	23.65
11	6	0.2	0.8	24.32
12	6	0.2	1.2	24.39

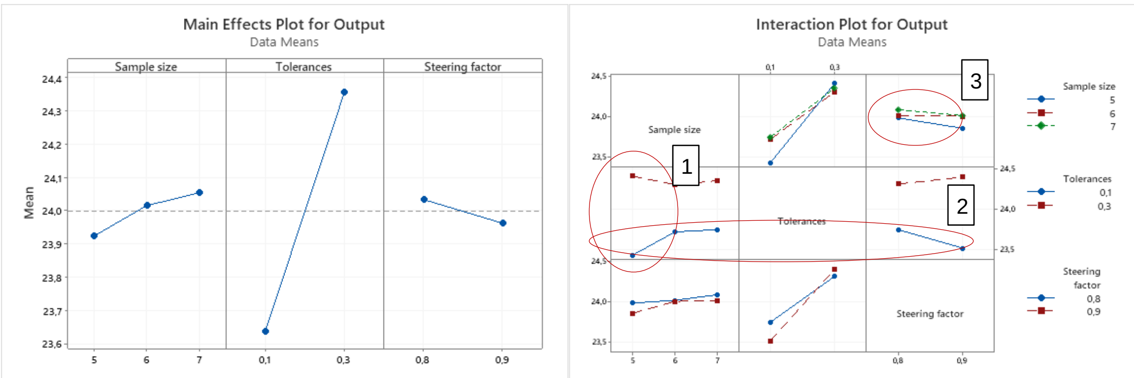


FIGURE 82: MAIN EFFECTS AND INTERACTOIN PLOT OF THIRD DOE PER PARAMETER.

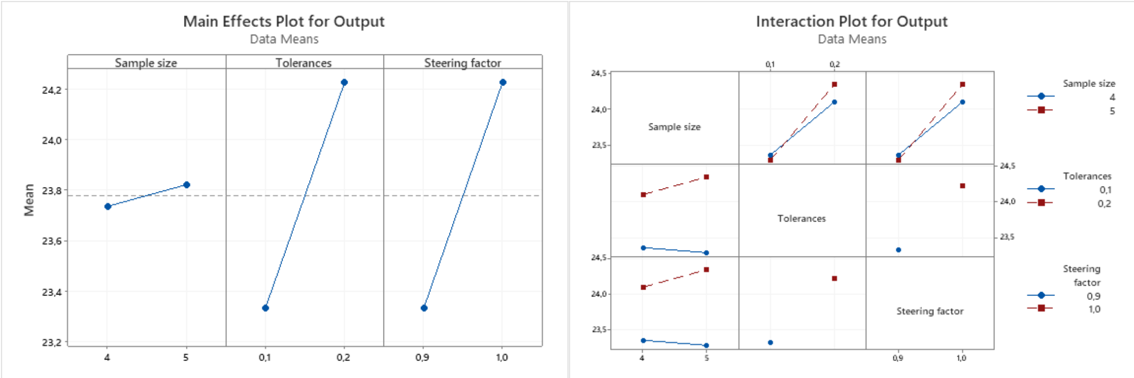


FIGURE 83: MAIN EFFECTS AND INTERACTION PLOT OF THE FOURTH DOE PER PARAMETER.

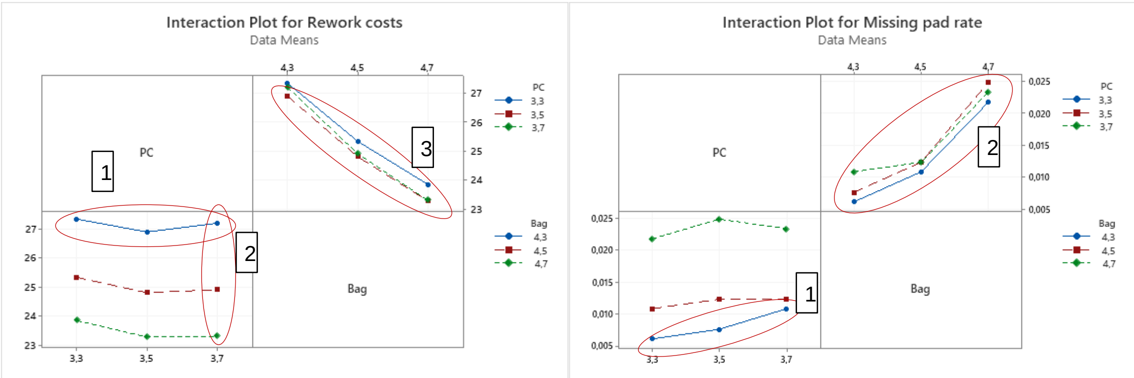


FIGURE 84: INTERACTION PLOT FOR THE PRODUCT CARRIER AND BAG REJECTION LIMITS ON COFFEE IN REWORK COSTS (LEFT) AND MISSING PAD RATE (RIGHT).

TABLE 32: SENSITIVITY ANALYSIS EXPERIMENTS.

Experiment	Sample size	Tolerance	Steering factor	Delay	PC rej. Limits	Bag rej. Limits	Coffee in rework costs rate	Missing pad rate
1	3	0.1	0.9	12	+/- 3.3	+/- 4.4	26.33	1.1%
2	4	0.1	0.9	12	+/- 3.3	+/- 4.4	26.09	1.4%
3	**6**	**0.1**	**0.9**	**12**	**+/- 3.3**	**+/- 4.4**	**26.25**	**0.8%**
4	**7**	**0.1**	**0.9**	**12**	**+/- 3.3**	**+/- 4.4**	**26.15**	**0.6%**
5	5	0.2	0.9	12	+/- 3.3	+/- 4.4	26.95	1.6%
6	5	0.3	0.9	12	+/- 3.3	+/- 4.4	28.22	1.4%
7	5	0.4	0.9	12	+/- 3.3	+/- 4.4	29.58	1.7%
8	5	0.1	0.7	12	+/- 3.3	+/- 4.4	26.70	1.2%
9	**5**	**0.1**	**0.8**	**12**	**+/- 3.3**	**+/- 4.4**	**26.10**	**0.9%**
10	5	0.1	1.0	12	+/- 3.3	+/- 4.4	26.08	1.3%
11	5	0.1	1.1	12	+/- 3.3	+/- 4.4	26.69	0.6%
12	5	0.1	0.9	13	+/- 3.3	+/- 4.4	33.95	2.0%
13	5	0.1	0.9	14	+/- 3.3	+/- 4.4	36.18	3.0%
14	5	0.1	0.9	12	+/- 3.2	+/- 4.4	26.07	1.4%
15	5	0.1	0.9	12	+/- 3.4	+/- 4.4	25.82	1.4%
16	5	0.1	0.9	12	+/- 3.3	+/- 4.3	27.36	0.6%
17	5	0.1	0.9	12	+/- 3.3	+/- 4.5	25.35	1.1%

APPENDIX G: RESULTS OF EXPERIMENTS PER BAG SIZE

In this appendix, the results for the design of experiments for all bag sizes is listed (except for 48 pads which is included in the experiments chapter).

Bag size 32 pads

DOE	Sample size	Tolerances	Steering factor
1	4		0.7
2	5	0.1	0.8
3	6	0.2	0.9

Exp.	Sample size	Tolerance	Delay	Steering factor	PC (+/-)	Bag (+/-)	rework	Missing pad rate
1	4	0,1	12	0,7	3,3	4,5	20,70	0,8%
2	4	0,1	12	0,8	3,3	4,5	20,79	0,5%
3	4	0,1	12	0,9	3,3	4,5	20,86	0,5%
4	4	0,2	12	0,7	3,3	4,5	20,95	0,5%
5	4	0,2	12	0,8	3,3	4,5	20,95	0,5%
6	4	0,2	12	0,9	3,3	4,5	20,90	0,6%
7	5	0,1	12	0,7	3,3	4,5	20,70	0,5%
8	**5**	**0,1**	**12**	**0,8**	**3,3**	4,5	**20,70**	**0,6%**
9	5	0,1	12	0,9	3,3	4,5	20,82	0,8%
10	5	0,2	12	0,7	3,3	4,5	20,78	0,3%
11	5	0,2	12	0,8	3,3	4,5	20,93	0,3%
12	5	0,2	12	0,9	3,3	4,5	20,98	0,8%
13	6	0,1	12	0,7	3,3	4,5	20,76	0,6%
14	6	0,1	12	0,8	3,3	4,5	20,78	0,6%
15	6	0,1	12	0,9	3,3	4,5	20,84	0,5%
16	6	0,2	12	0,7	3,3	4,5	20,88	0,3%
17	6	0,2	12	0,8	3,3	4,5	20,99	0,3%
18	6	0,2	12	0,9	3,3	4,5	20,91	0,8%

DOE	PC (+/-)	Bag (+/-)
1	3.4	4.7
2	3.5	4.8
3		4.9

Exp.	Sample size	Tolerance	Delay	Steering factor	PC (+/-)	Bag (+/-)	rework	Missing pad rate
1	**3**	**0.1**	**12**	**0.7**	**3,4**	**4,7**		
2	3	0.1	12	0.7	3,4	4,8		
3	3	0.1	12	0.7	3,4	4,9		
4	3	0.1	12	0.7	3,5	4,7		
5	3	0.1	12	0.7	3,5	4,8		

6	3	0.1	12	0.7	3,5	4,9		

Bag size 36 pads

DOE	Sample size	Tolerances	Steering factor					
1	4		0.7					
2	5	0.1	0.8					
3	6	0.2	0.9					

Exp.	Sample size	Tolerance	Delay	Steering factor	PC (+/-)	Bag (+/-)	rework	Missing pad rate
1	4	0,1	12	0,7	3,3	4,5	20,70	0,8%
2	4	0,1	12	0,8	3,3	4,5	20,79	0,5%
3	4	0,1	12	0,9	3,3	4,5	20,86	0,5%
4	4	0,2	12	0,7	3,3	4,5	20,95	0,5%
5	4	0,2	12	0,8	3,3	4,5	20,95	0,5%
6	4	0,2	12	0,9	3,3	4,5	20,90	0,6%
7	5	0,1	12	0,7	3,3	4,5	20,70	0,5%
8	**5**	**0,1**	**12**	**0,8**	**3,3**	4,5	**20,70**	**0,6%**
9	5	0,1	12	0,9	3,3	4,5	20,82	0,8%
10	5	0,2	12	0,7	3,3	4,5	20,78	0,3%
11	5	0,2	12	0,8	3,3	4,5	20,93	0,3%
12	5	0,2	12	0,9	3,3	4,5	20,98	0,8%
13	6	0,1	12	0,7	3,3	4,5	20,76	0,6%
14	6	0,1	12	0,8	3,3	4,5	20,78	0,6%
15	6	0,1	12	0,9	3,3	4,5	20,84	0,5%
16	6	0,2	12	0,7	3,3	4,5	20,88	0,3%
17	6	0,2	12	0,8	3,3	4,5	20,99	0,3%
18	6	0,2	12	0,9	3,3	4,5	20,91	0,8%

DOE	PC (+/-)	Bag (+/-)						
1	3.4	4.6						
2	3.5	4.7						

Exp.	Sample size	Tolerance	Delay	Steering factor	PC (+/-)	Bag (+/-)	rework	Missing pad rate
1	**5**	**0.1**	**12**	**0.7**	**3,4**	**4,6**	**20,640**	**0,8%**
2	5	0.1	12	0.7	3,5	4,7	20,532	1,3%

TABLE 33: EXPERIMENTS OF THE FIRST DOE FOR REJECTION LIMITS OPTIMISATION, INCLUDING RESULTS.

Experiment	PC	Bag	Coffee in rework costs rate	Missing pad rate
1	**3.3**	**4.3**	**27.36**	**0.6%**
2	3.3	4.5	25.35	1.1%

3	3.3	4.7	23.87	2.2%
4	**3.5**	**4.3**	**26.91**	**0.8%**
5	3.5	4.5	24.82	1.2%
6	3.5	4.7	23.29	2.5%
7	3.7	4.3	27.22	1.1%
8	3.7	4.5	24.92	1.2%
9	3.7	4.7	23.32	2.3%

Bag size 40 pads

DOE	Sample size	Tolerances	Steering factor					
1	4		0.7					
2	5	0.1	0.8					
3	6	0.2	0.9					

Exp.	Sample size	Tolerance	Delay	Steering factor	PC (+/-)	Bag (+/-)	rework	Missing pad rate
1	4	0,1	12	0,7	3,3	4,4	22,15	0,7%
2	4	0,1	12	0,8	3,3	4,4	22,11	0,5%
3	4	0,1	12	0,9	3,3	4,4	21,88	0,7%
4	4	0,2	12	0,7	3,3	4,4	22,13	1,2%
5	4	0,2	12	0,8	3,3	4,4	22,32	0,9%
6	4	0,2	12	0,9	3,3	4,4	22,42	0,5%
7	5	0,1	12	0,7	3,3	4,4	22,00	0,5%
8	**5**	**0,1**	**12**	**0,8**	**3,3**	**4,4**	**21,72**	**0,5%**
9	5	0,1	12	0,9	3,3	4,4	21,91	0,5%
10	5	0,2	12	0,7	3,3	4,4	22,16	0,9%
11	5	0,2	12	0,8	3,3	4,4	22,26	0,7%
12	5	0,2	12	0,9	3,3	4,4	22,42	1,4%
13	6	0,1	12	0,7	3,3	4,4	21,95	0,7%
14	6	0,1	12	0,8	3,3	4,4	22,04	0,2%
15	6	0,1	12	0,9	3,3	4,4	22,01	0,2%
16	6	0,2	12	0,7	3,3	4,4	22,00	0,5%
17	6	0,2	12	0,8	3,3	4,4	22,25	0,5%
18	6	0,2	12	0,9	3,3	4,4	22,13	1,4%

DOE	PC (+/-)	Bag (+/-)						
1	3.2	4.3						
2	3.3	4.4						
3	3.4	4.5						

Exp.	Sample size	Tolerance	Delay	Steering factor	PC (+/-)	Bag (+/-)	rework	Missing pad rate
1	**5**	0.1	**12**	0.8	**3,2**	**4,3**	**22,19**	**0,2%**
2	**5**	0.1	**12**	0.8	3,2	4,4	21,86	0,2%
3	**5**	0.1	**12**	0.8	3,2	4,5	21,54	0,6%
4	**5**	0.1	**12**	0.8	3,3	4,3	22,05	0,5%
5	**5**	0.1	**12**	0.8	3,3	4,4	21,66	0,5%
6	**5**	**0.1**	**12**	**0.8**	**3,3**	**4,5**	**21,41**	**0,6%**
7	**5**	0.1	**12**	0.8	3,4	4,3	22,18	0,5%
8	**5**	0.1	**12**	0.8	3,4	4,4	21,79	0,6%
9	**5**	0.1	**12**	0.8	3,4	4,5	21,44	0,8%

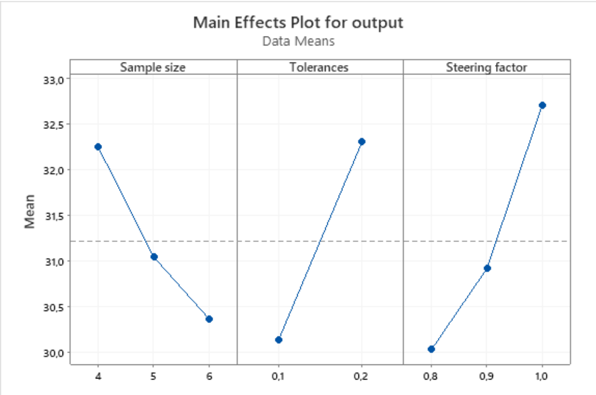
Bag size 54 pads

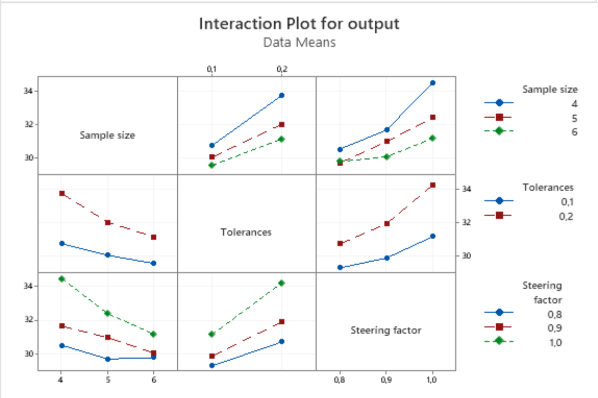
First DOE:

TABLE 34: DOE AND LISTED EXPERIMENTS WITH OUTPUT FOR BAG WITH 54 PADS

DOE	Sample size	Tolerances	Steering factor		
1	4		0.8		
2	5	0.1	0.9		
3	6	0.2	1.0		
Experiment	**Sample size**	**Tolerances**	**Steering factor**	**Delay**	**Output**
1	4	0,1	0,8	12	29,59
2	4	0,1	0,9	12	30,51

3	4	0,1	1	12	32,17
4	4	0,2	0,8	12	31,51
5	4	0,2	0,9	12	32,85
6	4	0,2	1	12	36,85
7	5	0,1	0,8	12	29,11
8	5	0,1	0,9	12	29,81
9	5	0,1	1	12	31,28
10	5	0,2	0,8	12	30,35
11	5	0,2	0,9	12	32,17
12	5	0,2	1	12	33,57
13	6	0,1	0,8	12	29,26
14	6	0,1	0,9	12	29,40
15	6	0,1	1	12	30,09
16	6	0,2	0,8	12	30,38
17	6	0,2	0,9	12	30,78
18	6	0,2	1	12	32,31





Second DOE:

DOE	Sample size	Tolerances	Steering factor	Delay	
Low	5	0.1	0.7	12	
Mid	6		0.8		
High	7				

Experiment	Sample size	Tolerances	Steering factor	Delay	Output
1	5	0,1	0,7	12	29,04
2	5	0,1	0,8	12	29,11
3	6	0,1	0,7	12	29,33
4	6	0,1	0,8	12	29,26
5	7	0,1	0,7	12	29,62
6	7	0,1	0,8	12	29,31

The best possible parameter settings are:
Sample size: 5
Tolerance: 0.1
Steering factor: 0.7
Delay: 12
The probability of accepting a bag with a missing pad is 2.03%.

DOE for best possible rejection limits:

DOE	PC	Bag
Low	3.2	4.3
Mid	3.3	4.4
high	3.4	4.5

Experiment	PC	Bag
1	3,2	4,3
2	3,2	4,4
3	3,2	4,5
4	3,3	4,3
5	3,3	4,4
6	3,3	4,5
7	3,4	4,3
8	3,4	4,4
9	3,4	4,5

Bag size 60 pads

TABLE 35: FIRST DOE AND LISTED EXPERIMENTS WITH OUTPUT FOR BAG WITH 60 PADS

DOE	Sample size	Tolerances	Steering factor			
1	4		0.6			
2	5	0.1	0.7			
3	6	0.2	0.8			

Experiment	Sample size	Tolerances	Steering factor	Delay	Output	Probability accepting missing pad
1	4	0,1	0,6	12	40,23	3,9%
2	4	0,1	0,7	12	39,12	3,6%
3	4	0,1	0,8	12	39,19	3,6%
4	4	0,2	0,6	12	42,97	3,6%
5	4	0,2	0,7	12	43,05	4,0%
6	4	0,2	0,8	12	45,18	4,0%
7	5	0,1	0,6	12	41,42	4,0%
8	5	0,1	0,7	12	39,97	3,6%
9	5	0,1	0,8	12	38,73	4,0%
10	5	0,2	0,6	12	43,83	4,5%
11	5	0,2	0,7	12	42,08	4,4%
12	5	0,2	0,8	12	42,65	3,3%
13	6	0,1	0,6	12	43,30	2,5%
14	6	0,1	0,7	12	39,40	3,1%
15	6	0,1	0,8	12	39,05	3,4%
16	6	0,2	0,6	12	44,24	3,1%
17	6	0,2	0,7	12	42,75	2,5%

18	6	0,2	0,8	12	42,20	2,3%

TABLE 36:SECOND DOE AND EXPERIMENTS FOR 60 PADS BAG

DOE	**PC limit (+/-)**	**Bag limit (+/-)**		
1	3.4	4.1		
2	3.5	4.2		
3		4.3		

Experiment	**PC limit (+/-)**	**Bag limit (+/-)**	**Output**	**Probability accepting missing pad**
1	3,4	4,1	50,75	2,5%
2	3,4	4,2	45,91	3,3%
3	3,4	4,3	41,88	3,9%
4	3,5	4,1	50,50	1,7%
5	3,5	4,2	45,88	2,8%
6	3,5	4,3	41,95	3,6%

TABLE 37:THIRD DOE AND EXPERIMENTS FOR 60 PADS BAG

DOE	**PC limit (+/-)**	**Bag limit (+/-)**		
1	3.5	3.9		
2	3.6	4.0		

Experiment	**PC limit (+/-)**	**Bag limit (+/-)**	**Output**	**Probability accepting missing pad**
1	3,5	3.9	63,81	1,1%
2	3,5	4.0	56,19	1,4%
3	**3,6**	**3.9**	**62,90**	**0,8%**
4	3,6	4.0	55,78	1,2%

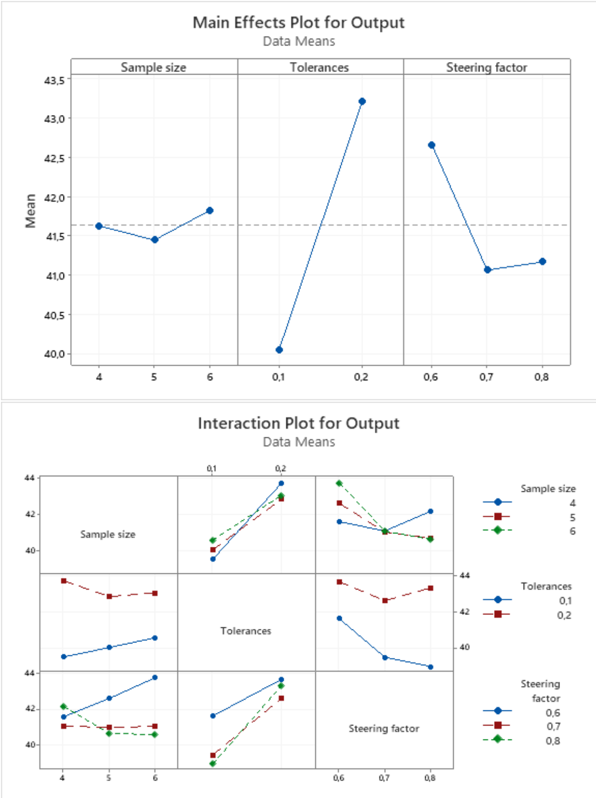


FIGURE 85:INTERACTION PLOT OF FIRST DOE FOR BAG OF 60 PADS (OBJECTIVE IS COFFEE IN REWORK COSTS)

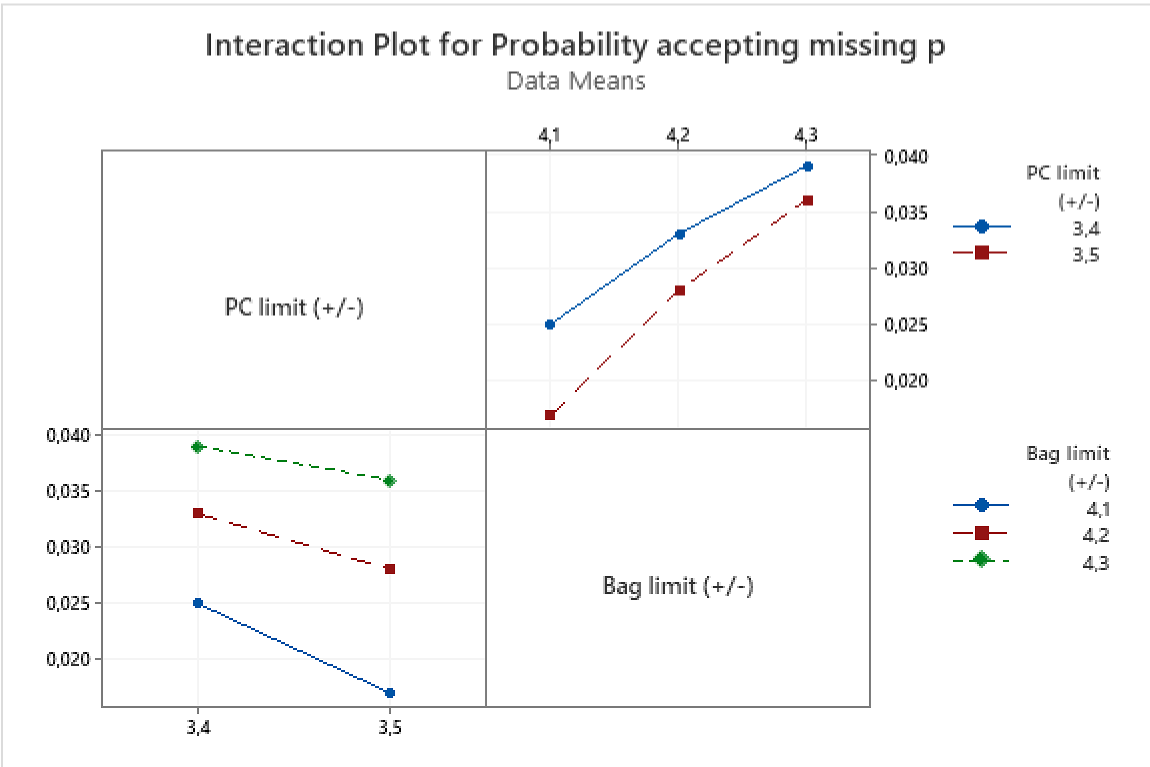


FIGURE 86: INTERACTION PLOT OF SECOND DOE ON REJECTION LIMITS (OBJECTIVE IS PROBABILTY BAG WITH MISSING PAD IS ACCEPTED).

Bag size 72 pads

DOE	Sample size	Tolerances	Steering factor			
1	4		0.7			
2	5	0.1	0.8			
3	6	0.2	0.9			

Experiment	Sample size	Tolerance	Delay	Steering factor	Rework	Missing pad rate
1	4	0,1	12	0,7	130,19	1,4%
2	4	0,1	12	0,8	124,01	1,9%
3	4	0,1	12	0,9	125,13	1,4%
4	4	0,2	12	0,7	148,18	2,3%
5	4	0,2	12	0,8	148,84	2,6%
6	4	0,2	12	0,9	159,00	2,1%
7	5	0,1	12	0,7	135,02	1,6%
8	5	0,1	12	0,8	124,13	0,9%
9	**5**	**0,1**	**12**	**0,9**	**121,57**	**0,9%**
10	5	0,2	12	0,7	147,95	0,9%
11	5	0,2	12	0,8	144,89	2,8%
12	5	0,2	12	0,9	149,15	1,6%
13	6	0,1	12	0,7	140,35	1,2%
14	6	0,1	12	0,8	127,25	0,9%
15	6	0,1	12	0,9	123,58	0,9%
16	6	0,2	12	0,7	152,04	1,9%
17	6	0,2	12	0,8	145,36	1,2%
18	6	0,2	12	0,9	32,31	

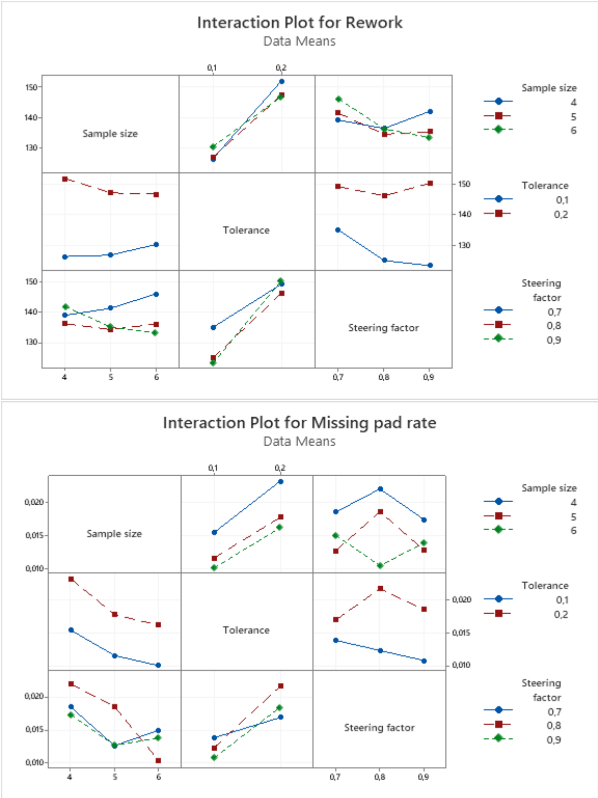


FIGURE 87: INTERACTION PLOTS OF FIRST DOE ON BOTH COFFEE IN REWORK COSTS RATE AND PROBABILITY OF ACCEPTING A BAG WITH A MISSING PAD.

APPENDIX H: LIST OF RESULTS IN THE INITIAL AND BEST POSSIBLE SITUATION PER BAG SIZE

TABLE 38: EXTENSIVE TABLE WITH RESULTS PER BAG SIZE (1/3)

Experiment nr.	*1*	*394*		*2*	*389*		*3*	*366*	
Bag size		**16**			**18**			**32**	
	Old	**Best possible**	**Difference**	**Old**	**Best possible**	**Difference**	**Old**	**Best possible**	**Difference**
Sample size	10	6	-4	10	4	-6	10	3	-7
Tolerance	0,7	0,1	-0,6	0,7	0,1	-0,6	0,7	0,1	-0,6
Adjustment factor	0,5	0,7	0,2	0,5	0,7	0,2	0,5	0,7	0,2
Delay	25	12	-13	25	12	-13	25	12	-13
PC Lower Limit	3	3,4	0,4	2	3,4	1,4	2	3,4	1,4
PC Upper Limit	4	3,4	-0,6	4	3,4	-0,6	4	3,4	-0,6
Bag Lower Limit	4	4,9	0,9	4	4,9	0,9	5	4,9	-0,1
Bag Upper Limit	10	4,9	-5,1	10	4,9	-5,1	10	4,9	-5,1
Coffee in rework costs rate	13,6251	15,857	**16%**	34,9484	15,913	**-54%**	15,6184	20,046	**28%**
Product carrier rejection rate									
Bag rejection rate									
Overfill (overall)	-21149	-11741	44%	18354	12298	33%	-29271	-22248	24%
Probability accepting bag with missing pad									

TABLE 39: EXTENSIVE TABLE WITH RESULTS PER BAG SIZE (2/3)

Experiment nr.	*4*	*308*		*5*	*284*		*6*	*150*	
Bag size	**36**			**40**			**48**		
	Old	**Best possible**	**Difference**	**Old**	**Best possible**	**Difference**	**Old**	**Best possible**	**Difference**
Sample size	10	5	-5	10	5	-5	10	5	-5
Tolerance	0,7	0,1	-0,6	0,7	0,1	-0,6	0,5	0,1	-0,4
Adjustment factor	0,5	0,7	0,2	0,5	0,8	0,3	0,5	0,8	0,3
Delay	25	12	-13	25	12	-13	25	12	-13
PC Lower Limit	2	3,4	1,4	2	3,3	1,3	2	3,3	1,3
PC Upper Limit	4	3,4	-0,6	4	3,3	-0,7	4	3,3	-0,7
Bag Lower Limit	5	4,6	-0,4	3,5	4,5	1	3,5	4,4	0,9
Bag Upper Limit	10	4,6	-5,4	9	4,5	-4,5	10	4,4	-5,6
Coffee in rework costs rate	41,622	20,639	**-50%**	68,4681	21,408	**-69%**	139,8743	26,335	**-81%**
Product carrier rejection rate									
Bag rejection rate									
Overfill (overall)	11659	10557	9%	55511	50031	10%	65924	33652	49%
Probability accepting bag with missing pad									

TABLE 40: EXTENSIVE TABLE WITH RESULTS PER BAG SIZE (3/3)

Experiment nr.	*7*	*408*		*8*	*235*		*9*	*251*	
Bag size	**54**			**60**			**72**		
	Old	**Best possible**	**Difference**	**Old**	**Best possible**	**Difference**	**Old**	**Best possible**	**Difference**
Sample size	10	5	-5	10	5	-5	10	5	-5
Tolerance	0,7	0,1	-0,6	0,7	0,1	-0,6	0,7	0,1	-0,6
Adjustment factor	0,5	0,7	0,2	0,5	0,8	0,3	0,5	0,9	0,4
Delay	25	12	-13	25	12	-13	25	12	-13
PC Lower Limit	2	3,4	1,4	2	3,6	1,6	2	3,6	1,6
PC Upper Limit	4	3,4	-0,6	4	3,6	-0,4	4	3,6	-0,4
Bag Lower Limit	3,5	4,2	0,7	6	3,9	-2,1	4,2	3,9	-0,3
Bag Upper Limit	15	4,2	-10,8	14	3,9	-10,1	4,2	3,9	-0,3
Coffee in rework costs rate	124,4288	35,231	**-72%**	58,2075	62,899	**8%**	114,1704	121,568	**6%**
Product carrier rejection rate									
Bag rejection rate									
Overfill (overall)	14682	9.667	34%	56677	49460	13%	56766	20611	64%
Probability accepting bag with missing pad	s								