Using Discrete Event Simulation (DES) to improve productivity of Shell Ghent's grease manufacturing plant

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Management summary

Research goal and context
Shell's Grease Manufacturing Plant (GMP) in Ghent is a key player in their lubricants supply chain. The plant produces a total annual volume of around 12k ton of different greases, on different production lines. In the past seven years, Shell has observed an increase in the demand of their specialty greases. In the current situation, two of its production lines are fully constraint on their capacity. On two of the six production lines, a total of 78% of the annualized volume is realized. These production lines, R109 and U400, do currently not have the extra production capacity to adapt to uncertainty in demand, the acceptance of rush orders, or the implementation of plant trials as requested by the R&D department. The capacity issues regarding Shell's production lines is identified as the core problem, and leads to the following research question:

"How could Shell increase their production capacity by 8-12% on production lines R109 and U400 in order to deal with rush orders, uncertainty in production demand and RD test requests?"

Modeling approach
Analyzing the current performance and capacities of production lines R109 and U400 is done by means of interviews, observations, and data-analysis. The interviews and data-analysis shed light on several different bottlenecks that are present for these production lines. First, we observed that the current EOL-section is inefficient and stops the production process frequently. The EOL-section ensures that all the greases that are filled in SKUs, are eventually palletized and made ready for transport to the end-customer. Palletizing is done by means of a palletizing robot. This robot is failure prone and had an average OEE of 22% for a 12-week period, where its target was set at around 65%. As operators are responsible for fixing the palletizing robot's failures, it reduces the overall efficiency and productivity of the manufacturing line. Second, the filling capacities for different SKUs are in practice almost 50% lower than the filling capacities as used by the scheduling department. This is mainly caused by time-consuming SKU handlings and a direct result of the failures regarding the palletizing robot, that need to be fixed by process or filling operators.

On a tactical level, we observed the plant suffers from extra production downtime as a result of the inefficient filling and EOL-processes. As the scheduling department schedules the next batch in the process based on its bottleneck time (longest process step on one of the three production kettles), we observed that in several occasions the process suffered from a shifting bottleneck. A shifting bottleneck occurs when a batch has a different bottleneck step, with regards to its schedules bottleneck step. This could lead to production waiting times in case the bottleneck is found on the EOL-section, and not on one of the three production kettles. This EOL-section is connected to both the production kettles and the filling process. This shifting bottleneck causes process downtimes as the filling process is not yet finished before the arrival of a new production batch. To identify and quantify the process downtimes, we make use of Discrete Event Simulation (DES). DES is widely used in the manufacturing industry, to address dynamic (stochastic) and complex systems and allows for both complex decision-making and testing of multiple production scenarios.

We conducted the simulation study in three steps. First, we analysed the baseline scenario for production lines R109 and U400. Second, we tested for individual improvement factors such as increased palletizing capacity, availability, and increased filling capacity. Third, we tested the interaction effects of the individual improvement factors to obtain the best performing combination of improvement scenarios. For each of the three steps, we made use of the same Key Performance Indicators KPI, namely the waiting time for the scrape buffer vessel, the average cycle time per filling order and the average daily volume produced.

Results
The simulation model of the current baseline scenario showed that production line R109 has around 98.8 hours of downtime per six months. U400 did not suffer from any downtimes, due to having batch sizes that are twice as small compared to production line R109. Smaller batch sizes are less likely to process downtimes as the filling capacities are similar for both production lines, and will therefore take twice as long. With the implementation of the individual improvement factors (step 2), we observed that the increase of the palletizing capacity and the robot's availability would in the best cases reduce the overall production downtime to around 70.1 hours per six months. This result was obtained for a palletizing capacity of 400%

and an availability of 90%. Also, the average cycle times for the filling processes were significantly less in compared to the baseline scenario (from 424 minutes in the baseline scenario to 348 minutes). However, the total daily volume remain unchanged. Increasing the filling capacity by 200% for the 18 kg SKU fill station on production line R109, reduced the overall waiting time to 31.6 hours per six months, a reduction of 68% compared to the baseline scenario. The average cycle filling time for 18 kg SKUs, was reduced from 424 minutes to around 339 minutes.

In step 3, we analysed the interaction of the individual improvement factors. We observed that the best performing scenario was marked by the implementation of a palletizing robot with 90% availability and the increased filling capacity (200%) for 18 kg SKUs on production line R109. The total waiting time in the production process was reduced from 98.8 hours in the baseline scenario, to a total of 23.7 hours in this scenario. This improvement scenario yielded a total waiting time reduction of 76%. This improvement scenario also showed the best reduction in SKU filling time for 18 kg SKUs on production line R109 (424 minutes to 339 minutes). Linking the overall waiting time reduction to capacity improvements for the plant, results in an extra capacity of 4.7% for production line R109, or an annual extra volume of 275 tons (34 batches) of grease, as described in Figure 1.

Table 1: Overview of the extra batches that could be produced after implementation of the best experiments

Best performing experiments	Baseline waiting time (hours)	Scenario waiting time (hours)	Improvement (hours)	Theoretical extra batches produced	Annual extra batches produced	Extra volume (tons)
400% palletizing speed	98.8	70.0	28.8	6	12	97
90% robot availability	98.8	70.0	28.8	6	12	97
Increased FS1 capacity	98.8	31.6	67.2	15	30	242
90% robot availability and increased FS1 capacity	98.8	23.7	75.1	17	34	275

With this result, we created an understanding of the current bottlenecks in the production process. First, Shell should address the filling capacities for especially 18 kg SKUs, as this bottleneck has the largest contribution to the overall waiting time. Second, Shell should take measures to either buy a new palletizing robot with a capacity of 400% or put efforts in increasing the robot's availability to 90%. Both options are equally good, but improving the availability of the current robot is most likely the most cost effective option as a processing speed of 400% seeks the placement of a new palletizing robot.

Conclusion and recommendation

For Shell Ghent, it currently is possible improve their current production capacity of their biggest production line (volume wise) by 4.7%. This is realized by the implementation of a palletizing robot with a 90% availability, and an increased filling capacity of 200% for filling station 1 on production line R109. Cost-wise, this is currently not the best option, as it has a fairly high payback period of around 27 months. The improvement scenario with the lowest payback period is the implementation of increased filling capacity for filling station 1. This results in a total payback period of 16.5 months, with a total extra volume of around 242 tons per year. These implementations are capex long term investments, and will seek approval of senior management in order to be realized. On a shorter term, the efforts of the maintenance department regarding extensive Root Cause Analysis (RCA) could be further deployed for increased palletizing availability.

Further research should be focused on the addition of the remaining production lines to the current simulation model. As we only incorporated two production lines, the overall effect of the current bottlenecks could potentially be larger. Further analysis and optimization of the indirect filling process on U400, and reduction of overall filling cycle times for combined filling orders (multiple SKUs) on both production lines are other topics that should be further researched to increase the baseline performance of the plant in terms of productivity.

Preface

This master ”Using Discrete Event Simulation (DES) to improve the productivity of Shell Ghent’s grease manufacturing plant” concludes my master in Industrial Engineering and Management, at the University of Twente. Conducting and completing this research has not been possible without the help and support of others. I would like to take this opportunity to thank everyone around me that helped me realise this challenging research.

First of all, I would like to thank Shell Ghent for the opportunity of doing my master thesis research within their manufacturing plant. I want to thank Davy Poelman for his support, the numerous chats regarding the topic of my thesis, and his phenomenal padel skills during several matches. Your sliced backhand is out of this world! I think Rafeal Nadal could learn a thing or two from your technique. I would also like to thank Raquel Gomez for her inspiring leadership skills and motivational speeches when I was nearing the end of the research. I am sure you will do a fantastic job in bringing the plant to new heights.

Second, I want to say thank you to both Matthieu van der Heijden and Amin Asadi, my supervisors from the University of Twente. It was an absolute blessing getting feedback, comments and insightful conversations with regards to my topic. This overall helped me bringing my research to higher levels, and I am very proud of the end result.

At last. I want to thank my parents and my friends, who helped me through this graduation period. My parents were always there for me on the toughest moments, and I’m grateful for their love and patience. They really helped me to identify and celebrate the small milestones within this research, Finally, I want to thank Robin Rust, Sanne Wopereis and Samson Loboka, with whom I spend the last 2 years studying. We were all in the same boat, and I couldn’t be happier with the way we managed our way through the endless hours of studying inventory models, simulation models, and operations research. Thanks for everything.

I wish you a pleasent reading.

Jesse de Heij

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Glossary

ABS Agent Based Simulation.

AS/RS Automated Storage and Retrievel System.

CSM Current State Map.

DCS Distributed Control System.

DES Discrete Event Simulation.

DOE Design Of Experiments.

DS Dynamic Systems.

EOL End-of-Line.

ERP Enterprise Resource Planning.

FCFS First Come First Serve.

FSM Future State Map.

GMP Grease Manufacturing Plant.

IBC Intermediate Bulk Container.

KPI Key Performance Indicator.

MTBF Mean Time Between Failures.

MTS Make-To-Stock.

MTTR Mean Time To Repair.

OEE Operational Equipment Effectiveness.

OPEX Operational Expenditure.

R&D Research and Development.

RCA Root Cause Analysis.

RCC Resource Capacity Constraints.

SD System Dynamics.

SKU Stock Keeping Units.

TOC Theory of Constraints.

VSM Value Stream Mapping.

WIP Work In Progress.

1 Introduction

This chapter introduces the company, the problem statement and the main research question. Section 1.1 introduces Shell and gives a brief description of its production process, after which section 1.2 identifies the problem. In section 1.3, the problem description is given, after which the research objective and the statement of the research goal are presented in sections 1.4, and 1.5, respectively. Within section 1.6, the main research question and the sub-questions are presented. At last, the scope of the project and the projected timeline, are presented in sections 1.7, and 1.8.

1.1 Context

The Grease Manufacturing Plant (GMP) of Shell Ghent, is the main factory in Shell's grease supply chain. With a total produced volume of around 12k ton of different greases annually, it is Shell's second largest production plant of industrial greases. Not only the plant's volume, but also the wide variety of different greases in its portfolio, is a characteristic for the Belgium based plant. In comparison to other grease plants, the plant produces around 59 unique products, sub-divided over 300 different Stock Keeping Units (SKU).

The products produced in Ghent, are the so-called lubricating greases, which is a chemical mixture of soap, oil, and additives. Its applications are within the manufacturing, marine, and both the energy and automotive industries. Lubrication greases are commonly applied to capital assets that seek higher lifespans, essential for bearings systems and rotating equipment. As these products need to withstand severe conditions when applied, such as extreme temperatures, water or high pressures, they seek strict quality demands.

Next to the production of highly specialized greases, the plant has access to a Research and Development (R&D) facility. This facility develops and tests new products, that are demanded by Shell's customers. The first step of testing new products is done on a laboratory scale. After the laboratory tests, pilot testing is performed on the product lines within the plant. By means of this R&D facility, Shell Ghent is able to further increase and diversify their product portfolio.

Over the past seven years, Shell has observed an increase in demand for their specialty greases. The plant is currently running on full capacity, while they are not producing on the theoretically maximum capacity. In order to be able to fully serve their current and new customers while also adapting to future developments, Shell is looking for extra production capacity within their current production set-up.

1.2 Research motivation

Shell's production plant can be classified as a low-volume, high-mix production process. This is mostly due to the fact that the plant only produces their greases by batches, and therefore capable of producing a high variety of different grease products. The plant also operates by the Make-To-Stock (MTS) production philosophy, since their products end up at different warehouses, where stock levels are being maintained, waiting for further transportation to their end customers.

Ghent's GMP is a plant that produces a wide variety of greases. The plant is set up in four different sections, namely the preparation, core processes, after-process treatment, and the filling section. Figure 1.1 depicts a global overview of the different sections in the manufacturing plant.

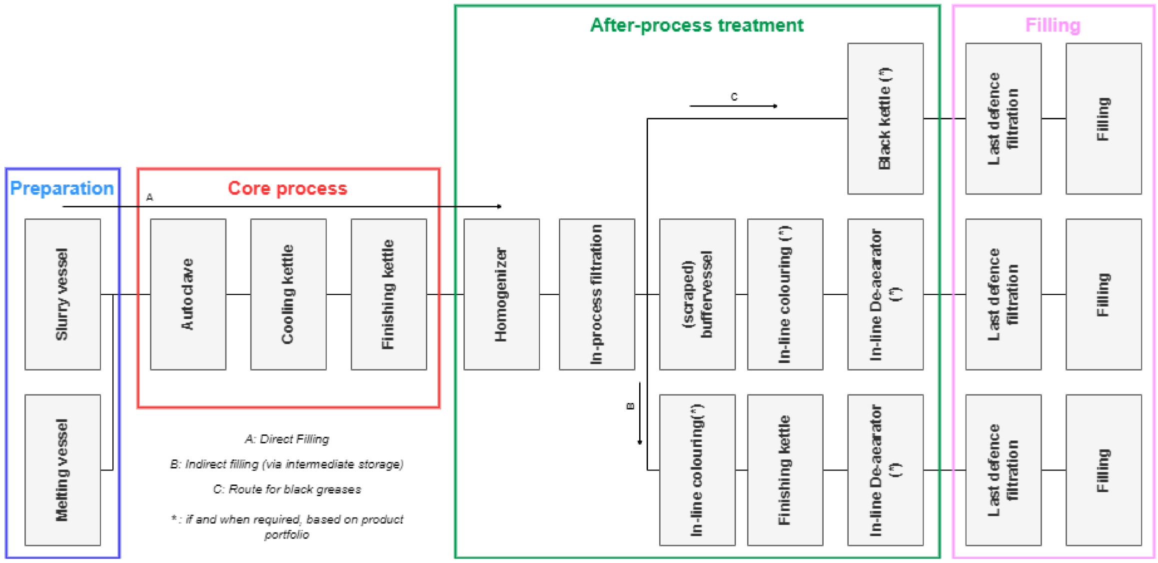


Figure 1.1: Global representation of Shell's production process within Ghent's GMP

Production starts with the preparation section, where dry ingredients with base oil are mixed with each other in to a suspension. This suspension serves as raw material for the majority of the different greases, and is pumped to the core process section.

Within the core process section, a total of three different kettles are responsible for the overall production of the different greases. The suspension is pumped in the autoclave where a chemical reaction, also called saponification, is initiated by the supply of external heat. The saponification process eventually ensures the formation of soap within the oil, up to a level of 20-25% soap is diluted within the oil. After the process in the autoclave, the mixture is further pumped to the cooling kettle. Within the cooling kettle, a physical reaction is initiated that further develops the structure of the soap by gradually cooling and stirring the mixture in the kettle. This process is continued until the 12-15% of the soap has been diluted in the base grease. After this step, the oil/soap mixture is further pumped to the finishing kettle. This kettle is mostly used for the addition of performance additives and adjustments towards the grease's consistency.

The production of Ghent's greases is performed by a total of five different production lines. Three of these production lines, namely the R109, U400, and the Polyurea are currently constrained by their capacity. Operating at full production capacity, means that the production lines are always occupied by production orders scheduled by the scheduling team. Therefore, Shell is incapable of accepting emergency orders, unable to anticipate on high demand forecasts or schedule test runs for the purpose of testing new products. If emergency orders were accepted, it could disturb current production schedules, result in higher lead times and result in potential stock-outs at their warehouses. As demand is also growing over the years, Shell is looking to further increase their current capacities on its R109 and U400 production lines. This is due to the fact that these production lines account for over 78% of the annualized volume produced. The believe of senior management is that 8-12% extra production capacity could be generated on those production lines by further focusing on production efficiency.

1.3 Problem description

In the previous section, a brief description of Shell's production process and an introduction to the problem Ghent's GMP is currently facing, has been given. However, multiple root-causes are supporting the current core problem. Figure 1.2 depicts the problem cluster.

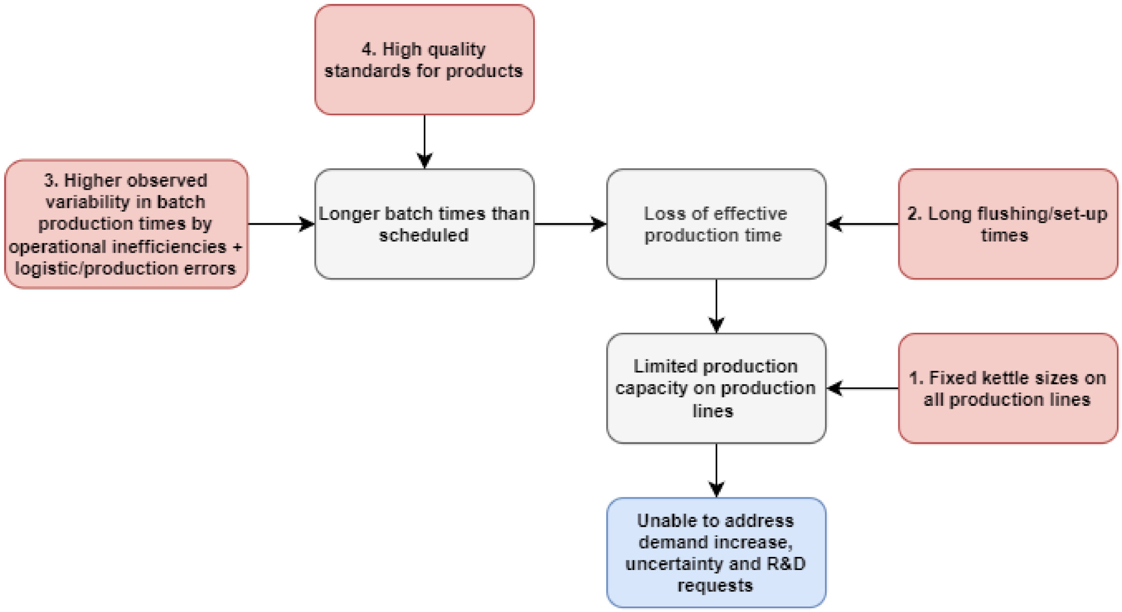


Figure 1.2: Cluster of the problems currently observed within Shell's production site

The initial problem Shell is currently facing is the inability to address increased demand, uncertainty in demand and R&D test requests. This initial problem is caused by the problem that there is limited production capacity on production lines R109 and U400.

The limited production capacity on production lines is caused by one core problem. Core problem one is the fixed kettle sizes that are used for the formation of the greases. Since the kettles are currently used to their full potential, it constrains the production lines in creating extra capacity. An increase in the kettle sizes (and thus the batch sizes) could potentially lead to increased capacity.

The limited production capacity on the production line is caused by the loss of effective production time. The scheduling department believes that the loss of effective production time is directly caused by core problem two, the long flushing and set-up times. Due to the contamination hazards of products, flushing is needed. During a flushing run, the productions lines are unable to be used for production purposes. Shell's quality standard's require all the kettles to be cleaned, to prevent any form of contamination hazards between different product types.

A loss of effective production time is also caused by longer batch times than scheduled. This is sub-ordinate to core problems three and four. Core problem three, which is described as the increased batch time variability due to operational inefficiencies. These inefficiencies are found within the core process and the filling sections. For the core process, it is observed that operators perform manual actions in order to produce the different products, which increases the likelihood of operational inefficiencies. An example of a manual action performed in the core process section, is the transport of additives to the production line and the eventual addition of additives to the greases in the kettle. For the filling section, operators perform multiple manual handlings that cause longer filling times. Other operators have also indicated that there are certain production stops due to inefficiencies regarding the filling section and the End-of-Line (EOL) section.

Core problem four, causing longer batch production times than scheduled, is caused by the high quality standards of Shell's products. Its quality is mainly obtained by long production times. According to the scheduling department, extra capacity could be obtained by reducing the batch production times or by reducing the quality of their products. Therefore, it is necessary to research to what extent batch production times could be reduced to increase capacity.

Based on the presented core problems in the problem cluster, it is believed by the engineering and operations department, that a focus on core problem three will most likely result in the highest capacity improvement.

Therefore, we will research the production process and further analyse the bottlenecks that we observe. We will test the hypothesis as described by senior management, that 8-12% extra production capacity could be realized when focusing on the current operational inefficiencies and production errors.

1.4 Problem statement

Shell's GMP is currently unable to address increased demand, uncertainty in demand, and the ability to perform R&D requests. Based on the information presented in sections 1.2 and 1.3, the following problem statement has been formulated:

"Shell Ghent has no production capacity to respond to peak market demands or R&D requests, due to the overall complexity of the production process and limited production capacity on production lines R109 and U400."

1.5 Research objective

In order to tackle the core problems, and the problem statement as described in sections 1.3 and 1.4, the following main research question has been formulated:

How could Shell increase their production capacity by 8-12%[1] *on production lines R109 and U400 in order to deal with rush orders, uncertainty in production demand and R&D test requests?*

In order to properly answer the research question, and propose solutions that captures the essence of the problem context, it is useful to list the deliverables that are obtained by this research:

1. **Context study:** Key to the understanding on how the different core problems affect the production capacity, a descriptive context study will be performed. This study gives an analysis on the production process. It also describes the tactical decisions made within the production process and how those are related to the core problems as identified in section 1.3. In case further inefficiencies are observed that contribute to capacity losses, those will be further explained as well.
2. **Bottleneck analysis:** With further understanding of the production process, we will identify and quantify the bottlenecks in this chapter. This will result in the understanding and relating each of the bottlenecks towards the production capacity. A Root Cause Analysis (RCA) will be done to understand the underlying reasons for the current bottlenecks. We will also map further inefficiencies if found in the production process.
3. **Simulation model and solution validation:** A simulation model is build to test multiple improvement scenarios for the production capacity of the plant. Within this simulation, the different production lines are recreated and the effectiveness of the different strategies and impact on production capacity are tested. As an input for this simulation model empirical data from historical demand forecasts, historical production data, flushing sequences and the downtimes of the production lines are needed. To simulate the different batches that are produced in the process, we need flushing matrices of in-between production runs (also called set-up times) and the batch times per product type on the production kettles.

1.6 Research questions

To further answer the research question formulated in the previous section, different sub-questions are needed. In total, 6 different research questions are needed that will answer the research question. Each question is subdivided in to a specific chapter.

Chapter 2: Context study

1. *How are production lines R109 and U400 set up and used, and where are current bottlenecks in the production process observed?*

[1] Statement from senior management, as described in section 1.2

It is important to understand the current production process and the decisions made on both operational and tactical levels to grasp Shell's production strategy and philosophy. To further understand the process of manufacturing within Shell's GMP, both scheduling and operational departments will be questioned. Also, different production shifts are attended to understand the complexity of Shell's production process. Furthermore, we analyse the relation of each of the core problems as identified, to the production capacity.

To subsequently deal with the bottlenecks found in the production process, data-analysis must be performed to understand the dynamic of each bottleneck and its limiting factor to the production capacity. To perform an analysis to identify the bottlenecks within the core problems, data is needed. Depending on the different bottlenecks that are observed in the current production process, the data will be collected by the Distributed Control System (DCS) that logs the actions that are performed in the process. The maintenance and production departments have both access to the DCS system and are able to provide the specific data that is needed.

Chapter 3: Literature review

2. *Which methods are available within literature to address the bottlenecks found in the production process?*

This sub-question focuses on the literature review, conducted when both knowledge about the production process and the bottleneck formation in the production process are obtained. First, it is key to understand the fundamentals regarding bottleneck identification and solving current bottlenecks in a manufacturing process. Then, our literature review provides the knowledge for the design and application of simulation modeling to Shell's production process. With the use of a simulation model, we quantify the bottlenecks as observed in the production process, and relate the simulation output to the production capacity.

Chapter 4: Simulation model and experimental design

3. *What should a simulation model look like for Shell's GMP and what possible strategies could be implemented to remove the current bottlenecks that are observed in the production process?*

Based on the content from chapter 2 and chapter 3, we proceed by creating a baseline model of the current production process in which we can both identify and justify the observed bottlenecks. Within this sub-question, a further analysis on the implementation of the model, is given. The model should be created in cooperation with both senior engineers and the operational department, since the model should represent the constraints and production philosophies by Shell. It should simultaneously incorporate the stochastic behaviour of the production process.

Chapter 5: Experimental results

4. *Which model configuration results in the most efficient way of removing the current production bottlenecks and obtain more production capacity?*

In order to answer this research question, the production process is recreated in Siemens' Tecnomatix Plant Simulation 13.2. This tool is capable of incorporating the uncertainty and unpredictability within the production process. Open source tools exist, but we choose Siemens' simulation software due to the pre-existing knowledge on simulation modeling. We further test with the experimental design as described in chapter 4. Finally, we perform additional experiments with the best performing scenarios that show the most improvement with regards to the baseline production capacity.

Chapter 6: Implementation

5. *How can Shell Ghent implement the suggested simulation model within their production lines to remove the current bottlenecks?*

The last sub-question mainly answers the main research question, and combines efforts and results from the previous sub-questions, to answer which model can be considered as the best practice and how Shell could implement the proposed solutions to fulfil the need for extra production capacity.

1.7 Scientific contribution

The scientific contribution of this research, is mostly found in the usage of state of the operations management tools in conventional sectors such as the oil and gas/chemical industry. Simulation modeling, especially Discrete Event Simulation (DES), has not been used in these industries as it mostly concerns continuous processes that do not lend themselves for a discrete approach. These processes are mostly characterised by differential equations that describe the constant change in process parameters. Since the production of grease is concerned by a batch process with mostly discrete process parameters and statistical input values, it is perfectly suited for optimization by DES.

1.8 Scope

For this problem, changing the planning and scheduling of products over the different production lines is not taken into account. This is due to the fact that the planning of production activities is performed by an external Shell office. Also, with Shell's standardized production scheduling tools, it is also cumbersome and redundant to include the scheduling procedure within this research. The standardized Shell tools are already provided with the latest heuristics and algorithm's that should further schedule planned activities to optimality.

This research project also excludes eventual changes to the Enterprise Resource Planning (ERP) system used by both the planning and scheduling department. Since these systems are interconnected with multiple production sites and local warehouses, it is undesired to further change its settings.

Data analysis during the creation of the research proposal indicated that current R&D requests are not significantly using current production capacities. Therefore, this aspect is not considered to be part of the problem cluster and will not be taken into account during this research. With regard to the production process, the different production departments that are listed in figure 1.1, are taken into account. This includes the preparation, core process, after-treatment and filling sections. We will not consider the outbound logistics process since this process is outsourced by a third-party company.

Next to production lines R109 and U400, there is another production line fully constraint by its capacity. This production line is called Polyurea (R105), and is a standalone line that operates next to production line R109. Production of grease on this line, does not interfere with the production processes of R109 and U400. However, it has a shared resource, found in the EOL-section. We will exclude this production line from the scope of this research project, since its annual volume is significantly lower than the volume of the R109 and U400 combined. Senior management believes that more improvements are to be made on the two major production lines R109 and U400.

2 Context study: Production and process description

This chapter answers the research question: “How are production lines U100 and U400 organized and where are current bottlenecks in the production process observed?”. Section 2.1 describes the production layout of the production facility, after which the End-of-Line (EOL) section is explained in a more detailed manner in section 2.2. In section 2.3 we proceed with explaining the observed bottlenecks in the production process, and in 2.4 we conclude this chapter with the conclusion.

2.1 Production Layout

As described in section 1, Shell’s plant is organized as a batch production plant with the presence of different production units such as the U100, U400 and the Polyurea unit. Figure 2.1 depicts the different process flows in the plant.

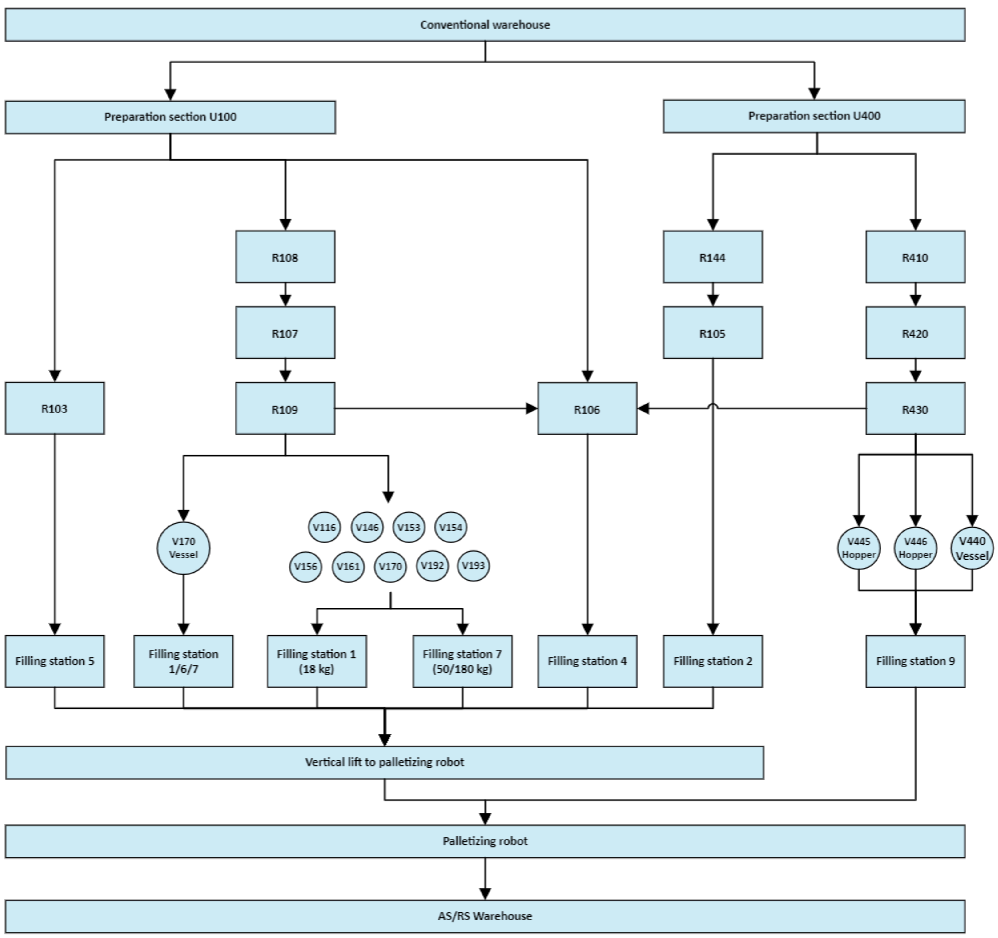


Figure 2.1: Flowchart of the production lines within Ghent’s manufacturing plant.

We classify the layout type of Ghent’s factory as a process layout. Which is described as a layout type in which products, the greases in this case, are transported from one workstation to the other. As depicted in Figure 2-1, we describe the different processes within Ghent globally as the conventional warehouse, the preparation section, core process, the EOL-section and the AS/RS warehouse. This type of layout as depicted above is characterized by specialized supervision and diversified tasks for personnel where its layout type is usually used in low-volume and high variety production settings, which also best describes Ghent’s volume-variety profile. [1]

For each of the production lines, a standard routing for the production from raw material to eventually grease can be defined. This route follows the different process steps which can be shortly summarized. A descriptive and more technical analysis on the conventional warehouse, preparation section and the core processes, can be found in Appendix A:

- Conventional warehouse: Storage of additives, raw materials and packaging materials for each SKU. The warehouse is manually operated by logistics operators and is used to replenish the production units with components for the production of greases. This warehouse is not used for the storage of finalized products.
- Preparation section: Two facilities located near each production unit that allow for weighing and collecting each of the additives and raw materials needed for the production of a batch of grease. Production operators manually weigh each of the components in advance of producing a new batch.
- Core process: The core process characterizes the three production kettles necessary to produce grease. The autoclave is the starting reactor, after which grease is pumped through to the cooling and finishing kettles. Some greases follow different routes, such as the clay and black greases, which are made and finalized on separate kettles. From the core process, products are pumped through to the hoppers (indirect filling) or to a buffer vessel just before the filling sections where the products are being filled (direct filling).
- EOL-section: The EOL-section consists of the filling stations, vertical lift from the R109 production line and the palletizing robot. Here, the finalized greases are filled in SKUs and palletized by the palletizing robot.
- AS/RS-warehouse: Automated storage and retrieval warehouse where palletized SKUs are stored and awaiting final transport to the warehouses. The warehouse is operated and managed by the third-party logistics service provider.

The plant operates in a three-shift system where only from Monday until Friday products are produced. Monday's first shift starts at around 05h45 in the morning, and Friday's last shift is due at 02h45 on Saturday morning. For producing different greases, a production schedule is prepared for a three-week ahead period. The first week of this three-week schedule is fixed, and can therefore not be changed. If a certain batch cannot be finished due to uncertain events such as equipment failures or a lack of workforce, it will not be produced in the current production schedule. It will either be delayed until the next schedule, or it will be cancelled.

During the first phase of this research project, both the production lines from the R109, U400 and the EOL-section have been analysed for potential bottlenecks. Bottlenecks are, in this case, defined as constraining steps in the production lines that limit the throughput of the production processes or time-wise, create delays in the production process. Identifying bottlenecks was done by means of empirical research such as interviews with management, production and the scheduling departments. As the majority of the bottlenecks were identified in the EOL-section, we further analyse and research this section of the production process. We proceed by giving an extensive description about the EOL-section, after which we identify the different bottlenecks.

2.2 End-of-Line (EOL)

As earlier described, is the EOL-section connected to the filling stations and the core process. Here, all the products that are in need of small pack filling (18 to 180 kg) are being filled by filling operators. After filling of each of the SKUs, the products are transported to the palletizing robot, which ensures palletizing of the different products onto pallets. Figure 2.2 gives a schematic overview of the filling stations from both R109 and U400, and the EOL-section. The EOL-section is marked by the weighing station for the filled SKUs, the palletizing robot and the plastic wrapping machine.

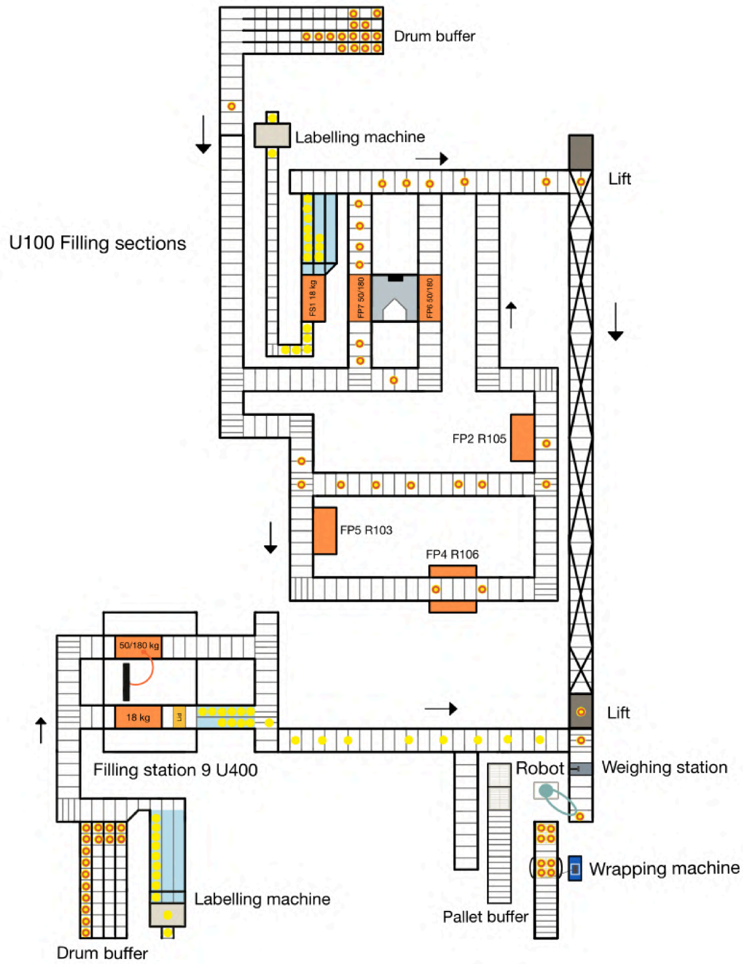


Figure 2.2: Schematic overview of EOL-section. Orange blocks correspond with the filling stations. Yellow dots represent 18 kg pails where yellow/red dots represent 50 or 180 kg drums.

The filling sections and the EOL-section are configured by means of a product layout, where each of the stations is placed along the production line. Advantages of a product layout for this part of the production process are amongst others simple and logic material flows and the use of less skilled personnel. However, this layout type is directly affected by the slowest station in the production chain and could create a stoppage to the entire production chain in case of equipment failures or downtimes. Within Appendix A, different pictures from the filling stations and the palletizing robot are depicted.

For both production units, there are buffers present for the 50 and 180 kg drums that are in Figure 2.2 denoted as the drum buffers. Here, newly arrived drums are stocked until needed for filling with greases. The 18 kg pails are not stocked by means of drum buffers, but are manually retrieved by the operators from the conventional warehouse and then manually inserted in sets of 32 up to 64 pails in the labelling machine that is connected to the conveyor belts of the filling stations. From the filling stations of the U100, each of the

SKUs is transported by means of a vertical lift in combination with a conveyor belt, that transports SKUs from one side of the plant to the other side. Eventually, SKUs from both the production units come together just before the weighing station. If filling occurs on both U100 and U400, a blockage is created just before the weighing station, as the robot is only able to handle one pallet at a time.

2.2.1 Filling sections

Filling of the SKUs is initiated by filling orders. These orders are, along with the production orders, scheduled for a three-week ahead period with a fixed filling schedule for the next week. Filling is usually performed by dedicated filling operators, since this process is considered quite complex, as each SKU requires different handlings. U400 is equipped with one filling operator per shift, whereas R109 has a total of two filling operators per shift for six filling stations. The different filling stations can be briefly summarized:

- *Filling station 1:* A dedicated filling line for filling 18 kg pails within the R109 production line. This station can be used for both hopper and direct fills from the production line.
- *Filling station 2, 4 and 5:* These filling stations are directly connected to the R103, R105 and R106 finishing kettles and are used as dedicated filling stations for the Polyurea, black grease, and clay greases. Only 18, 50 and 180 kg packaging materials are filled in these stations (45 and 170 kg filled volumes are packaged in the same 50 and 180 kg drums for all filling stations).
- *Filling station 6 and 7:* Two dedicated filling lines for filling 50 and 180 kg drums within the R109 production unit. Filling station 6 is used for the direct filling of products, whereas filling station 7 is used as primarily a hopper/indirect fill station.
- *Filling station 9:* Dedicated filling station for the U400, which directly fills from the production line and from the hoppers. Equipped with two lanes for filling 50 kg and 180 kg drums on one line, and filling 18 kg pails on the other. Due to the current set-up of the filling station, it is only possible to fill one SKU at a time.

The operator in charge of each of the filling stations must perform multiple handlings based on the different SKUs that are being filled. Between the 18 kg pails and the 50 and 180 kg drums, noticeable differences are found for their filling procedures. In the table depicted below, an overview of the activities and handlings per SKU type are given.

Table 2: Activities performed per pack type to ensure the filling of the SKUs

Activities performed per SKU type	**18 kg (pails)**	**50 kg (kegs)**	**170/180 kg (drums)**
Retrieval of SKU in conventional warehouse	x		
Retrieval of lids in conventional warehouse	x		
Retrieval of product information labels	x	x	x
Automatic retrieval of SKU from drum buffer		x	x
Manually inserting SKU in buffer lanes	x		
Labelling machine for product information	x	x	x
Manually labelling of product information stickers		x	x
Filling of the SKU	x	x	x
Manually sticker QR-codes on SKU lids	x	x	x
Automatically closing SKUs lid	x		
Manually closing SKU lid		x	x
Plastic liner		x	x

The complexity for completing 18 kg pails is higher than that for the 50 and 180 kg drums, since more activities need to be performed before the filling procedure could be started. 18 kg pails consist of a pail (bucket) and a lid, which need to be retrieved manually from the conventional warehouse, whereas the other two SKUs are being delivered as a complete SKU, including the lids. A drum is for both production units stored in the drum buffers, which are located next to the filling sections. Then, filling operators proceed by retrieving the right product information stickers, which are placed manually on drums and kegs. For pails, a labelling machine is used that labels both sides of the pails. A filling operator is needed to manually insert the labels to the machine, which is directly connected to the buffer lane for the pails. After successfully labelling of the pails, the operator requests the transport of the SKUs to the filling stations. Here follows a semi-autonomous filling process where both the drums and pails are one for one automatically filled.

After filing of each of the SKUs at the filling stations, there are buffer lanes in place that are filled up to the total number of SKUs that fit on a pallet. The 18 kg pails are palletized per 32[2] SKUs, 50 kg kegs are palletized per nine SKUs and 170/180 kg drums are palletized per four[3] SKUs. The finished SKUs are in the U100 transported by means of a vertical lift and a conveyor belt that is connected to the palletizing robot. The conveyor belt for the U100 is also simultaneously used as a buffer, which can contain one full pallet of 18 kg pails.

2.2.2 Vertical lift U100

All finalized SKUs from U100 follow the route to the palletizer by making use of the vertical lift that connects both the palletizer and the U100 with each other, Figure 2-6. Here, each SKU is moved individually into the lift and is transported by a conveyor belt to the other lift module. It is frequently observed that the vertical lift is not able to process all the incoming SKUs from the filling sections, or that the lift itself shuts down. The former issue is a result of the slow processing speed of the lift and the lack of trays where SKUs could be placed, where the latter is a result of the palletizing robot that gets into error mode. The lift is equipped with a total of six trays that pick SKUs from the filling stations (U100) and drop them off at a platform above the filling stations. From here, the conveyor belt moves the SKUs to the palletizing robot. Each 12 seconds, a SKU can be picked up from the filling stations, which brings its total capacity to around 5 SKUs per minute.

2.2.3 Palletizing robot

The palletizing robot marks the end of both the R109 and the U400 production line. The robot ensures that each of the final products is placed on a pallet, after undergoing a last set of quality checks for each of the final products:

1. Weighing: Each of the products is weighed by a checkweigher to verify the total weight of the packaging material and the grease, to ensure that the customer receives the correct quantity according to the EU packaging legislation (council directive 78/1031/EEC). The product weights are logged in a dedicated server.
2. Data-matrix scanner: Each of the products is equipped with a unique data-matrix that is labelled on the lid of the packaging material. A 2D camera is mounted above the scale to read the matrix. This piece of data contains information with regard to the batch number, product id, packaging material and the filling operator that filled the particular SKU.
3. Handle alignment: For the 18 kg SKUs, an additional mechanic is introduced that rotates each of the pails to ensure that the handle of the pails is placed correctly. Each of the pails should palletized by the same way.

2.3 Bottlenecks within the production units

To understand the formation of bottlenecks in the production process, we first describe the production lines in a more simplistic way. As described in more detail in Appendix A, both production lines from U100 and U400 produce in either a direct or indirect route. Greases that are produced direct, are filled directly after production, whereas indirect greases are temporarily stored in buffer/hopper units. Ghent's production philosophy is based around a bottleneck scheduling method, in which the scheduling department takes into account the longest step in the production process (bottleneck) and schedules the next batch for that production line around this bottleneck. We can further simplify both the production units in terms of a

[2] Asian production orders are palletized per 24 SKUs due to the smaller pallet dimensions for this market
[3] Asian production orders are palletized per three SKUs due to the smaller pallet dimensions for this market

three-kettle process, combined with the filling process and the EOL-section. Figure 2.3 depicts the production process with the presence of the three different production kettles and an extra dot representing the buffer kettle and the following filling and EOL processes. In this overview, four different bottleneck scenarios that arise within the production process of direct product fills, are illustrated.

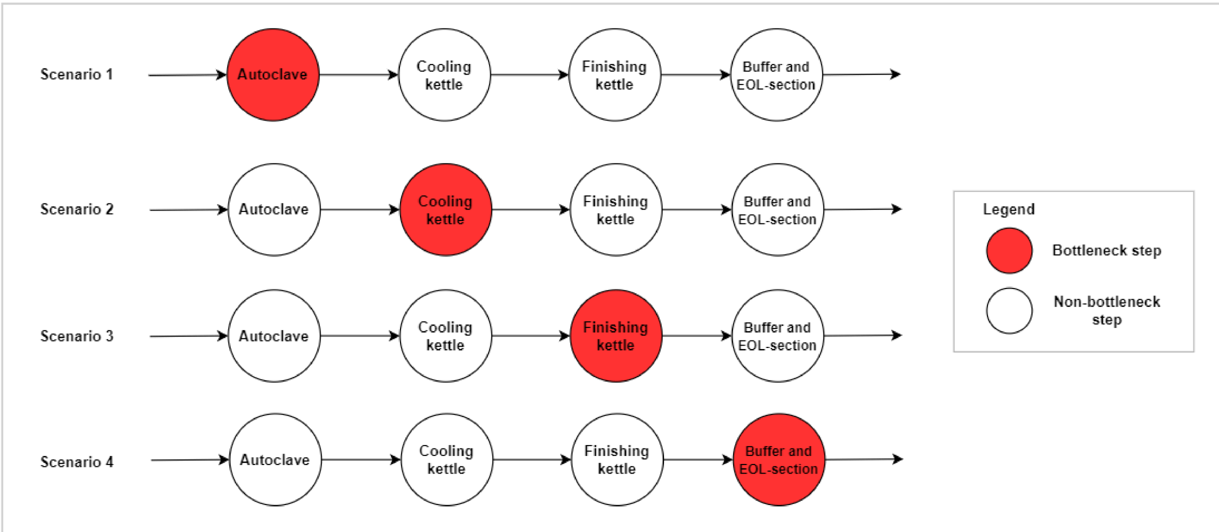


Figure 2.3: Overview of the bottlenecks in the production processes for both the R109 and the U400 production lines, with the red marked circles identifying the bottlenecks in the production process.

Figure 2.3 depicts both the R109 and U400 in terms of their production process. Scenario one occurs with products that have the longest process step in on the autoclave kettle. In this scenario, the next batch could be entered in the system whenever the current batch is done processing on the autoclave. For scenarios two and three, which are marked by bottlenecks found on the cooling and finishing kettle respectively, multiple batches can be initiated as long as the bottleneck kettles are empty at the arrival of the next batch. In each of the scenarios, there is a buffer vessel present and located after the finishing kettle. This buffer allows for the finished product to await for the filling process. In the first three scenarios, the filling times are lower or equal to the scheduled filling times which ensures that the buffer vessel is empty before the arrival of the next batch.

In the last scenario, scenario 4, there occurs a shift in the bottleneck. This is caused by a longer time period to empty the contents of the buffer vessel. A longer emptying process of the buffer vessel is marked by, amongst others, a slower filling process or operational issues in the EOL-section. These operational issues eventually cause a delay in the production process as products need to wait on the kettles until the next in line is empty. During the attendance of production shifts, we observed that both inefficiencies regarding the filling process and downtimes of the palletizing robot caused a shift in the bottleneck from scenario three to scenario four. In the sections below, we further describe the issues that have been observed.

2.3.1 Frequent breakdowns in the EOL-section

The palletizing robot is located in the EOL-section and ensures that all the filled SKUs from the filling stations are palletized. Currently, there is one palletizing robot present that needs to fulfil the palletizing activities for both the production units. During the attendance of several palletizing cycles, we observed that the palletizing robot stopped working in 15 of the 18 occasions. Whenever the robot stops working, the EOL-section becomes a bottleneck for the connected filling stations and the production process, since filling operators cannot continue their filling activities until the issues regarding the robot are solved. The stoppage of the palletizing section can cause a cascade of events: filling operators that need to resolve the ongoing palletizing issues, a delay in the filling process and eventually a delay in the production process as filling is not done in the time that is set by the scheduling department.

Based on interviews with the operators and the production department, it occurs around twice a month that the production process is delayed due to a stoppage in the EOL-section. This bottleneck can be linked to core problem three, which describes the issue where batch production times are increased or batches are delayed as a consequence of operational inefficiencies and issues. The palletizing robot ensures palletizing of all the SKUs that are filled in either 18, 50 or 170/180 kg packages. It makes use of a hydraulic system to grip, lift, and place the SKUs on a pallet, as such it can be stored in the AS/RS warehouse.

The palletizing robot stops working in case an error mode is received in the control system. Currently, the error modes can trigger either a “long” or a “short” stop. A long stop is characterized by a stop that takes longer than 240 seconds, whereas all other stops are labelled as short stops. Short stops are in most cases solved by a system reboot or reset, which is performed by the system itself. In case of a long stop, an operator from the filling station or from the production units walks to the robot, after which it checks for the specific problem and proceeds by solving it. If the operator is not able to solve the current issues by themselves, a shift supervisor is asked to solve the issue. The difference in frequencies for short and long stops, and respectively their durations, are depicted in table 3.

Table 3: Overview of short and long error modes as logged by the EOL-section for a three-month observation

Type	#Stops	Percentage of total stops	Total duration of stops (min.)	Percentage of total duration
Short	35083	93,4%	8410	22,3%
Long	2481	6,6%	29407	77,7%
Total	**37564**	**100%**	**37817**	**100%**

This data is a three-month observation from the error modes that are logged by the control system that in the EOL-section. The total number of long stops is lower than the total number of short stops. However, the total time of all long stops combined is significantly larger than the total time the robot spends in short stops. As the short stops are solved by the system itself, we only take the long stops in further consideration. If we further analyse the dataset to understand the impact of the downtimes of the EOL-section on a production shift, we obtain the following data as depicted in Table 4.

Table 4: Impact of downtimes in the EOL-section on the filling times of a filling operator

Impact of long stops on a filling shift	
Number of long stops in observed period	2481
Number of worked shifts in observed period	181
Avg of long stops per shift	14
Number of long stops per hour	1,75
Avg downtime per long stop (min.)	11:58
Avg downtime per hour per shift (min.)	20:44

Filling operators encounter on average 1,75 long stops per hour with an average length of 20:44 minutes per hour. This means that the EOL-section is currently not working efficiently, as there are unnecessary downtimes that limit both the EOL-section and filling operator’s efficiencies. Root causes for the large number of stoppages are amongst others: the plastic wrapping machine, general warnings, the palletizing robot, the pallet buffer and the lift section for production line R109. These are responsible for over 80% of the total failures encountered in the EOL-section. At the time of writing, we cannot link the types of stops to the duration of the stops since that specific data connection is currently not in use by the maintenance department. Figure 2.4 depicts a Pareto analysis of the failures as observed at the palletizing robot.

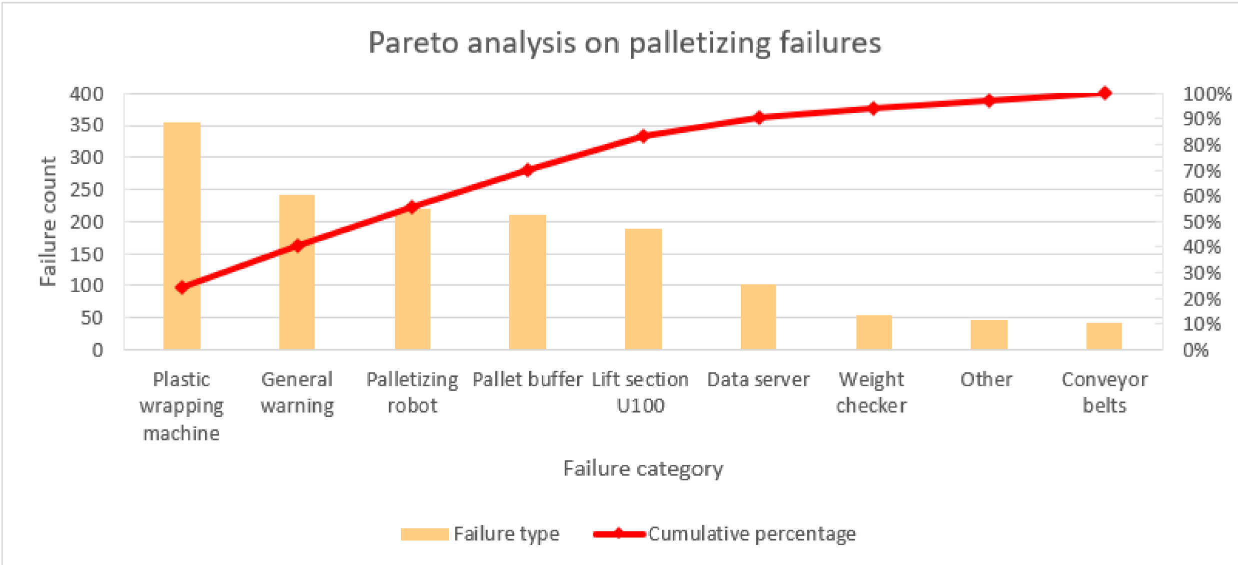


Figure 2.4: Pareto analysis of the failure categories and failure counts for the systems and processing units surrounding the palletizing robot

At last, we determine the Operational Equipment Effectiveness (OEE) for the palletizing robot as Shell's performance measurement for their equipment is quantified by means of the OEE. The OEE is a measure of equipment's availability, performance, and quality. We quantified the OEE by means of the formula below, which is used by Shell to determine the OEE. Here, the scheduled production time of the robot is based on the theoretical time it takes for all filling orders to be palletized. At the moment, the current performance rate of the robot is set at 60% as a higher rate was previously causing issues such as losing grip of the SKU.

$$OEE(\%) = \frac{Scheduled\, palletizing\, time\ -\ Down\, time\, robot}{Planned\, palletizing\, time} * \frac{Current\, processing\, rate}{Ideal\, processing\, rate} \tag{2}$$

The target OEE for the robot is 65%, which the robot fails to meet in any of the occasions. On average, the robot has an OEE of 22%. The OEE for week 7 was 0% and significantly lower than the other weeks. This observation is explained by a downtime of the palletizing robot that was as long as the scheduled palletizing time. This specific instance is caused by reduced filling volumes on the filling station of U400, which is located closer to the palletizing robot than the filling stations of U100. Since the distance for operators to cover from the U100 to the robot is longer than for the operators from the U400 to the robot, it takes twice as long for an operator to resolve issues regarding the robot.

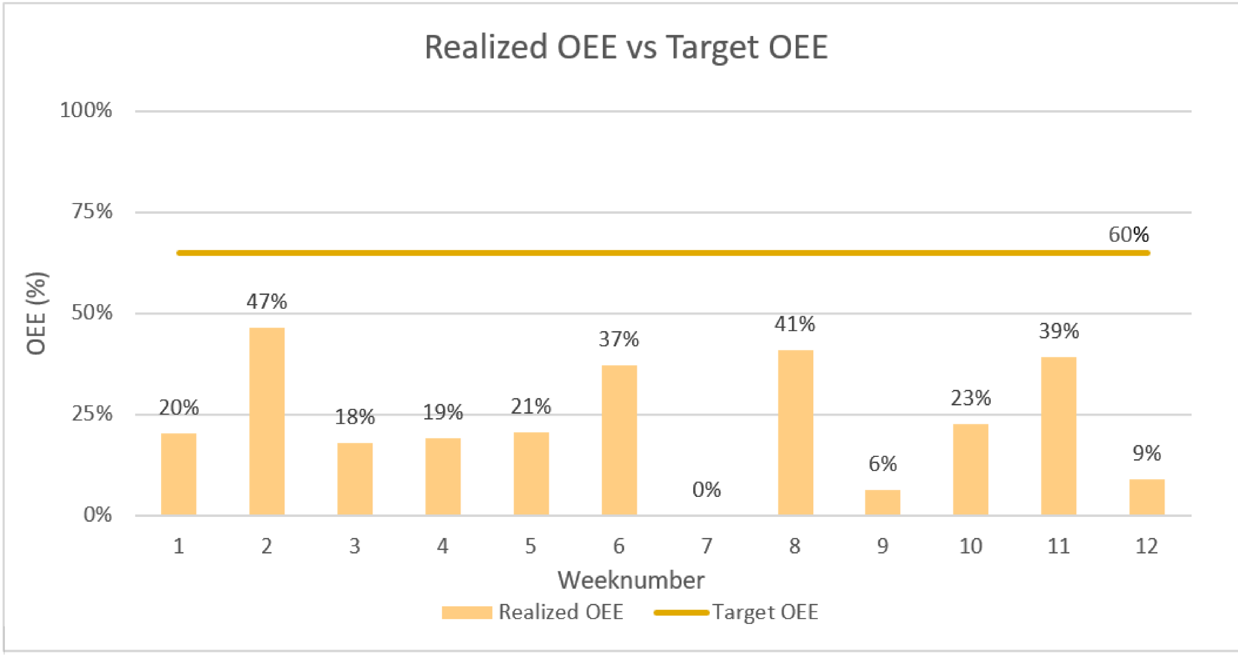


Figure 2.5: Development of the OEE Key Performance Indicator (KPI) for the palletizing robot during the first 13 weeks of 2022

Currently, neither the production nor the scheduling departments have an idea on the impact of the palletizing issues on the production capacity. What is known, is that a blockage of the EOL-section and the production process happens on a regular basis, around twice a month, and that these problems cause a delay in the production process. This is confirmed by operators and production management, where both departments stated that the production process is delayed as a result of the low OEE and failure modes of the EOL-section. Another observation, is that current inefficiencies regarding the stoppages of the EOL-section are affecting efficiencies of the filling stations, as the operators of those stations are constantly bothered by resolving issues within the EOL-section. This causes even further delays in the filling process.

2.3.2 Reduced filling capacity and increased filling cycle times for the filling stations

Another bottleneck that has been identified, is the reduced filling capacity of the filling stations in comparison to the intended specifications for which the filling stations have been designed. In the initial design, the capacities of the filling stations are determined by a pump that is connected to each of the filling stations. In practice, this capacity is not achievable since filling operators need to perform several handlings that limit the amount of SKUs that they can fill. Another reason for not meeting the designed filling capacities is due to an installed homogenizer before the filling station, which currently causes pressure loss in the filling station. At last, the issues regarding the palletizing robot in the EOL-section reduce the effective filling capacity of the filling stations due to the downtimes that need to be resolved by the filling operators. The combination of the mentioned three factors, result in overall lower filling capacities.

Hence, the effective filling capacity is not limited by the connected filling pumps, but by the numerous handlings and inefficiencies that filling operators encounter to keep the filling stations operational and ongoing. In Table 5, we analysed the effective filling capacity, the realized filling capacity, and the designed filling capacity. In which the latter is used by the scheduling department to schedule all the filling orders. The effective filling capacity is the effective time needed to fill all the SKUs, whereas the realized filling capacity is the total time needed to complete a filling order and includes downtimes, operator handlings and movements to ensure filling.

If we compare the current filling procedures for each of the SKUs, we observe that filling of 18 kg pails is currently taking almost twice as long as scheduled. The realized filling capacity for the average order size and

Table 5: Filling capacities for the filling stations that ensure direct filling straight from the production process into SKUs

Direct filling capacities				
Filling station	**SKU type**	**Scheduled filling capacity (units/hour)**	**Effective filling capacity (units/hour)**	**Realized filling capacity (units/hour)**
FS9	18	85	79,6	52,1
FS9	50	60	41,2	19,0
FS9	180	45	24,1	13,0
FS1	18	85	82,9	49,5
FS6	50	60	45,6	27,0
FS6	180	45	24,3	13,0

duration, is averaged at 50,8 SKUs per hour (for filling station 1 and 9), whereas the scheduling department uses 85 units/hour as the current filling capacity. A discrepancy between both values is observed due to inefficiencies regarding the filling process. Inefficiencies are defined as availability losses and are added to the realized filling capacities. These availability losses could be explained by failures from the palletizing robot, the complexity regarding the 18 kg pails, retrieving wrong SKU labels or the slow material handling process of SKUs to the palletizing robot. This material handling process is within Shell called as the branching process from SKUs from the filling stations to the palletizing robot. This process is in more detail described as the removal from 18 kg pails from the filling stations to the palletizing robot. Currently, at U400s filling station (FS9), operators need to wait approximately 7 minutes per 32 SKUs to continue their filling process, as there is no buffer in the process that allows the operator to continue its filling process. For filling station 1 (R109), this process is more efficient as the operator has a buffer of 16 pails which he/she can fill after completing a full pallet of pails (32 units).

Linking the slower filling speeds of especially the 18 kg SKUs to increased waiting times in the production process, is conducted by analysing the production data from 2021. Here, we linked production runs that subsequently needed to be filled in 18 kg pails and analysed for each of these products where its bottleneck was located in the process. This could be on one of the three different kettles in the production process, and by increases waiting time, shift to the EOL-section. In case more than 2 batches needed to be filled directly in 18 kg, we could observe increase waiting time in the process, as it simply takes too long for an entire batch to be filled before the arrival of a new batch.

We analysed FS1, which is the 18 kg filling station from R109. This filling station fills on average 325 SKUs per filling order. Its effective filling capacity is around 82,9 units per hour, whereas its realized filling capacity falls just short of 50 units per hour (Table 5). The difference in filling a complete order is around 3 hours extra, in comparison to the target time that the scheduling department uses for their production schedules. The decrease in the filling capacity and hence, the increase in filling times, resulted for this filling station in extra waiting times in the core process. Table 6 describes for 19 different production runs, which we obtained by analysing the production data from 2021, the extra waiting times that occurred when filling in 18 kg SKUs.

Table 6: Analysis of production runs in 2021 with the total number of batches per run larger or equal to two, and the total waiting time per batch due to an inefficient filling and EOL-process.

Production run	**Batches in run**	**Total duration of filling (hr.)**	**Waiting time due to filling bottleneck (hr.)**
1	3	14,0	0,0
2	2	9,7	0,0
3	3	24,9	8,7
4	2	13,5	3,2
5	2	19,6	5,8
6	2	13,0	1,5
7	2	11,6	1,1
8	2	8,1	0,0
9	3	17,9	2,6
10	6	34,7	0,0
11	2	8,7	0,5
12	6	44,0	5,8
13	5	22,3	3,1
14	2	15,9	3,1
15	5	20,3	3,6
16	3	27,6	3,0
17	3	20,6	7,2
18	2	16,3	5,2
19	4	25,1	8,7
Total			62,9

Based on the analysis for FS1, we observe that in total, 63 production hours on the U100 production line could not have been used for production purposes solely due to waiting times. Due to the increase in waiting times before greases could be directly filled, the scheduled batch times for the production process could not have been met. This is described as the phenomenon that operators indicated, that the production process is halted due to the inefficiencies in the filling section. For FS9, the filling station of U400, we did not observe delays in the production process as a result of the slow filling capacity due to the smaller batch sizes. However, the inefficiencies regarding FS9 are mostly a result of the direct connection to the palletizing robot which causes unnecessary movements and handling for the filling operators. Further, optimizing the filling capacities and reducing the EOL-section failures, will most likely improve the current baseline performance of production waiting times, and improve operator utilization in the filling sections.

2.4 Conclusion

In this chapter, we answered the first research question ‘How are production lines U100 and U400 organized, and where are current bottlenecks in the production process observed?’. We observed that the current production process is prone to several bottlenecks. In the EOL-section, the palletizing robot stops working on average 20 minutes per hour. Its OEE was averaged for a 12-week period at 22%, which is below Shell’s target of 65%. This results in a very inefficient EOL-process, since the robot is currently not performing whilst it should be palletizing finished SKUs. It is currently not known what the impact of the issues regarding the palletizing robot are in terms of productivity and production capacity.

Next to the issue regarding the palletizing robot, we observed that there are delays in the production process whenever greases are directly filled from the production lines (direct filling route). Especially for the R109 production line, we observed that the filling process takes 54% slower in comparison to the scheduled filling times. For R109, this is especially a problem since the batch volumes are twice as large in comparison to U400, and that a slow filling process of 18 kg SKUs causes a delay in the process. We identified and quantified the delays for the R109 whenever 18 kg SKUs were to be filled directly from the production line. As we understand the delays in the production process due to a slow filling process, we currently do not know how this impacts the overall production capacity of R109 production line.

To further understand and research the impact of the delays in the production process and the inefficiencies regarding the EOL-section, we need to create a simulation model that provides insights in the performance of the current production process. Then, we proceed by the simulation of production improvements that improve the baseline performance of the production process. This includes scenarios for the palletizing robot (increasing OEE or the implementation of a different robot) and the filling capacities (reducing operator handling and possible redesigns of the filling stations). Within the simulation model, we should pay close attention to defining performance measurements for the production process. These measurements should identify the total time that is lost in the process, such that we can quantify the number of extra batches that could be produced extra, as a result of the improvement scenarios.

3 Literature review

In this section, we answer research question two 'Which methods are available within the literature to address the bottlenecks found in the production process?'. We proceed by explaining bottlenecks in general, how a bottleneck is identified and how mitigating bottlenecks in a production setting can be performed. In section 3.2 we further research simulation models as a functional tool to identify bottlenecks in a process and link to production performance. We conclude this chapter by explaining how a Discrete Event Simulation (DES) study is performed (section 3.3) and how incorporating lean's principles and tools in a simulation model further improves the baseline performance of a production process (section 3.4).

3.1 Bottlenecks within manufacturing processes

In order to understand what each of the identified inefficiencies mean for the production process, we must clarify the term bottleneck and how bottleneck dynamics influence a production process. According to Goldratt [2] and Lenort [3], bottlenecks are defined as the weakest links in a production process that disrupts the process' continuity and material flow and impact's capacity utilization. Bottlenecks can be encountered in multiple qualities, but based on current literature, we can conclude that there is no unanimous consensus about the exact definition or whereabouts of a bottleneck in a system. Lawrence and Buss [4] described that there is no uniform expression for bottlenecks, but that in general, they can be described as follows:

- Congestion points or bottlenecks, primarily occur when manufacturing resources required in a given time period are unavailable
- A bottleneck is defined as a process that limits throughput
- Production bottlenecks are considered to be temporary blockages to increased inputs
- Facilities, functions, or departments that impede production
- Bottleneck operations are operations that limit the outputs

Given the numerous definitions of bottlenecks, we observe that bottlenecks can be formed by both resources, operators, equipment and certain processes within a production chain. Lin et al. [5] states that a bottleneck is in general found in a machine that has the slowest production rate, or that the bottleneck is a buffer in which its Work In Progress (WIP) is the largest of all buffers. In comparison to Li, Chang et al. [6] describes a bottleneck as the machine's which has the highest sensitivity to the overall system's throughput.

However, not all the capacity limiting factors in a process are bottlenecks. In literature, there is a difference made between bottlenecks and Resource Capacity Constraints (RCC). According to Hohmann [7], bottlenecks are defined as resources with capacity less or equal to the demand that flows through the plant, while an RCC is often a limiting factor to an organization's performance. A constraint can be called a bottleneck, but a bottleneck cannot always be called an RCC. In case of multiple bottlenecks, it is always the resource with the slowest production rate that can be defined as both an RCC and a bottleneck.

For this research we use the definition as explained by Goldratt [2] and Lenort [3], that a bottleneck is defined as the weakest link in the production process that disrupts continuity and material flow. In Shell's production process, we observed breakdowns and decreased filling speeds in the EOL and filling sections respectively. These sections are therefore considered as the bottlenecks in the production process.

3.1.1 Identifying bottlenecks

Identifying and managing bottlenecks was described in the Theory of Constraints (TOC), which is a production philosophy focusing on the weakest links in the production process to improve throughput. It is assumed within TOC that there are no stable systems present in the manufacturing space that do not have a bottleneck. Every system is to a certain extent facing some sort of bottleneck that limits for greater throughputs. For increasing a manufacturing's throughput and efficiency, as well as other performance measurements such as productivity, cycle or lead times, identifying and managing process bottlenecks is a key element for continuous improvement.

Implementation of TOC, according to Goldratt and Cox [8], follows a five-step iterative process which is called the Five Focusing Steps (5FS). This method should be used for identifying and resolving bottlenecks in production processes and can be briefly summarized as follows:

1. Identify the system's constraints
2. Decide how to exploit the system's constraints
3. Subordinate everything else to the above decision
4. Elevate the system's constraint
5. If, in any of the previous steps a constraint is broken, return to step 1

The first step describes the constraints that are currently observed in the system and which should be quantified in terms of performance. Performance measurements for a production plant are mostly expressed in terms of cost, quality, delivery (lead times), and flexibility [9]. Goldratt and Cox further emphasize the performance measurement of a production system in terms of throughput, inventory, and the overall operating expenses. Then, exploiting the current bottleneck means that we look for the highest achievable output by eliminating the certain limitations around the bottleneck. At last, we subordinate the entire production chain to the bottleneck found in the previous step, along with its capacities and throughput and start a new iteration to identify new bottlenecks in the production chain [8].

Ronen and Spector [10] state that from the initial design of 5FS, it became unclear to what extent a system needed to be improved and what performance measurement in this case was used to enhance performances. Therefore, they improved the 5FS with two additional questions that should be answered before starting the iterative process to understand the eventual goal of the researched system and its performance measurements:

1. Set-up and define the overall goal of the system
2. Determine the global performance measurements of the system

Lenort and Samolejová [3] describe the practical implementation of identifying bottlenecks in a low volume and high product-mix setting such as a metallurgical production plant. In such a production facility, the production output and throughput are strongly determined by the overall product-mix and the different SKUs that need to be produced. The characteristics of this plant are in line with Ghent's production plant, where many product types of greases are produced and eventually are being filled in numerous SKUs. For such a manufacturing plant, by observation and experience bottlenecks could be identified. For more complex processes, bottlenecks could be found in operations that are often delayed or stock that is accumulated within certain processes. In case bottlenecks are not found in first sight, capacity calculations should be performed for both the general production process as the individual workplaces. This will create insights in spots with either over or under capacity. At last, a computer simulation model turns out to be a universal and efficient tool in identifying the capacity bottlenecks if the first two steps suffice in finding bottlenecks [3].

3.1.2 Mitigating bottlenecks

After identifying bottlenecks, one should proceed by improving the equipment, machine, or utility, that is marked as a bottleneck. Chang et al. [6] describe that there are in general four different initiatives to improve the identified bottlenecks. The first initiative is to increase a machine's Mean Time Between Failure (MTBF), or in other terms, its reliability. This parameter is described by the overall time in between equipment or machine failures and is described by the failure rate (λ) and the MTBF formula [11]:

$$MTBF = \frac{1}{\lambda} = \frac{Total\, operating\, time}{Total\, failures} \tag{3}$$

Increasing the MTBF will increase the time between failures, and is achieved by lowering the failure rate or increasing the operating time of the machine or equipment. The second initiative is reducing the Mean Time To Repair (MTTR) for an identified bottleneck. Reducing the time to repair broken down equipment, is described by the repair rate (μ) and the MTTR [12]:

$$MTTR = \frac{1}{\mu} = \frac{Total\, number\, of\, maintenance\, actions}{Total\, maintenance\, down\, times} \tag{4}$$

Reducing the MTTR is achieved by focusing on maintenance efforts that will more easily fix a current equipment failure. This could be achieved by simplifying the design of equipment which makes it easier to repair, or more awareness should be created that certain equipment is for example in a failure mode and that maintenance engineers reduce the total maintenance downtime.

At last, Chang describes that increasing buffers before and after the bottleneck, as well as increasing the bottlenecks' capacity, could be a potential solution to reducing bottlenecks in a production process. The downside of introducing buffers in to the process, is that it increases work in process (WIP) and in-process inventories. This is against the principles of lean thinking (section 3.4.1) and increases the overall operational expenditure (OPEX) to finish all the products [6].

3.2 Simulation models for bottleneck identification

Simulation models have been an emerging method to identify and mitigate bottlenecks within production or logistics systems [13]. The use of simulation models and its exact definition are shortly described by Law [14] as 'in simulation, we use a computer to evaluate a model numerically, and data are gathered in order to estimate the desired true characteristics of a model'. We make use of simulation models to recreate existing systems that are too complex to be approximated by analytical methods. Simulation models are, just as numerical methods, based on mathematical models to capture the characteristics of equipment, operators, or material flows in a production setting but allow for more complexity. Alternatives to creating simulation models for production systems are depicted in Figure 3.1.

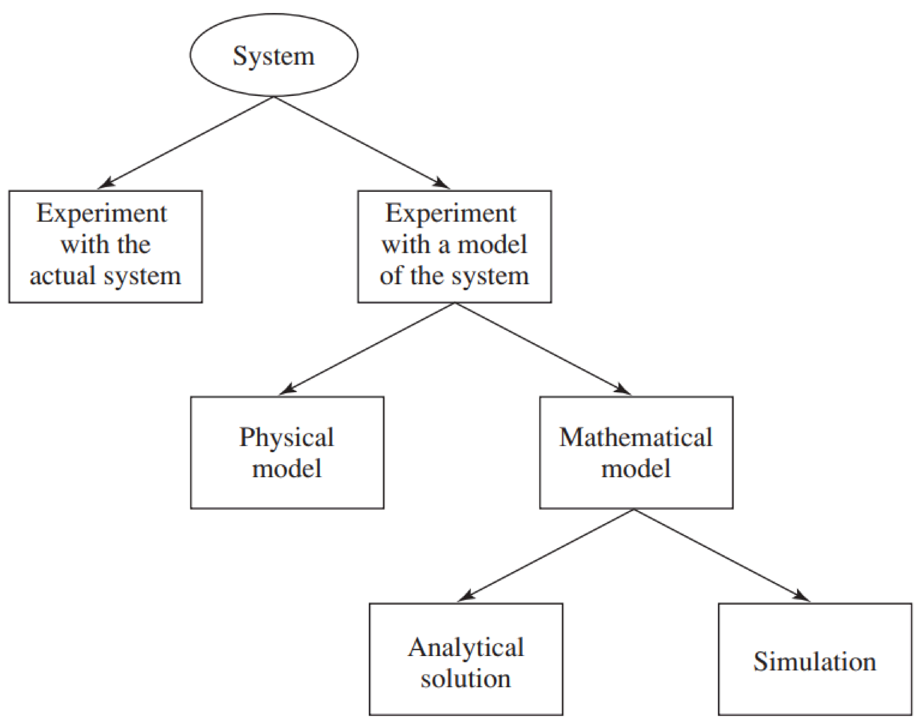


Figure 3.1: Different ways to analyse production or logistic systems (Law, 2005)

Analysing production, logistic or business process systems can be performed based on experiments with actual systems or models. In practice, this is not recommended since it can heavily affect the process that is subject to experiments, and it can be very costly to change a current system and its dynamics. Therefore, it is more common to either make use of physical models (e.g. scale models of a system itself) or mathematical models (such as analytical or simulation models) as described previously, which allow for recreating a system by means of computer program's.

3.2.1 Analytical solutions and simulation modelling

In recent literature, Li et al. [15] describe the usage of simulation models and analytical models for production environments, as more process and production data are nowadays becoming more easily available. Bottleneck detection can either be done analytically or by means of simulation models. Analytical models are a simplified version of real models, where machine characteristics such as its down-time and the processing times of the jobs are assumed to be exponentially distributed, in most cases. Law [14] agrees with using analytical models for simplified production processes and describes that analytical models are only used in case system relations are simple enough and therefore can be described by probability theory or calculus. For simple production lines with one machine and a buffer, analytical models generally work quite well in approximating the simulated solution.

Bottleneck detection based on analytical models is done by an iterative algorithm called decomposition, which breaks down the production line in smaller segments in order to analyse each of the segments individually [15]. Gashwin [16] states that the amount of evaluations for the proposed algorithm increases as a result of increased production line length, and that the time to solve an analytical model is described by $O(k^3)$, where k is denoted as the total machines present within the production line. A clear downside of analytical models is that in complex production lines, with more than two machines and the presence of product buffers, obtaining exact solutions can be quite cumbersome and time-consuming. As analytical models are generally constructed by many assumptions of a machine's characteristics, as for example the probability distributions of the machines and processing times of certain jobs, they fall short in approaching long-term system behaviour. This make them mostly useful in obtaining short term system performances and quick insights in production bottlenecks. For Shell's production process, we are looking to obtain insights in the current and its future production performance, which is why we make use of Discrete Event Simulation DES.

3.2.2 Types of simulation models

According to Jahangirian et al. [13], are simulation models found in multiple different types, each with their specific advantages and applications. Simulation models that are widely used in manufacturing and business applications are amongst others, Discrete Event Simulation (DES), System Dynamics (SD), Agent Based Simulations (ABS) and Dynamic Systems (DS) [17]. Figure 3.2 depicts the overall differences in the different simulation models that have been explained.

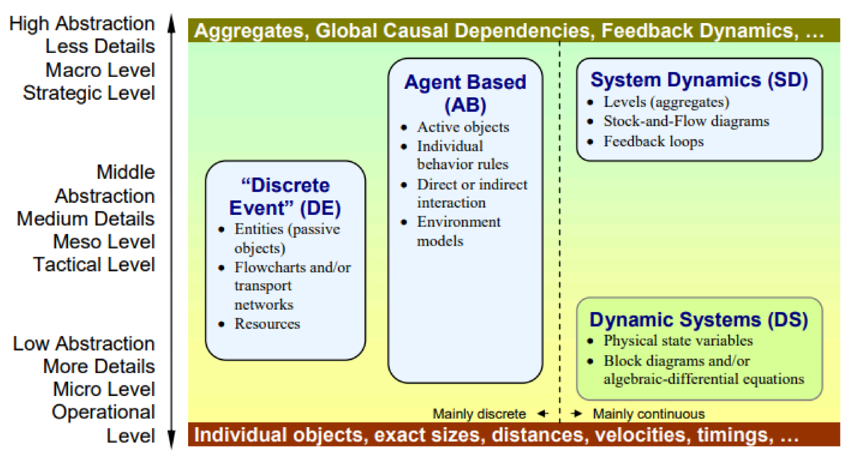


Figure 3.2: Overview of the different simulation types and the usage of each of the approaches within the different management levels (Borschev & Filippov, 2004)

DES is considered to be the most used simulation method, as around 40% of all published research papers make use of this simulation type [13]. DES differentiate itself from other methods as it is perfectly suited for operational and tactical production management, and is highly applicable in incorporating the stochastic behaviour of a system. DES makes use of a system clock and certain events that occur spontaneous, and could therefore the system's state and its parameters. Events can be described as e.g. the arrival or departure of new jobs in an assembly line or the breakdown of certain equipment. A downside of using DES, is the longer time needed to create a simulation model that represents the production process accurately. Not only a large set of data is needed for creating the probability distributions for each of the equipment and processing stations, but also it is time-consuming to program the logic within the production process.

SD and ABS are simulation models that are more applied to tactical and strategical management levels. SD focuses on expressing state parameters of complex systems by a top-down approach, where from a macro perspective a complex phenomenon or system is being described in terms of its long-term dynamics. SD is described by means of a set of continuous functions, which follow differential equations to describe the changes over time. In comparison to SD, ABS is designed in a discrete and bottom-up manner, that takes into account agents (e.g. companies or individuals) in a certain environment and the interactions between the agents in case policies changes over time [13] [18]. Both of these methods are not perfectly suited to simulate a production environment, as they do cover strategical objectives and long-term system behaviour of a certain system. DS, also makes use of continuous functions to describe changes in state variables, but in comparison to SD, focuses on operational level changes within a certain system. SD is mostly used in electrical or chemical engineering fields to describe physical changes in complex systems over time.

As DES is the most suitable simulation method to model Shell's stochasticity in the EOL-section, in which failure rates of equipment and processing speeds influence the current production efficiency, we proceed by further researching how we conduct a DES study.

3.3 Conducting a DES study in a production environment

Conducting a DES study is tight to a ten-step approach that helps in performing a sound and accurate study of a production system. Law (2015) [14] describes that during the execution of a simulation study, attention must be paid to a variety of concerns such as modelling the randomness of the system in the model, validation of the simulation model, the statistical analysis and interpretation of the output data and at last, project management. Figure 3.3 depicts the ten steps that are performed in a simulation study [14]:

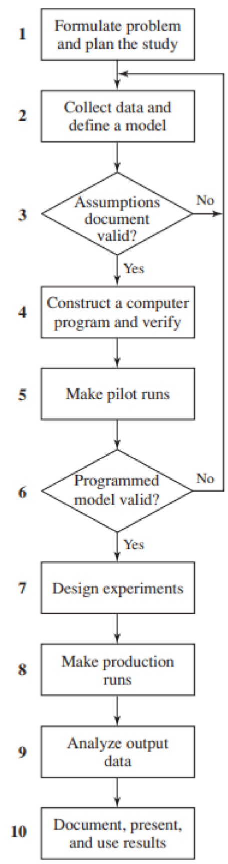


Figure 3.3: Ten-step approach in performing a simulation study (Law, 2015)

The ten steps as described in Figure 3.1 can be divided in three different phases. Phase 1 describes the problem definition phase, and consists solely of step one. Here, the overall objectives of the simulation study, the scope, and the performance measurements are defined by the project team.

Phase two is described as the 'model construction' phase. Steps two till six can be ascribed to this phase, where the simulation model is created. It is important to list all the assumptions and objectives that need to be included in the first simulation model. Then, create a simplistic model that runs without errors and represents the objectives and assumptions as defined. We proceed by verifying the assumptions and the basic simulation model with managers and analysts. If this is according to the current state of the production process, we proceed with step four, in which a simulation program is selected (e.g. Tecnomatix Plant Simulation), created and eventually debugged. Debugging is one method of model verification, and should explain if the model that has been created on paper has been correctly translated to the programmed model. In step five, we perform pilot runs of the simulation model such that we can validate the model in step six. Validating is a necessary step that compares the model's output with the system's output. Comparing the different outputs is usually performed by constructing confidence intervals of the mean and variances of both data sets (Welch's approach) or by comparing the summary statistics and the probability distributions of the output. If the programmed model has been validated correctly, we proceed to phase three.

In phase three, the experimental design, we eventually construct a set of experiments that could have a potential effect on the performance measurement. For Shell's production process, this could for example be a change in palletizing robot for dedicated 18 kg pails, increased OEE for the palletizing robot, increased filling capacities or better routing and/or prioritization rules for the different SKUs. With the different set of experiments, we again perform a set of simulation runs to obtain statistically significant results. In step nine, we proceed by analysing the obtained data, and we finalize the ten-step approach by documenting the results [14].

3.3.1 Output analysis for a simulation model

Simulation models are amongst others used in simulating logistic, production, or healthcare systems. Each of these systems have their own characteristics and lengths of operating. For a production plant that runs in a three-shift system, the weekends are usually not used for production purposes as the plant is closed. We call such a natural event in a simulation study, the occurrence of terminating simulation. As different simulation runs make use of different random numbers, we can treat the output of each simulation run as an Independent and Identically Distributed (IID) random variable.

In other cases, such as a healthcare system or a manufacturing plant which runs for 24 hours per day for seven days per week, we do not have a natural event causing a terminating simulation. In that particular case, we refer to a non-terminating solution. The output for such a simulation model can only be treated as the steady-state behaviour of the random variable. As for Shell's production system, we consider the system to be emptied at the end of Friday night. Therefore, we assume that we make use of a terminating event simulation that needs to make use of different production runs by means of different random numbers [14].

3.4 Lean thinking within production processes

Based on the previous sections in which we explained the suitability of DES, we further research how we can address current inefficiencies in Shell's production process. Melton [19] describes that current inefficiencies such as failures and increased waiting times, as observed in Shell's production process, can be identified as one of the types of waste within the concept of lean thinking in the process industry. These operations, are not adding any particular value to the customer, and only increase internal production lead times. Lean thinking is described as 'the antidote to waste' according to Womack and Jones [20], and focuses on creating value to the customer by reducing waste (e.g. waiting time, failures, and cost etc.) within the production process or supply chain. Another aspect of lean thinking is creating flow within a production process by implementing pull-strategies to reduce in-process inventories.

In typical manufacturing processes such as the automotive industry, lean thinking has been applied ever since its existing, as it is perfectly suitable to high-volume and low product variety processes. For the chemical process industry, which classifies Shell's GMP, the implementation of lean thinking has not been evident. No specific explanation has been given for this phenomenon, but Melton [19] links this to the unwillingness of the process industry to change its production philosophy and mentality, which is needed to successfully implement the concept of lean. For the process industry, value is primarily defined as product produced with the right specification, by a low and competitive unit cost, delivered on time and eventually packed in the right SKUs in the right volumes [19]. As cost price per unit is a very important driver for Shell's GMP to remain competitive, efforts should be made to reduce the overall operating cost and reduce waste within the facility. To eliminate waste and add value to either a production process or final product, tools such as Cellular Manufacturing (CM), kaizen, kanban, workplace organization (5S), poka-yoke, Total Production Management (TPM) and Value Stream Mapping (VSM), could be used within the concept of lean thinking.

3.4.1 VSM in combination with DES

To implement DES within a production process, there should be an understanding of the waste, inefficiencies, and non-value added activities in the process. Value Stream Mapping (VSM) is a process mapping tool that is build around the principle of identifying all value, non-value, and necessary non-value adding operations needed to bring a product to a customer [21]. By removing the non-value adding operations in a production process, it is assumed that the total cycle time (the time it takes to complete an SKU in the production process), will be reduced. Within Shell's production process, we observed that it takes too long for SKUs to be filled, palletized, and moved to the warehouse, which is mainly due to the large number of failure discovered around the EOL-section. In combination with simulation modelling, VSM is considered to be an effective method to visualize and quantify bottlenecks and strive for improved production efficiency, and improved throughputs by reducing the cycle time [22]. This is due to the fact that VSM creates a snapshot of the Current State Map (CSM) of the production processes with all its characteristics. In combination with simulation modelling, which serves as an extension to VSM, multiple production scenarios could be simulated that further reduce the presence of non-value added activities and enhance the performance of the production process. The simulated production scenarios eventually result in the Future State Map (FSM), which cannot be mapped by using a standalone VSM analysis, as this requires to implement the different improvement scenarios in practice. Figure 3.4 describes the differences in VSM and the integration of VSM in simulation modelling.

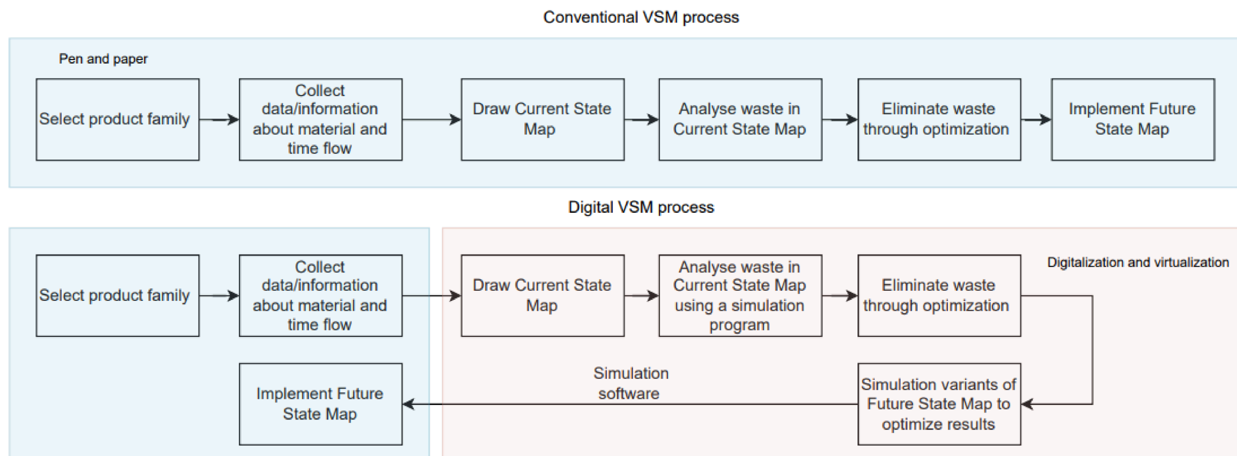


Figure 3.4: Overview of the differences in approaches between the traditional VSM and the combination of simulation modelling and VSM. (Esfandyari et al., 2011)

Parthane and Buddhakulsomsiri [23] showed in a case study for the coffee industry, that capacity problems were identified and solved using VSM and DES. This eventually resulted in reducing the total number of overtime hours worked and operators needed to perform operations in a batch production setting. Xia and Sun [24] describe that VSM as a standalone tool is not sufficient to capture the stochastic behaviour of a discrete production process and should be combined with DES to simulate different production scenarios and to incorporate the stochasticity like equipment break down and product variety. Velumani and Tang [25] performed a similar study for a serial batch production line, in which the options of adding a new machine or increasing machine maintenance were simulated and justified by the eventual improvement of production efficiency. The different simulated production scenarios resulted in overall waiting time reduction in the production process and reducing the in-process bottlenecks.

3.5 Improving OEE performance measurement for the palletizing robot

According to En-Nhali, Meddaoui and Bouami [26], can OEE measurements be improved by the implementation of lean tools. Based on the specific nature of the waste, multiple lean tools are available for both detection or improvement purposes with regard to the availability, performance, or quality aspects within OEE. In the current production set-up, there are no systems in place that warn either the production operators or the logistics personnel of a palletizer breakdown. Operators are only aware of a breakdown once the complete product buffers from the filling stations are completely filled and the conveyor belts stop functioning. This creates unnecessary congestion and waiting times within the production process. Hence, the OEE of the robot is low due to the operators being unaware of a breakdown.

For the palletizing robot, the primary source of waste can be classified as "waste of defects" [27], as the equipment ends up in long stops around 14 times per production shift due to equipment defects. Detecting "waste of defects" can be realized by either the 5 why's procedure or by means of a Pareto analysis. Both are suitable methods to find root causes and detect the underlying issues that affect the current OEE. In terms of OEE improvement, Poke-a-Yoke (PY)/mistake proofing, kaizen events, cause and effect diagrams and 5S housekeeping are often used for improving the underlying issues as detected. PY is a lean tool that eliminates process errors by the implementation of inspection systems within the process or specific equipment. Kaizen is a manufacturing philosophy that gradually improves a system performance by improvement projects. At last, cause, and effect diagrams are a tool to identify root causes whilst 5S housekeeping is a method to improve cleanliness of workspaces.

Lazarevic et al. [28] describe that PY has two different functions to achieve mistake proofing in practice: preventing and detection functions. Preventing functions are mostly concerned with implementing control and warning systems to either stop a production process (control) or warn process operators (warning) in case a failure is made within the process. Detection functions are different, as those are mostly concerned with eliminating product errors during the production process. This is achieved by the implementation of in-process inspections such as shape, size or colour inspections. Creating awareness amongst the process operators can be achieved by making use of PYs preventive function, by implementing visual tools at the filling stations that indicate whether the palletizing robot is currently in a breakdown. In case always good products are produced, it is unnecessary to further implement detecting measures as this is redundant and does not contribute to reducing the MTBF.

3.6 Conclusion

Within this chapter, we answered the second research question "Which methods are available within the literature to address the bottlenecks found in the production process?". Identifying bottlenecks can, based on literature, be done by focusing on production steps that have the lowest capacity or throughput within a production process. For Shell's production process, all the production steps are measured by means of the cycle time needed per production process. This is described as the total time it takes to produce a product from the beginning to the end of the process. As Shell's product portfolio consists of different products, where each product has a different production and cycle time, we research what the potential capacity of the EOL-section should be in order to prevent the filling and EOL-sections to become a bottleneck. We will focus on increasing the availability and the processing speed of the palletizing robot, and combine this with two scenarios in which we increase the capacity of the filling stations.

In recent literature, both analytical and simulation models have been used to mitigate bottlenecks in a production process. For Shell's production line, we will make use of DES, to simulate and improve the current production process. DES is well suited for incorporating stochastic process characteristics and does, in comparison to analytical models, not solely rely on exponentially distributed processing or breakdown times. Also, by making use of DES, we can simulate production scenarios more efficient and obtain insights in the long term performance of each scenario.

Improving OEE measurements can be achieved by means of enhancing the overall availability of the robot, since it is already processing at its maximum capacity. With increased availability, the MTBF is reduced or the MTTR is therefore improved. For Shell's current situation, we are mainly looking to experiment with factors such as increased availability and increased processing speed of the palletizing robot to obtain information on how the EOl-section should be designed to remove current bottlenecks. With regards to the filling section, we will mainly look for an increased processing speed (capactity) to improve the baseline scenario of the process. By means of VSM we make comparisons to the reduced in waste (bottleneck time) for the baseline scenario and the future states of the production process (future states include improvement scenarios).

4 Simulation model and experimental design

Within this section, we further design the conceptual simulation model for Shell's production process and give an answer to the research question: "What should a simulation model look like for Shell's GMP and what possible strategies could be implemented to remove the current bottlenecks that are observed in the production process?". First, we take a closer look in to the conceptual model design for the simulation model.

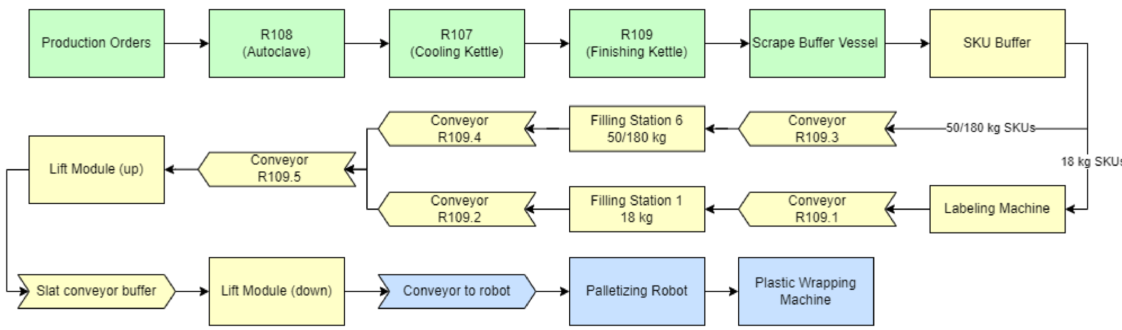
4.1 Conceptual model design

As described in section 3.3, a simulation study follows a three-step approach, which is further subdivided into ten different steps. Within the first step, we define the problem, determine the scope, and describe KPIs that need to be incorporated within the model to both quantify and justify certain improvement scenarios. We define the current problem of the production process as: an inefficient EOL-process that is marked by frequent and long breakdowns of the palletizing robot, with slow filling capacities that are causing delays in the production process. In order to determine what the real effect of the downtimes in the EOL-section is on the production capacity and how we can improve the baseline performance of the plant to improve efficiency and productivity, we will simulate the production process for both the U100 and U400 production lines. This simulation study will be improvement based, which means that we will propose several solutions and improvements to the current production process and verify the effectiveness of the solution in the long run. The effectiveness of each solution is obtained by the reduction in cycle time for the four potential bottleneck locations, in comparison to the baseline scenario.

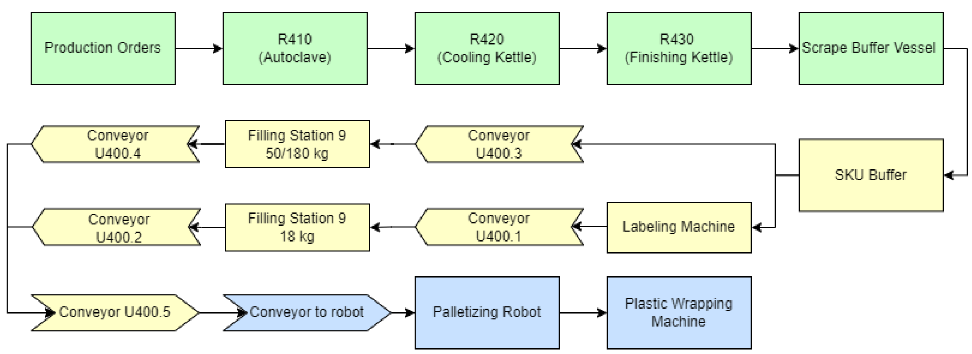
Both the plant manager and the production manager have stated that the capacity of the production plant is heavily influenced by the different products that are produced. Both the U100 and the U400 are producing around 33 different product types each. Each of these products have their own specific residence times in the three kettles in the production process, and each of the products can be filled in different SKUs (18 kg, 50 kg or 180 kg). This makes the determination for the annual capacity on each of the production lines, hardly doable. In order to make an accurate estimate of created production capacity, we make use of historical production schedules for a 8-week period ahead, as an input for the simulation model. This schedule is based on the production data from March 2022 up to the end of April 2022. We choose this time frame, as the plant managed to produce a record number of grease (in terms of volume) in these months. Important for this simulation study is to obtain the overall waiting times in the production process that are incurred due to the inefficiencies observed in the flling and EOL-sections. We mainly focus on improving the cycle times for these two sections, as this will result in faster filling processes and reduce the overall waiting times as result of a domino effect in the production process but only in the EOL-section.

4.1.1 Lay-out of the production system

Following the description of the production process in sections 2.1 and 2.2, we describe the two different production lines by means of flowcharts. Figure 4.1 depicts the lay-out of the production process for both production lines. Both lines come together in the EOL-section, and do not have shared resources in the core or filling process.



(a) Production line R109



(b) Production line U400

Figure 4.1: (a) Production line R109 (b) Production line U400. The colors in both figures represent the different production departments: core process (green), filling section (yellow) and EOL-section (blue).

Core process scope

In the green sections, the core process, the product is produced. Here, we initiate production orders that contain all the information of the type of product that need to be produced, its residence times on each of the kettles and the type and number of SKUs that the product needs to be filled in. All finished products that are in need of direct filling, are collected in the scrape buffer vessel. The core process is modeled explicitly, as the potential shift in bottlenecks due to the slow filling and EOL-process is directly noticed in the production process. We make use of statistical distributions to mimic the residence times of each of the products on the three different process kettles. We also do not model the occurrence of logistic errors and the replenishment of raw materials in the production process explicitly. These situations are, however, indirectly included in the statistical distributions for the residence times of each of the products on the different kettles. As logistical errors and the replenishment of raw materials increases the residence time of a product on a kettle, we capture the extra time on the kettles by using statistical distributions. We do not include the presence of operators in the production process, as we are mostly interested in the system's behaviour regarding total waiting time on the different production kettles that is incurred due to the inefficient filling process and EOL-section.

The simulation model will also include the rework of greases. This process is not depicted in Figure 4.1. Reworking of greases occurs within the finishing kettle in case a grease fails to meet the right product specifications during the production process. As we determined probability distributions for each of the products based on their historical production times of 2021, we include the time for a rework in the total time needed to produce a grease on the finishing kettles.

Filling section scope
Once the scrape buffer vessel is empty and a new production order arrives, the filling orders are initiated and the filling process can be started. In the filling process, the production order that just arrived in the scrape buffer vessel, is read by the system. All the information regarding the number and type of SKUs is communicated, and all the necessary SKUs are collected in the SKU buffer. In some production orders, we only have one type of SKUs that needs to be filled. In other cases, we have two (eg. 18 kg and 180 kg) or even three (eg. 18 kg, 50 kg and 180 kg) different types of SKUs that need to be filled from one production batch. In this simulation model, we only include a combination of one and two SKU type filling orders. As a three type filling order is not very common, we decided that the complexity to model these type of order, would be too time consuming. We will only look at the filling processes of the 18, 50 and 180 kg SKUs. These are the only SKUs that are being filled at the filling stations. Other SKUs such as the 0,8 kg cartridges and 1200 kg Intermediate Bulk Container (IBC) are filled on standalone smaller lines, and do not cause stoppages in the production process. Therefore, we do not include these SKUs in the simulation model.

As we model explicitly the direct production and filling process of greases, we do not include the filling process of indirect filling products. Indirect production orders are marked for long production runs in which around 48 tons of grease are produced in one production run. These indirect greases are in most cases subject to long testing procedures before filling can eventually start. Due to the complexity of filling these orders along with the uncertainty in the testing procedures, we decided to not include these filling processes in the simulation model. We do model the production of these certain products, as that can be very easily implemented in a simulation model.

Once the SKUs are collected in the SKU buffer, they proceed in case of 18 kg SKUs by a labeling machine. Here, each product is manually placed in the machine, after which it moves to the designated filling station. The 50 and 180 kg SKUs are manually labeled at the filling stations, so those SKUs proceed directly to the filling stations. This process is also not modeled in the simulation study, as we assume that manually labeling takes place while the SKU is being filled. For the filling process, we do not take into account the presence of operators as we assume that the planning department always ensures that there are enough resources to realize the filling process. For each of the three SKU types, we constructed statistical distributions for the filling speeds, as we do not take in to account the differences in filling speeds for the different products (grease types). This would also be too time consuming and be beyond the scope of this research.

The filled SKUs are collected in the conveyors that are placed directly behind the filling stations. Here, the system waits for the number of SKUs that represent a full pallet, after which the SKUs are moved to the next conveyor. The SKUs are not moved altogether, but instead are moved individually, each after 10 seconds. For the R109 production line, products move by means of a lift section and slat conveyor to the EOL-section.

EOL-section scope
The two production lines come together at the "conveyor to robot" conveyor belt. Here, we have a stream of incoming SKUs from production line R109 and U400. The EOL-section works by a First Come First Serve (FCFS) priority rule. This means that in a system with SKUs arriving from either production line, it palletizes the SKUs (until a a full pallet of that specific SKU is created) from the production line which arrived first at the "conveyor to robot" conveyor belt.

With regards to the palletizing robot, we model three different failure types that have been logged by the maintenance department, namely: logistical, operational and technical failures. For each of these failure modes, we created the MTBF, MTTR and availability, these parameters are sufficient for Tecnomatix Plant Simulation to construct a statistical distribution for each of the failure modes. We also assume for the EOL-section that there are always enough pallets present. In practice, this is not the case, but the operational failure mode already includes the stoppages of the palletizing robot that are caused by a lack of pallets. We also do not model the plastic wrapping machine explicitly, as this machine is located behind the palletizing robot. We only consider it's failure modes, which are included in both the operational and technical failure modes for the palletizing robot, as these ensure that the robot can fall in an error mode and stops the flow in the production line.

4.1.2 Logical flowcharts

Within this section, we further explain the previous section in more detail, by means of logic flowcharts. These flowcharts translate the logic that is found in to the production process, to text and logical sequences.

Core process
First, the production process is loaded with production orders. These production orders are loaded based on a production schedule which is read by the simulation model (Section 4.2.1 describes the created production schedule in more details). Each Monday morning, the simulation model reads the production schedule and it loads all the production orders in the production order buffer. Figure 4.2 describes the logic to create the production orders at the beginning of the simulation.

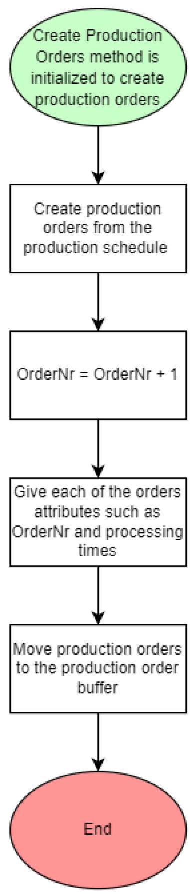


Figure 4.2: Flowchart of the initialization and creation of the production orders in the process. This logic holds for both the R109 and the U400 production lines.

After calling the production orders, the model waits until 7:00 AM on Monday morning, to start the first batch of the product process. After finishing this batch on the autoclave, a method is called "BottleneckControl", which searches for the optimal start time to let the next batch in to the process. As mentioned earlier in section 2.3, the production process follow the bottleneck planning procedure. This means that new products can start the production process as long as its bottleneck kettle is available at the time of arrival at that specific kettle. To mimic this behaviour in a simulation model, we mathematically approached the optimal start time for a the new batch. The optimal start time of a new batch, is subject to the bottleneck of the new batch, since this determines whether or not a new product can start. In general, we have different 3^2 different bottleneck scenarios (section 2.3 which we should take into account. This is based on the three different kettles in the core process and the two different bottlenecks that we encounter from the current batch in the process and the next batch in the process.

In short, we need to ensure that the bottleneck kettle of the next batch that we enter in to the system, is free, before we start with the new batch. Therefore, we need to determine the time difference between the moment the current batch is done on the bottleneck kettle of the next batch, and the moment of arrival of the new batch on its bottleneck kettle. Whenever the time for a batch is longer to get to its bottleneck kettle, than for the previous batch to finish on that bottleneck kettle, we can immediately call the new batch in to the system. If this is not the case, we calculate a waiting time that is needed to ensure that the bottleneck kettle of the next batch is free. To clarify the bottleneck scheduling method and the determination of the optimal start time of the next batch, we will explain some of the bottleneck scenarios:

- Scenario 1: The bottleneck kettle of the current batch (batch 0) is the autoclave kettle and the bottleneck kettle of the next batch (batch 1) is also the autoclave. Since we check the possible entry of the next batch on the moment that the current batch has completed on the autoclave, we can immediately enter the new batch in the system. If the current and the new batch do not have the same product type, we incur a flushing set-up time for the next batch on the autoclave. The start time of the next batch on the autoclave is then given by the following formula, with t_0 marking the time at which the autoclave kettle is done with the current batch:
$$t_{optimal} = t_0 + t_{flushing\,set-up\,time} \tag{5}$$
- Scenario 2: The bottleneck kettle of the current batch (batch 0) is the cooling kettle and the bottleneck kettle of the next batch (batch 1) is the autoclave. We can optimally start batch 1 on the autoclave, if we can ensure that the cooling kettle has finished processing batch 0. For this scenario, we determine the difference between the moment the cooling kettle is empty after processing batch 0 ($t_{ck,0}$) and the time it takes to finish batch 1 on the autoclave ($t_{ac,1}$). As batches coming from the autoclave must directly be pumped to the cooling kettle, due to quality regulations. If the current and the new batch do not have the same product type, we incur a flushing set-up time for the next batch on the autoclave. There are no other set-up times incurred in the production process. Hence, the optimal start time of the next batch on the autoclave is in this scenario given by the following formula:
$$t_{optimal} = t_0 + (t_{ck,0} - t_{ac,1}) + t_{flushing\,set-up\,time} \tag{6}$$
- Scenario 3: The bottleneck kettle of the current batch (batch 0) is the finishing kettle and the bottleneck kettle of the next batch (batch 1) is also the finishing kettle. In this scenario, we need to take into account all the kettles before the finishing kettle. Key in this scenario is that we ensure that the total needed time for batch 0 on the cooling kettle plus the finishing kettle, is smaller or equal to the total time of batch 1 on the autoclave and the cooling kettle. If this is not the case, batch 1 needs to wait an additional time before the finishing kettle is empty. The extra waiting time is the total time needed for the finishing kettle to be empty. If batch 0 and batch 1 do not have the same product type, we incur a flushing set-up time for batch 1 on the autoclave. The optimal start time of the next batch on the autoclave in this scenario is given by the following formula:
$$t_{optimal} = t_0 + ((t_{ck,0} + t_{fk,0}) - (t_{ac,1} + t_{ck,1})) + t_{flushing\,set-up\,time} \tag{7}$$
- Scenario 4: The bottleneck kettle of the current batch (batch 0) is the cooling kettle and the bottleneck kettle of the next batch (batch 1) is also the cooling kettle. In this scenario, we have two different situations. The first situation describes the optimal start time of the next batch on the autoclave, when the residence time of the cooling kettle for batch 0 is larger than the residence time of the autoclave for batch 1. If this is the case, we immediately start the batch 1 (subject to flushing set-up times or not). If this is not the case, we add an extra waiting time to ensure that batch 1 is finished on the autoclave, it can immediately start at the cooling kettle. This bottleneck scenario is described by the following formulas:
$$t_{optimal} = \begin{cases} t_0 + t_{flushing\,set-up\,time}, & \text{if } t_{ac,0} > t_{ck,1} \\ t_0 + t_{flushing\,set-up\,time} + (t_{ck,0} + t_{ac,1}), & \text{otherwise} \end{cases} \tag{8}$$

The other six bottleneck scenarios and their optimal starting times for the next batches are described in Appendix C. Figure 4.3 illustrates the bottleneck logic implemented in the simulation model.

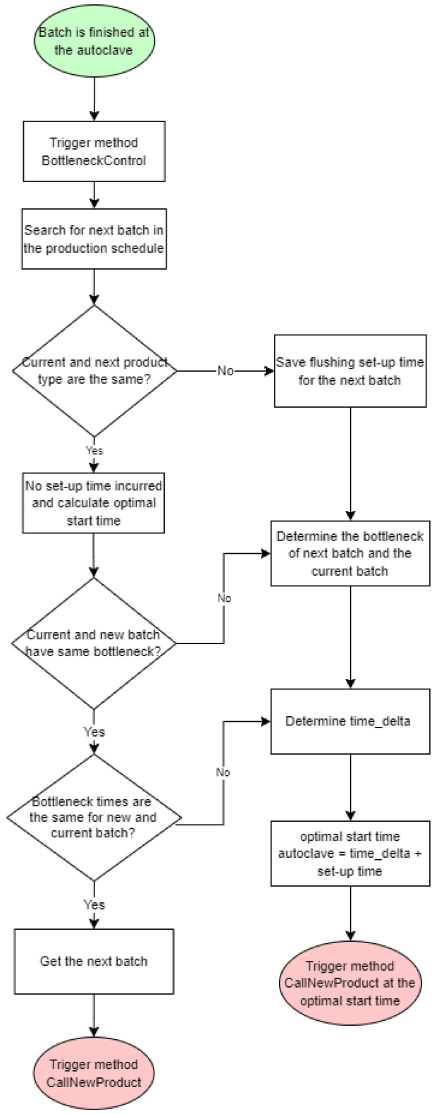


Figure 4.3: Flowchart of the bottleneck control mechanism in the production process. This logic holds for both the R109 and the U400 production lines.

Whenever a batch has successfully passed all three kettles, it moves to the scrape buffer vessel (buffer vessel for the filling section) if it is in need of direct filling. Here, all the characteristics for the filling process are read. Figure 4.4 describes the logic implemented in the scrape buffer vessel.

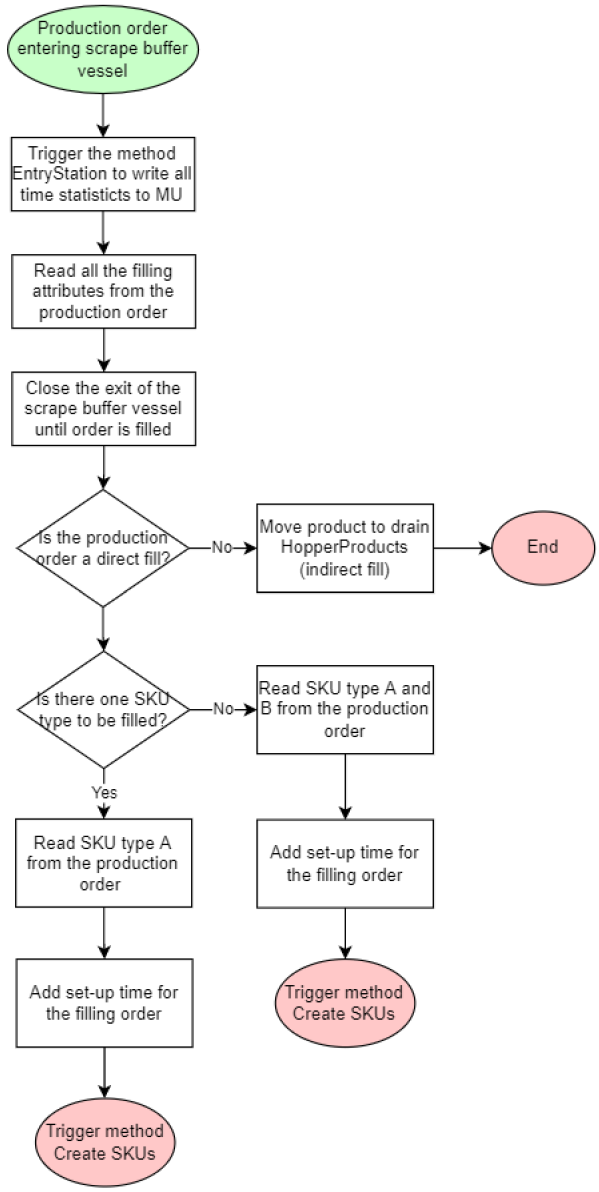


Figure 4.4: Flowchart of the production order entering the scrape buffer vessel after it has been processed on all three kettles. This holds for both the R109 and the U400 production lines.

Filling

With the product entering the scrape buffer vessel, we directly initiate the method in which SKUs for the filling lines are created. We check the composition of the filling order, and fill the buffers according the SKUs that need to be filled. Then, we proceed with prioritizing 18 kg pails whenever those need to be filled. In case there are no 18 kg SKUs to be filled, we prioritize 50 kg SKUs, since those type of SKUs take longer to fill. At last, we initiate the filling process by moving SKUs with the "CallSKU" method. Where we move the SKUs from the SKU buffers, to the filling stations. Figure 4.5 depicts the logic that is implemented to create the different SKUs, and initiate the filling procedure.

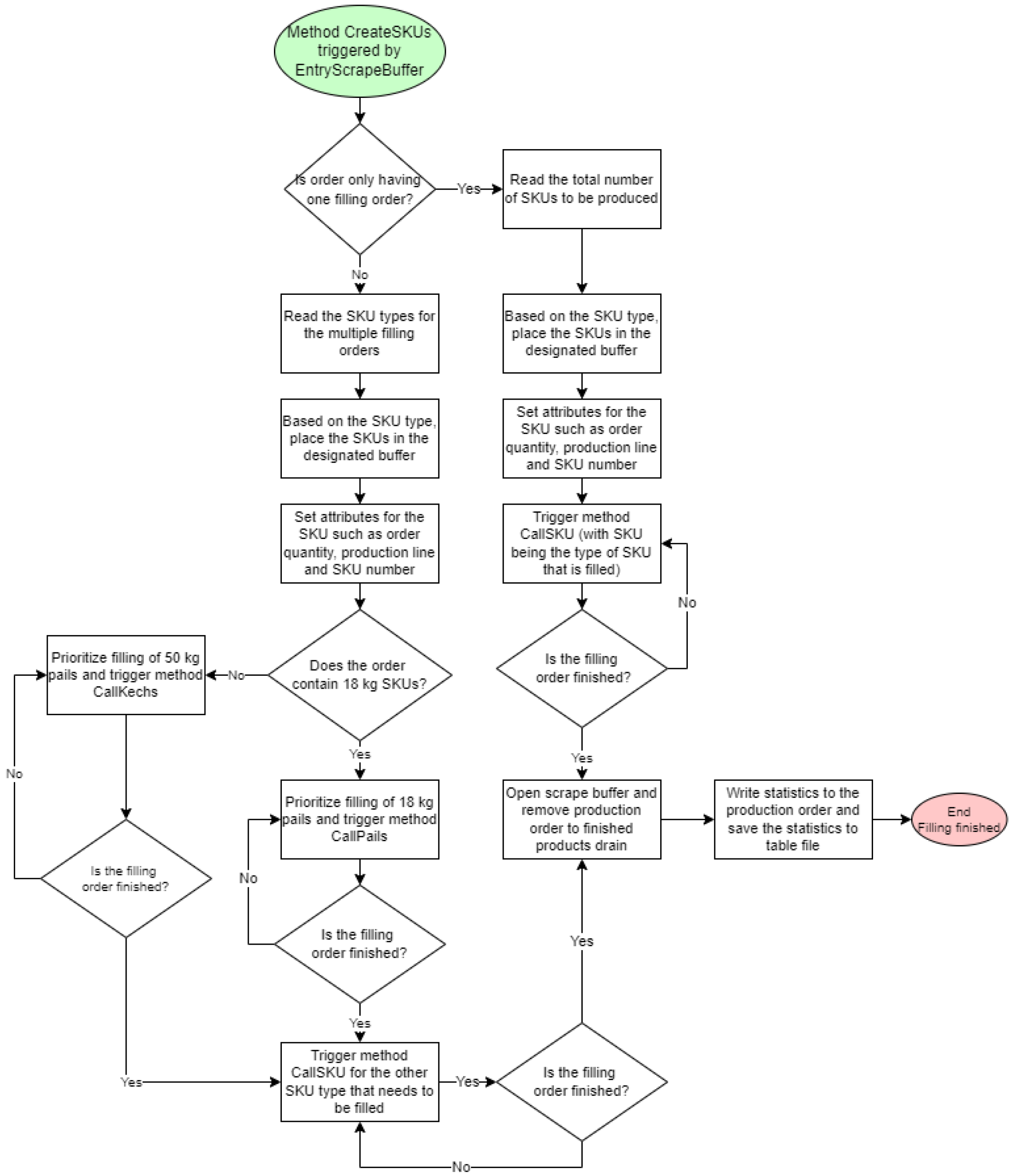


Figure 4.5: Flowchart of the creation of the SKUs after the production order has arrived in the scrape buffer vessel. This logic holds for both the R109 and the U400 production lines.

After successful filling of the SKUs, the SKUs are moved to the buffers located after the filling station. This is a fairly simple process, but the logic implemented in the production process is rather complex to translate to Plant Simulation. The complexity is mostly found in the control of the buffers after the filling stations, as we need to control the SKUs once the full quantities of a pallet are met. When the full quantities of a pallet are met we let all the products in the buffer with a waiting time of 10 seconds in-between products move to the EOL-section (or slat conveyor in case of the R109). For U400, we stop the filling process as the filling process and the moving process of filled SKUs cannot happen simultaneously. On the R109, we can continue the filling procedure due to the larger buffer size behind the filling station. While the products are moved from the buffers to the EOL-section, we check if there are more products of the same production order to be filled and we let those SKUs move to the filling station whenever there is space available. There is space available whenever the conveyor belts before the filling station are empty. Figure 4.6 depicts the logic around the buffer control mechanism.

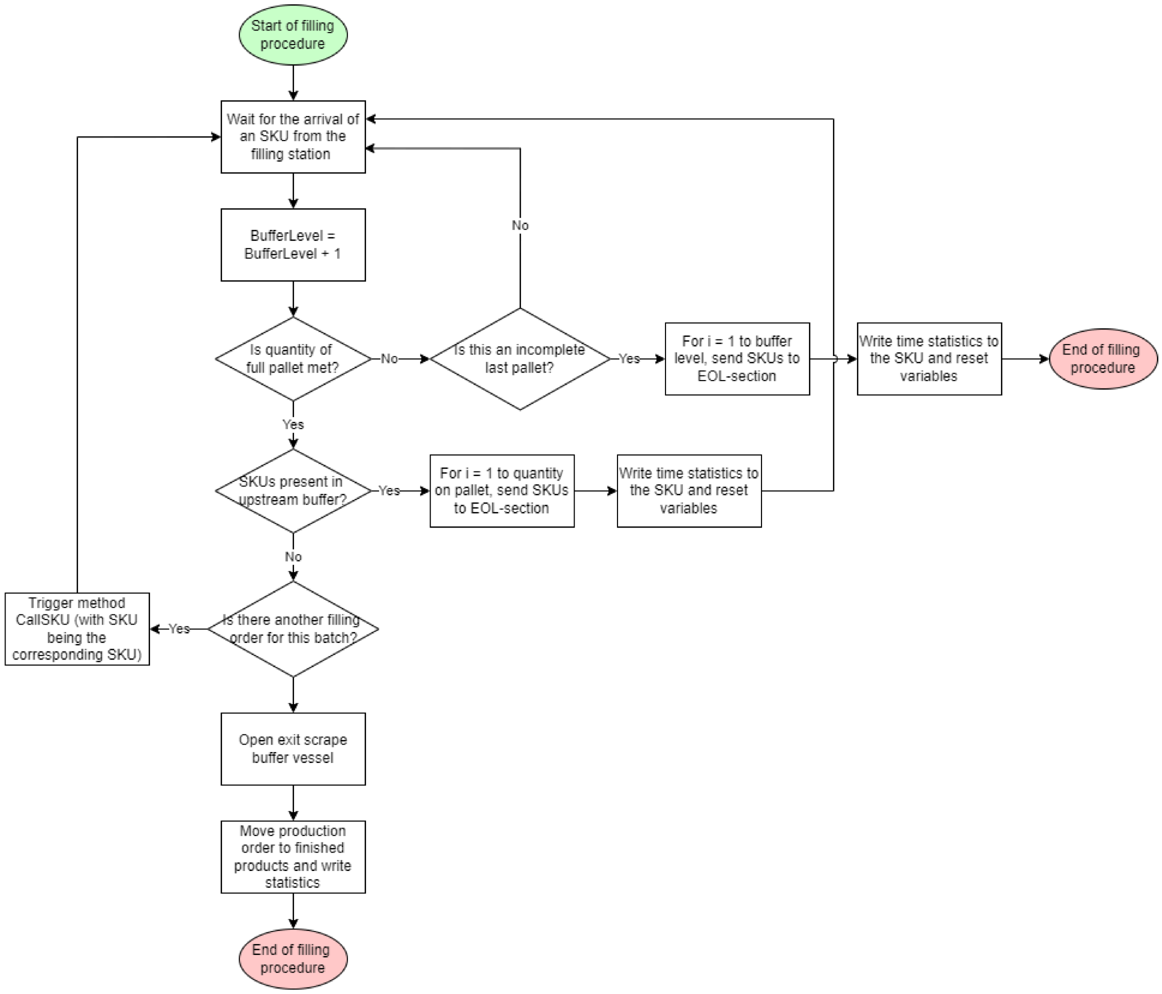


Figure 4.6: Flowchart for the buffer control mechanism that allows to move all the filled units to the EOL-section. This is dependent on whether or not a full pallet or the last pallet have been produced. For the U400, we simultaneously stop the filling station whenever a full pallet is being moved to the EOL-section.

4.2 Input for the simulation model

Making use of DES, requires a vast number of input data in order to operationalize the simulation model. We divide the input for the simulation model in different sections, which are amongst others, the general production settings, the core process, the filling stations, and the EOL-section.

4.2.1 General production settings

The plant operates on a three-shift basis. In this three-shift system, the plant is operational from Monday morning until Friday night. Table 7 describes the working hours for both the production and filling operators.

Table 7: The start and end times for shifts during the week for both the production and the filling operators.

Day	**Production shifts (hours)**	**Filling shifts (hours)**	**Breaks**
Mon	8:30-13:30, 13:30-21:30, 21:30-5:30	7:00-13:30, 13:30-21:30, 21:30-5:30	9:30-10:00, 17:30-18:00, 01:30-02:00
Tue-Wed-Thu	5:30-13:30, 13:30-21:30, 21:30-5:30	5:30-13:30, 13:30-21:30, 21:30-5:30	9:30-10:00, 17:30-18:00, 01:30-02:00
Fri	5:30-13:30, 13:30-21:30, 21:30-1:30	5:30-13:30, 13:30-21:30, 21:30-1:30	9:30-10:00, 17:30-18:00, 01:30-02:00

There is a minor difference in the working hours for both types shifts on Monday, Tuesday until Thursday, and Friday. This difference is found in the effective starting hours on Mondays and the finishing hour on the last shift on Fridays. On Mondays, the production operators perform multiple checks with regards to the production equipment, before they can effectively start producing. Therefore, we set the start time on Monday on 8:30 instead of 5:30. The filling operators can usually already proceed by filling SKUs from the hopper storage tanks, or, can fill the last produced batch from the previous week in case this has not been filled due to the limited amount of time that was left during the last shift on Friday. Therefore, we assume that the filling operators can start earlier with their operational activities such as the set-up of the filling procedure and the retrieval of SKUs.

A production schedule is constructed by input from the scheduling department. We make use of an eight week production schedule, starting from the first of March to the end of April. This data is used as the plant managed to produce record volumes on this two month period. In these months, we are guaranteed of exposing the current bottlenecks as observed in the production process, since the production lines were fully occupied with production orders. We choose to not include any stochastic variation in the production schedule since we do not need it to expose current issues regarding the filling and EOL-section. For simulation runs longer than eight weeks, we simply construct a schedule with repetitions of the 8 week production schedule. An example of a production order with its filling order is depicted in Figure 4.7.

	integer 1	string 2	integer 3	integer 4	integer 5	intege 6	intege 7	integer 8	integer 9	time 10	time 11	time 12	integer 13
string	Batch_Number	Product_Type	Quantity	SKU_Pack_Type_A	SKU_Pack_Type_B	FS_A	FS_B	Quantity_Filled_A	Quantity_Filled_B	Processing_Time_Autoclave	Processing_Time_Cooling_Kettle	Processing_Time_Finishing_Kettle	Bottleneck_Location
1	1	Gadus S2 V220 1	8856	18	50	1	6	200	20	1:28:20.0000	2:45:08.0000	3:37:16.0000	3
2	2	BGR(GHE) Gadus S2 V220 2	8000	0	0	0	0	0	0	1:42:41.0000	3:53:22.0000	25:44.0000	2
3	3	Gadus S2 V100 3	5220	180	0	6	0	29	0	2:06:05.0000	3:20:40.0000	3:08:48.0000	2
4	4	Gadus S2 V100 3	6900	50	0	6	0	138	0	2:01:42.0000	4:24:47.0000	2:59:57.0000	2
5	5	SKF MT33 (SNF)	8280	180	0	6	0	46	0	2:45:12.0000	4:13:44.0000	4:31:15.0000	3
6	6	SKF MT33 (SNF)	7560	180	0	6	0	42	0	2:06:24.0000	3:59:45.0000	4:03:53.0000	3
7	7	SKF MT33 (SNF)	7920	180	0	6	0	44	0	2:07:07.0000	4:08:07.0000	4:29:04.0000	3
8	8	SKF MT33 (SNF)	8100	180	0	6	0	45	0	2:01:10.0000	3:34:08.0000	4:15:12.0000	3
9	9	SKF MT33 (SNF)	7920	180	0	6	0	44	0	2:12:34.0000	5:12:55.0000	4:11:41.0000	2
10	10	SKF MT33 (SNF)	8280	180	0	6	0	46	0	2:27:20.0000	4:15:46.0000	4:35:47.0000	3

Figure 4.7: Example of a production schedule for the R109 with all the information regarding product type, quantity, residence times and the information regarding the filling of SKUs.

4.2.2 Core process settings

The core process, which is marked by the three kettle process in which the eventual grease is being produced, is completely modeled. Here, we modeled for both the production line R109 and U400, a set-up consisting of the autoclave, cooling kettle and finishing kettle. Within the three-kettle process, production orders arrive that contain all the necessary information for both the core process as well as the filling process. The information stored in the production orders are amongst others:

- Product description/Product type
- Total quantity of grease produced
- Total number of SKUs and type of SKUs to be produced
- Residence times on each of the kettles (pre-determined by product specific distributions)

Each Monday morning at around 7AM, the production process is initiated. Due to the three-shift system, Saturdays and Sundays are off-days. In the model, we simulated the production process in which a production schedule is read and loaded into the simulation model. This production schedule is created for both production lines R109 and U400, and is constructed manually, since it is hard for a plant like Ghent with over 70 different products, to construct a schedule. Therefore, we use an eight week period schedule which was created by the planning department. This planning is a forecast for the specific instance from March until the end of April in 2022. To obtain longer production schedules, we simply sequence each of the eight week schedules after each other since this schedule

Processing times
For the core process, a total of three different production kettles is present. For each of the products we determined their individual residence times by means of statistical distributions. These distributions were

created based on logged data for the processing times, which have been recorded over the past two years. Appendix E depicts for both production lines R109 and U400 the individual statistical distributions and their parameters. We made use of Easyfit as a statistical distribution fitting tool. Here, we test three different statistical methods to conclude whether or not a data set follows the proposed distribution. These methods are the Anderson-Darling, Kolmogorov-Smirnov, and the Chi-Square test statistic. The method regarding these test statistics can be found in F. In general, most product types do follow different distributions than the normal distribution, as data was simply not normally distributed. Based on the suggestions obtained from Easyfit, we conclude that many residence times are either distributed by a lognormal, gamma or weibull distribution.

Flushing procedure (set-up time)
Besides the bottleneck scenarios, we include the extensive flushing procedures within the core process of the simulation model. Each time a new production run (multiple batches of the same product) is initiated, a set-up time is incurred in-between the production runs. In practice, this set-up time describes the time it takes to fully rinse piping, filter and reactors within the process. From the production planning department, we obtained a detailed list with the average set-up time per product produced on the production line. The averages are calculated values from historical values, and range from zero minutes up to 24 hours. Appendix D describes the average set-up times for the different products.

4.2.3 Filling process settings

After the creation and processing of the production orders, we proceed with the filling processes. Here, we consider the direct filling processes from production lines R109 and U400. In a later section, the logic implemented in the filling process is thoroughly described by means of flow charts.

Filling orders
Filling orders are together with the production orders, predetermined by the scheduling department. Each production order contains all the specific information for the filling process, such as the type and number of SKUs to fill. Filling orders can either consist of one or two SKU types to be filled. We do not consider the possibility of three SKU types to be filled from one production batch, since this implementation was considered to be too complex.

Set-up time filling stations
For each filling order, a set-up time is incurred. This set-up time is used for actions that need to be performed by the operators, to ensure that the filling process can be started. These actions are amongst others: collection of SKU labels, retrieving SKUs and the preparation of the filling nozzle. For all these activities, the planning department calculates a fixed time of 20 minutes. In practice, this constant value is not always realized. Therefore, we assume that the set-up time is a random variable. Since there is no data present on the set-up time per production order, we assume that the duration (as this is dependent on the SKU type), is given by a uniform distribution with a minimum of ten minutes and a maximum of 30 minutes. A ten minute set-up time is generally applicable for 180 and 50 kg SKUs, whereas the set-up of 18 kg SKUs takes longer due to the extra preparation steps (Table 2).

Processing times of the filling stations
The processing times for each of the SKUs that are filled on the filling stations, have been analysed. Here, we obtained statistical distributions for each of the SKUs, based on the filling speeds realized from the 1st of January until the end of August. By making use of statistical distributions, we include variation in the production process and approach the real life production process better. Determining the statistical distributions was done by the same procedure as for the processing times on the different kettles. The different distributions used for the processing times at each filling station, are depicted in Table 8.

Table 8: Suggested distributions for the processing times of each SKU type at the different filling stations.

Filling station	SKU type	Suggested distribution
FS9	18	Gamma (3p) ($\gamma = 0.341, \alpha = 4.422, \beta = 0.122$)
FS9	50	Gamma (3p) ($\gamma = 0.470, \alpha = 3.587, \beta = 0.316$)
FS9	180	Gamma (3p) ($\gamma = 1.565, \alpha = 6.127, \beta = 0.082$)
FS1	18	Gamma (3p) ($\gamma = 0.518, \alpha = 1.744, \beta = 0.150$)
FS6	50	Gamma (3p) ($\gamma = 1.034, \alpha = 1.352, \beta = 0.486$)
FS6	180	Gamma (3p) ($\gamma = 1.490, \alpha = 5.119, \beta = 0.193$)

The processing times of each SKU at the filling station all follow the gamma distribution. We observed that the test statistics for the gamma distributions were all more favorable in comparison to the normal, lognormal, weibull and logistic distributions. The test statistics for each of the distributions are depicted in Appendix G. The test statistics are performed with an α value of 0.05. If the test statistic is larger than the critical value, we reject the H0 hypothesis in which we assume that the data follows the suggested distribution function. If the critical values are fairly close to the test statistic values, we will still accept the suggested distribution, as it is more likely to follow the proposed distribution instead of an empirical distribution. In case two of the three test statistics fail to reject the H0, we accept that distribution and will not further seek for an empirical distribution. All the test statistics that fail to reject the H0, are marked green.

Cycle time individual process steps

We described the layout of the production lines earlier in terms of flowcharts and their individual processing steps. Each of these individual process steps have their own cycle times and capacity. Table 9 depicts the different cycle times as measured in the filling process.

Table 9: Technical specifications of the individual processing steps for both production lines.

	Production line R109		Production line U400	
Process step	**Processing time (sec)**	**Capacity (units)**	**Processing time (sec)**	**Capacity (units)**
Labeling machine	3.5	1	3.5	1
Conveyor 1	225	96	105	96
Conveyor 2	320	48	320	32
Conveyor 3	190	9	105	9
Conveyor 4	40-90	9	40-90	9
Conveyor 5	10	5	85	12
Lift module (up)	13	3	n.a.	n.a.
Slat conveyor buffer	530	65	n.a.	n.a.
Lift module (down)	13	3	n.a.	n.a.
Conveyor to robot	15	5	7.5	5

4.2.4 EOL-settings

For the EOL components, we consider the slat conveyor and its lift sections, the conveyor belts towards the palletizing robot, the palletizing robot and the plastic wrapping machine. In this section, the filled SKUs are palletized after which they can be stored in the warehouse.

Palletizing robot

The palletizing robot is, as described in section 2.3.1, failure prone and unreliable. Based on data from the maintenance department, we decided to create three different error profiles for the robot. These error profiles are based on a review of the robot that has been ongoing for the last 10 weeks. In this review, the maintenance department monitored and logged each of the machine's failures, manually. The different error profiles that we integrated in the simulation model are: technical, operational and logistical. These failures capture the most common errors, such as issues with regards to the weight checker, the plastic wrapping machine and the robot itself. We make use of these error profiles as they all ensure that the palletizing robot stops working whenever one of the failures occur.

As there is no data logged by Shell in which the total duration of the stop is monitored, we logged data ourselves. This data represents 28 different instances in which the total downtime for the palletizing robot has been monitored. These downtimes are then averaged in to the MTTR. For each of the failure profiles, we constructed a statistical distribution based on the number of failures per failure profile, that have occurred in the total time span of 10 weeks. To construct the availability of the palletizing robot, we calculated the total time that the palletizing was actual operating based on the total pallets that have been processed during that time span. This resulted in a MTTR of around 16.82 minutes. We consider the Time To Repair (TTR) as a random variable, with the following distribution: TTR $\sim$ Erlang(25:24,17:57). In Table 10, we define the MTBF, MTTR and availability per failure profile for the palletizing robot.

Table 10: Failure count per failure type and their MTBF, MTTR and total availability.

Week	Logistical	Technical	Operational
1	1	57	0
2	3	42	1
3	0	7	1
4	1	30	0
5	4	38	1
6	3	37	2
7	4	31	3
8	6	17	0
9	0	20	0
10	1	20	4
Average of failures (per week)	2.30	29.90	1.20
Average of palletizing time (min.)	880	880	880
MTBF (min.)	382.49	29.42	733.11
MTTR (min.)	16.82	16.82	16.82
Availability (%)	96%	64%	98%

Plastic wrapping machine
For the plastic wrapping machine, we consider a constant processing time for each of the finished pallets. This is verified with the maintenance department and manually checked during the attendance of several wrapping procedures for different SKU types. The processing time of each pallet is fixed at 1:45 minutes. We do not take the failures of the plastic wrapping machine into account, as these failures are again connected to the palletizing robot.

4.3 Output of the simulation model

The output of the simulation model is the data that is obtained after each run. For this simulation model, we make use of KPIs that indicate the waiting time in the production process, and the daily production numbers. Shell does usually not make use of other KPIs, other than the total volume produced. Therefore, we introduce two other KPIs that will help in quantifying the bottlenecks at the filling process and EOL-section. First, we gather information regarding the *total waiting time on the scrape buffer vessel*. The blocking of this vessel results in the potential stoppages of the production process since a finished batch cannot be filled. With this KPI, we can quantify how the production process suffers from a shifting bottleneck. Second, we make use of the *average filling time* for a production order, since this KPI indicates per SKU type the time it takes for the scrape buffer vessel to be completely empty. At last, we are interested in the *average daily volume*, on each of the production lines.

4.4 Experimental design

In this section, we further explain the different experiments that will be performed within the simulation model. As our goal is to indicate the effect of the shifting bottleneck in the production process due to the inefficient EOL-section and the filling section, we set-up the following experiments that we will use to gather results with. Shell wants to gather information regarding the specifications of a palletizing robot that would remove the bottleneck from the filling and EOL-section. We do not make use of a standard Design Of Experiments (DOE) such as 2^k factorial, as we first want to gain insights in the individual effects for each of the improvement scenarios.

In the current situation, the robot is unreliable due to its low availability and its capacity. To obtain information regarding the specifications of a robot that meets the current demand of the manufacturing plant, we test for different availability and capacity settings (as the current robot's OEE fails to meet current targets).

Under the assumption that the robot does not have the capacity to process all of the SKUs demanded per hour, we proceed by increasing the capacity of the palletizing robot. Increasing capacity is currently not possible with the current robot, since it is already running at its maximum performance, however, it creates valuable insights in the desired palletizing capacities and the specifications that a likely new robot should have. We experiment with increasing the palletizing speeds by 125%, 150%, 200% and 400%. These factors were obtained in discussions with the engineering department, to obtain insights in the desired capacity for the palletizing robot, that would result in removal of the bottleneck at the palletizing robot.

The second set of experiments relate to an increase in the availability of the palletizing robot. With the current efforts of the maintenance department and their aim to increase the availability by focusing on the most occurring mistakes, we analyse what the effect of the availability value is on the performance of the production process. In agreement with the engineering department we decided that a robot should be having an availability target of at least 95%. This is currently unrealistic due to its unreliable nature, but we test for different availability values to search for an improvement in cycle and waiting times. For this set of experiments, we are only interested in the effect of the overall palletizing availability on the waiting time in the production process. Hence, we only change the availability factor of the palletizing robot in Plant Simulation, which results in a change in the MTBF of the robot. For the MTTR, we will not make any additional changes. We experiment with availability values ranging from 60.2% (baseline), 70%, 80%, 90% and 95%, as discussed with Ghent's senior engineer.

At last, we proceed with experiments with regards to the set-up of the filling stations. Here, we previously observed that filling of 18 kg pails can be time-consuming (Table 5) and takes significantly longer for an order to complete, due to the large number of SKUs that need be filled. Therefore, we analyse the impact of a multi filling station for 18 kg SKUs, which allows to fill multiple SKUs at once. We only take in to account that the potential new filling machine has the ability to process two SKUs at the same time and that therefore, the processing time is reduced by 50%. Increasing the filling capacity by more than two SKUs at the same time is hardly achievable in practice, due to the complexity of pumping greases through pipes. We constructed new statistical distributions for filling station 1 and 9, for half the processing times. Filling station 1 uses distribution $\Gamma(2.403, 3.530)$ with a threshold parameter of 14.75. For filling station 9, the new distribution is given by $\Gamma(4.790, 3.640)$ with a threshold parameter of 9.13.

Table 11: Experimental design of the experiments performed to obtain the effects of the different measurements to improve the filling and EOL-section.

Experiment	**Processing speed palletizing robot (%)**	**Availability palletizing robot (%)**	**Avg. processing speed fill station 1 (sec.)**	**Avg. processing speed fill station 9 18 kg (sec.)**
1	125	60.2	46.50	51.10
2	150	60.2	46.50	51.10
3	200	60.2	46.50	51.10
4	400	60.2	46.50	51.10
5	100	70	46.50	51.10
6	100	80	46.50	51.10
7	100	90	46.50	51.10
8	100	95	46.50	51.10
9	100	60.2	23.25	51.10
10	100	60.2	46.50	25.55

After the individual effects, we proceed by using a fractional factorial design (2^{3-1}) for the interaction effects between the different improvement scenarios. As we deal with three different process variables and we analysed the individual effects separately, we obtain a design with four different experiments. Table 12 depicts the additional set of experiments between the best performing individual improvement scenarios (obtained from the individual effect experiments).

Table 12: Further experiments performed to obtain the interaction effects between the best performing improvement scenarios

Experiment	**Best performing robot speed**	**Best performing robot availability**	**Best performing filling station capacity**
Baseline	Not implemented	Not implemented	Not implemented
12	Implemented	Implemented	Not implemented
12	Implemented	Implemented	Implemented
13	Not implemented	Implemented	Implemented
14	Implemented	Not implemented	Implemented

4.5 Verification and validation

This section explains both the verification and validation of the simulation model. This is a crucial step in comparing the model to the real life production process, and ensure that the production philosophy and individual process steps as found in the production process, are translated in to the simulation model.

4.5.1 Verification

Verification is a process that mostly allows for the removal of errors within the simulation model. According to Law (2015), debugging can be used to verify whether or not the assumptions and concept that has been created on paper, are translated in to useful programming code and logic. We verified our simulation model after implementation of each method (programming code that implements the production logic in to the model). By means of debugging we removed all the errors that were present in the system. For debugging purposes, we used 70 production orders for both the production lines and obtained zero errors. Another method of debugging is enabling peer reviews to check and verify the assumptions that have been made in advance and were translated in to the simulation model. At Shell, we verified the simulation with both the deputy production manager and the senior project engineer. Here, we concluded that all the production steps as found in the production process, are correctly translated to a simulation model.

4.5.2 Validation

For the validation of the simulation model, we consider the output of two KPIs after a simulation run. First, we validate the model by analysing the total volume produced in the simulation model and compare that to the current production parameters. Second, we use the total number of batches produced as an indication of the effectiveness of the bottleneck scheduling method. In section 4.3 we consider different output parameters for the production process. However, the average waiting time on the scrape buffer vessel and the average filling time per production order, are currently not used and actively logged. Therefore, we only validate the model with the total volume and the number of batches produced. As Shell's scheduling and planning department uses fixed one week schedules for the production process, it is generally harder to determine the planning for an 8-week ahead period since these schedules are subject to change. Nevertheless, we still expect similar total numbers for both KPIs as the forecasted demanded generally needs to be met. Table 13 depicts the validation of the simulation for R109.

Table 13: Validation of the simulation model for production line R109

R109	**Number of batches**	**Avg. batches per week**	**Total volume (tons)**	**Avg. volume per week (tons)**
Realized	177	19.7	1395.7	155.0
Simulated	171	19.0	1372.4	152.5
Difference	6	0.7	23.3	2.5
Percentage of total (%)	3.34	3.55	1.67	1.61

For production line R109, we observe slight differences in the simulation model with regards to the realized production data. On average, the simulation model is slightly more pessimistic as in practice we produce 3.55% more batches. As the input schedules were not fixed, it means that changes could still be made to the fixed schedules and that in this case, extra batches could be produced in the production process. This is something we do not take in to account in the current model. At last, we analyse the total volume realized in the time frame of the input production schedule. Here, we observe minor differences of 1.67% in the total volume realized versus the simulated total volume. This difference is mostly explained due to the variation in batch yields being different than the realized batch volumes. As the chemical process itself does not always guarantee the same batch volumes, we observe more volume produced. Based on this data, we conclude that our simulation model accurately simulates the production situation regarding production line R109. Table 14 validates the simulation model for U400.

Table 14: Validation of the simulation model for production line U400

U400	**Number of batches**	**Avg. batches per week**	**Total volume (tons)**	**Avg. volume per week (tons)**
Realized	139	15.4	729.7	81.2
Simulated	132	14.7	716.3	79.6
Difference	7	0.7	13.4	1.6
Percentage of total (%)	5.04	4.55	1.83	1.97

Table 14 describes more or less the same situation as found at the validation of production line R109. Here, we realized slightly more batches and volume than scheduled. We observed that the simulation model was not able to finish the complete production schedule, which was likely too optimistically created, and that too many batches were scheduled in the eight week period that we used for the input schedule. In general, there were around 5.04% more batches realized and 1.83% more volume realized, than scheduled. With these numbers, we conclude that we can accurately enough simulate the production process.

4.5.3 Warm-up period and number of replications

Due to the various types of simulation models, we need to make a distinction between our model and the other simulation models. In theory, we have a simulation model whose output is either dependent on the initial conditions of the system or which is not dependent on the initial conditions of the simulation model. In our model, we start each simulation with the same initial conditions, which is an empty system with no jobs in it. On the beginning of the simulation, we start the initialization which loads all the production orders in to the system. Also, our model is not dependent on the run length, but rather on the different production orders on both production lines that occur simultaneously. Therefore, we consider the steady state behavior of the system, and not its transient behavior.

The second distinction is the distinction in terminating and non-terminating simulation models. Terminating simulation models have a natural event ending the simulation run, such as a factory closing at the end of the day. Non-terminating models have no such event. In our model, we do not have a natural event causing the end of the simulation run, therefore we consider our simulation model as a non-terminating variant. According to Law [14], we need to determine the warm-up period and number of replications as we deal with a non-terminating simulation. This is due to fact the our output values are in the beginning of the simulation run dependent on the initial state of the system.

In other to make the output values of the simulation model independent, we delete a fraction of the beginning input values to reach the steady state values. To determine the warm-up period we use Welch's graphical method, as, described by Law [29]. We conclude that a total of 17 periods/production days, is enough to reach a steady-state value for the total volume produced on a daily basis. Appendix I describes both the method used and the graphical outcomes to determine the warm-up period.

To determine the number of replications, we make use of a method as described by Law (pp. 493-497) [29]. We perform different replications from our simulation model until the width of the confidence interval of the average output is smaller than the standard error (γ). Appendix I further describes the method used to determine the number of replications. We choose for a total of three replications per experiment to obtain statistically significant results for our output values.

For the run length of the simulation study, we discussed internally what would be a sufficient simulation period. At first, we chose for a total run length of 52 weeks to mimic the behaviour of a full production year. However, due to the long computation time of 60-65 minutes per simulation run, we use a total simulation time of 26 weeks or 182 days to reduce the simulation run time to around 30 minutes. To obtain the full effects of the experiments over a full production year, we multiply the outcome of the different simulation runs by two (365 days).

4.6 Conclusion

To answer the research question "What should the simulation model look like for Shell's GMP and what possible strategies could be implemented to remove the current bottlenecks that are observed in the production process?", we created a simulation model in Tecnomatix Plant Simulation. First, we described the conceptual simulation model by a general description of the different production lines. Then, we proceeded with its scope, the logical flowcharts that translate the process dynamics into logical flowcharts, and the input parameters for the simulation model. We verified and validated our simulation model. Verifying was performed by stepping through and debugging the simulation model. We concluded that the model is bug-free and runs according to the steps performed in the production process. Validating our simulation model was done by comparing the simulation output to the output from March until the end of April 2021. Here, we concluded that the simulation model is accurate enough to simulate the simulation model as the realized production volumes and the average number of batches produced are deviating between one and five percent of the simulated volume and the average number of batches produced. We proceeded with constructing different strategies/experiments which would result in improving the efficiency of the filling and EOL-section in the production process. We constructed a main KPI, which is the total waiting time that is incurred on the scrape buffer vessel. This is the waiting time that is accumulated in the production process whenever the filling process is not efficient. It blocks the entry of the newly produced batch that is coming of the finishing kettle and needs to be filled in SKUs. For each of the experiments, we perform a total of three replications, with a run length of 183 days (half a year) and a warm-up period of around 17 days.

5 Results

In this section, we answer the research question "Which model configurations result in the most efficient way of removing the current production bottlenecks and obtain more production capacity?". We perform this by experimenting with the implementation of experimental design in our simulation model, as described in section 5.1. Then we proceed by combining the best performing improvement scenarios in section 5.2. Finally, we analyse the best performing experiments to obtain the most beneficial future state of the production process, as described in section 5.3.

5.1 Experimental design results

As described in Section 4.3, we test different scenarios to obtain insights regarding the impact of the current bottlenecks in production process on lines R109 and U400. We primarily focus on the accumulated waiting time before the scrape buffer vessel in the production process. This KPI is currently not used or logged by Shell. The other KPIs that we will analyse are the average cycle time per filling order (also not in use to measure the performance of the production line) and the total volume produced on a daily basis, per experiment. The daily volume produced KPI is used to benchmark daily production numbers, as also described in Section 4.3.

Our first experiment was regarding the baseline scenario of the production process. After that, we performed experiments for the ten different scenarios, in which the processing speed and availability of the robot were increased, as well as the filling capacity for 18 kg SKUs for both production lines. The baseline scenario or Current State Map (CSM) is used as reference point for the improvement scenarios that we highlighted in section 4.4.

5.1.1 Increasing the robot's processing speed

For the individual effects of the increased robot capacity, we take experiment 1-4 in to consideration. For these experiments, we increased the capacity from 100%, up to 400%. First, we analyse the effects of the increased capacity with regards to the total waiting time for the scrape buffer vessel in the production process. Figure 5.1 depicts the overall waiting time for this set of experiments.

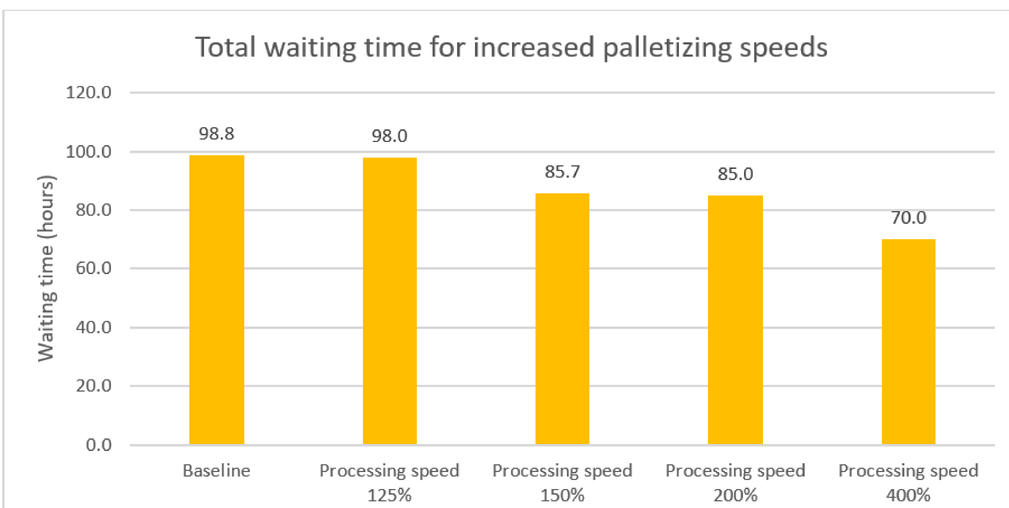


Figure 5.1: Overall waiting time for experiments 1-4 with an increased palletizing capacity

In the figure above, we observe that an increased palletizing capacity of 125% performs equally good as the current baseline scenario. We notice improvement from a processing speed of 150 and 200%, in which a 13 hour waiting time reduction has been obtained. This translates to a percentage wise waiting time reduction of 13.15%. The biggest improvement is found for a processing speed of 400%, with a total reduction of 28 hours (29.1% reduction). A faster palletizing robot, while maintaining the same availability, reduces the overall waiting time in the production process as it clears queue's faster and reduces the likelihood of the formation of an SKU-train in the EOL-section. Therefore, there will be less accumulation of SKUs on both production lines and generally less waiting time. Hence, we conclude that experiment number 4 (palletizing speed of 400%) obtains the best result. We proceed by further analysing the average daily volume for this set of experiments.

Figure J1 in Appendix J depicts the average daily volume for experiment 1-4. With regards to the total daily volume produced for experiments 1-4, we do not observe significant differences. We observe a stable volume trend of around 45 tons of greases produced per day (R109 and U400). An increased palletizing capacity does not result in extra volume produced. This is best explained by the fact that indirect produced batches can still be produced even though the scrape buffer vessel (direct batches) is still occupied. The scheduling department takes this reasoning in to consideration and actively plans for a stable balance between direct and indirect produced batches. Therefore we do not considers this to be of any effect on the daily produced volume.

At last, we analyse the average cycle times for the different SKUs for production lines R109 and U400. Figure 5.2 depicts the average cycle times for the different filling orders.

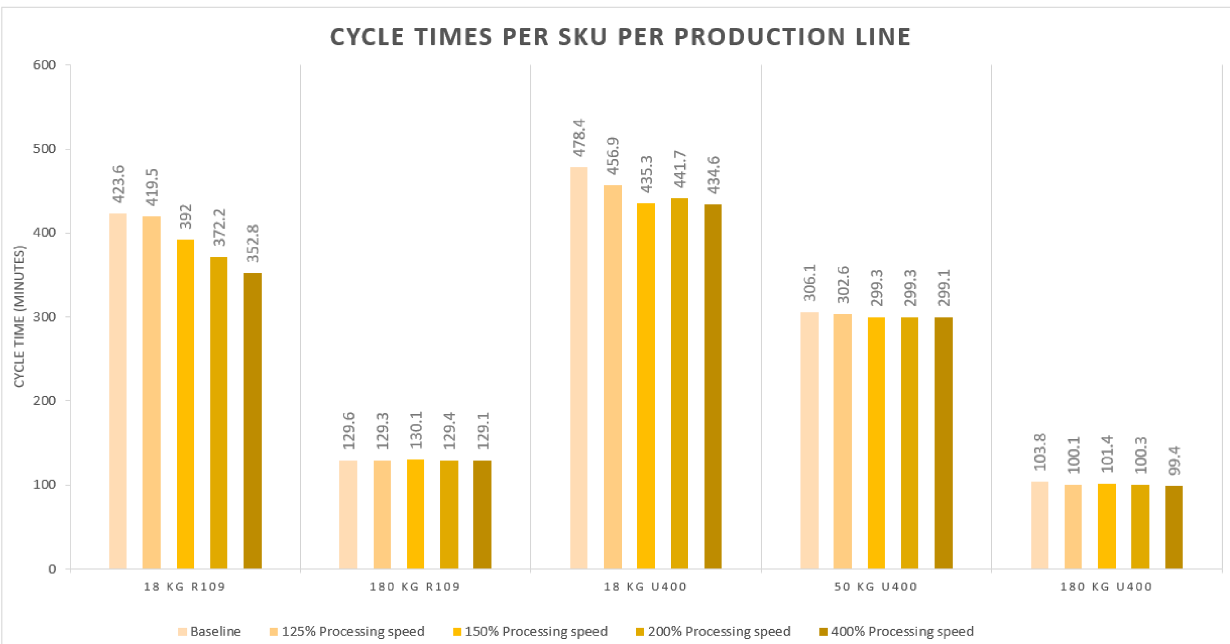


Figure 5.2: Results of the average cycle times per experiment 1-4 for the different SKUs filled at production lines R109 and U400

With regards to the average cycle times, we observe significant changes for the 18 kg SKUs on both production lines. For production line R109, we observe that the increased palletizing speed to 400% yields an 71 minute reduction in the total filling time. For U400, we observe that the difference from 200% to 400% does not make any significant changes, as we achieve similar values for the average cycle times. We observe that the palletizing robot is a bottleneck for both the filling of 18 kg SKUs, since we improvements are made with regard to the cycle times. This is best explained by the fact that the filling process of 18 kg SKUs contains more SKUs that need to be filled in the same time span as that of the other SKU types. Also, for production line R109 the improvements to the cycle time are bigger, since we deal with larger batch sizes which contain more SKUs to be filled. If the palletizing robot is able to handle to more SKUs per minute, there will be less congestion for this production line. We conclude that the experiment with a 400% capacity for the palletizing robot yields the best average cycle time reduction.

Finally, we conclude that the total waiting time in the production process and the average cycle time per filling order are minimized for a palletizing robot with a capacity of 400%. With regards to the daily average volume produced, we did not observe any significant changes.

5.1.2 Increasing the robot's availability

We proceed by testing a change in the robot's availability on the performance measurements as used in the previous section. First, we analyse the effect of the increased availability on the total waiting time in the production process. Figure 5.3 depicts the changes with regards to the waiting time in the process for the different availability settings.

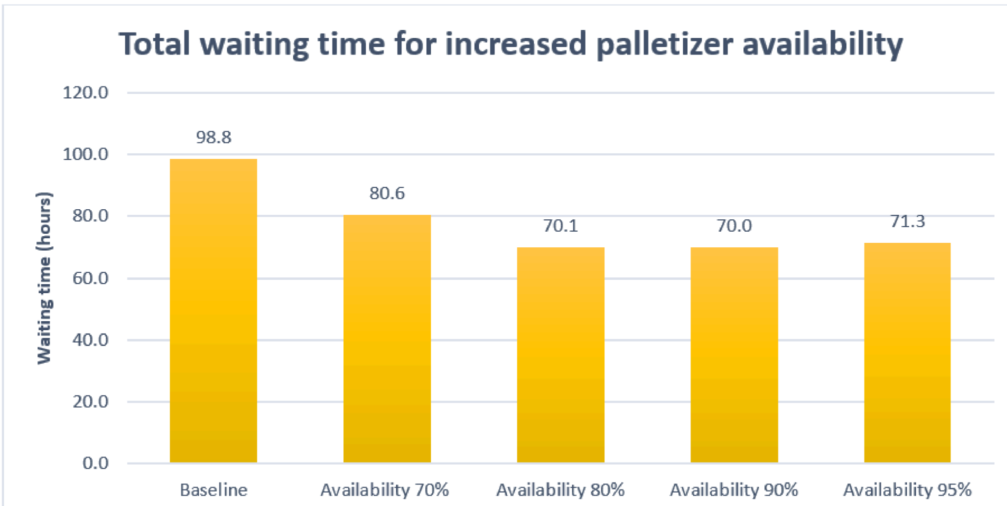


Figure 5.3: Overall waiting time for experiments 5-8 with an increased palletizing availability

The increased availability shows significant improvements with regards to the overall waiting time in the process, for experiments 6, 7, and 8. Experiment 5, in which the availability was increased to 70% improved the baseline scenario by 18 hours. In total, we improve the overall waiting time in the production process by 28 hours for the other experiments. Increasing the availability from 80% or 90% results in the same waiting time reduction compared to the availability of 95%. However, this value is 1.3 hours higher due to statistical variance and randomness in the simulation model. In comparison to the increase of the processing speed of the robot, does the availability increase result in the same waiting time reduction. We only need a palletizing availability of 80% to obtain the same result with a palletizing capacity of 400%. The palletizing bottleneck is solved for an availability of 80%, since we do not yield any waiting time reduction in the production process. We conclude that experiment 8, increasing the palletizing availability results in the best experiment. We also choose for this experiment due to the lower variance that we observed in our results.

Next, we analyse the changes in the daily volume for the increased availability experiments. We observe no significant changes to this KPI, as we also mentioned in Section 5.1.1. The same logic holds for the previous section, that indirect buffers can still be produced in case direct batches are waiting for their filling process in the scrape buffer vessel. Figure J2 in Appendix J depicts the daily volume for this set of experiments.

At last, we analyse the changes in the average cycle times for the filling orders, due to the change in availability values for the palletizing robot. Figure 5.4 depicts the changes in the cycle times for the different SKUs for each of the production lines and the different experiments.

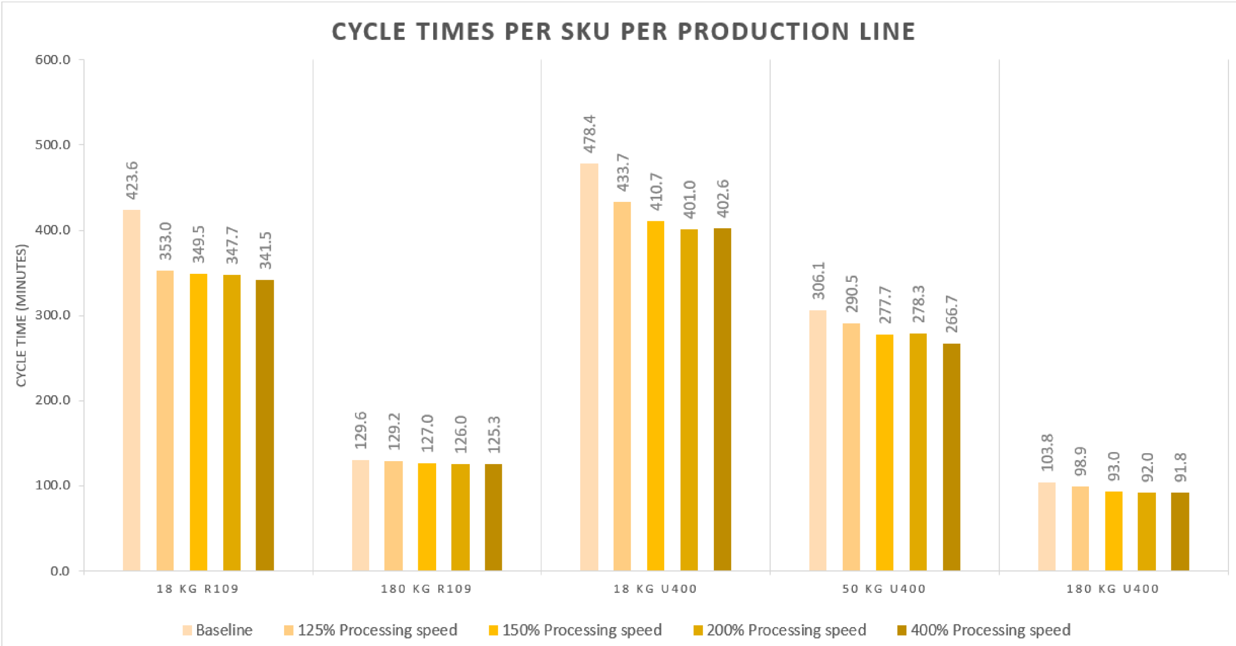


Figure 5.4: Results of the average cycle times per experiment 5-8 for the different SKUs filled at production lines R109 and U400

We observe significant changes to the average cycle times for the filling orders in comparison to the baseline scenario. This change is already noticeable for the starting availability value of 70%. This is explained by the fact that a palletizing robot with fewer failures, has less failures and is able to palletize more SKUs per hour. In comparison to the increased processing speed, does the availability result in lower cycle times. This is mainly due to the operators that do need to intervene less, which ensures a faster filling process. Also, do to less breakdowns, there will be a smaller queue formed in the filling stations at self as the conveyor belts will ensure that the SKUs will be transported to the EOL-section, and not be stopped in the filling station. We observe the biggest differences for a palletizing robot availability of 90%.

For the largest SKU orders, 18 kg fillings, we observe an cycle time reduction of around 82 minutes production line R109 (95% availability). This is still above the weighted average bottleneck time of 263 minutes (for all the batches produced), but reduces the likelihood of accumulated waiting time in the process by 18%. On U400, we observe a reduction from 478 minutes down to 401 minutes (90% availability). This production line deals with an average weighted batch times of around 383 minutes. As this production line has generally longer batch production times, there is a lower chance of accumulated waiting time in the production process. The availability value of 90% obtains similar results as an availability value of 95% (18 kg U400). In practice, it is more costly to achieve and maintain an availability of 95%, therefore we choose experiment 8 with an availability performance of 90%.

We conclude that a palletizing robot of 95% reduces the overall waiting time in the process to a minimum. For U400, we do not observe significant improvements for choosing a palletizing robot with an availability of 90% over a 95% availability. Due to the low number of failures that a 95% availability robot could make in practice, we choose for a robot with an 90% availability, since this is generally easier to realize, with less resources. We choose an availability value of 90% to further experiment with.

5.1.3 Improved filling station capacities

At last, we analyse the improved filling capacities for both production lines. Increased filling capacities are realized by the installation of a second fill nozzle. In practice, this has not been performed by Ghent or other grease manufacturing plants due to the technical specifications required to realize this idea. However, Shell was interest in obtaining information on improving the performance of both the filling and EOL processes. Therefore we further analyse this set of experiments (9-10).

First, we analyse the effect of the increased filling capacities on the total waiting time in the production process. Figure 5.5 depicts the overall waiting time in the production process when changing the filling capacities for filling line FS1 (R109) and FS9 (U400).

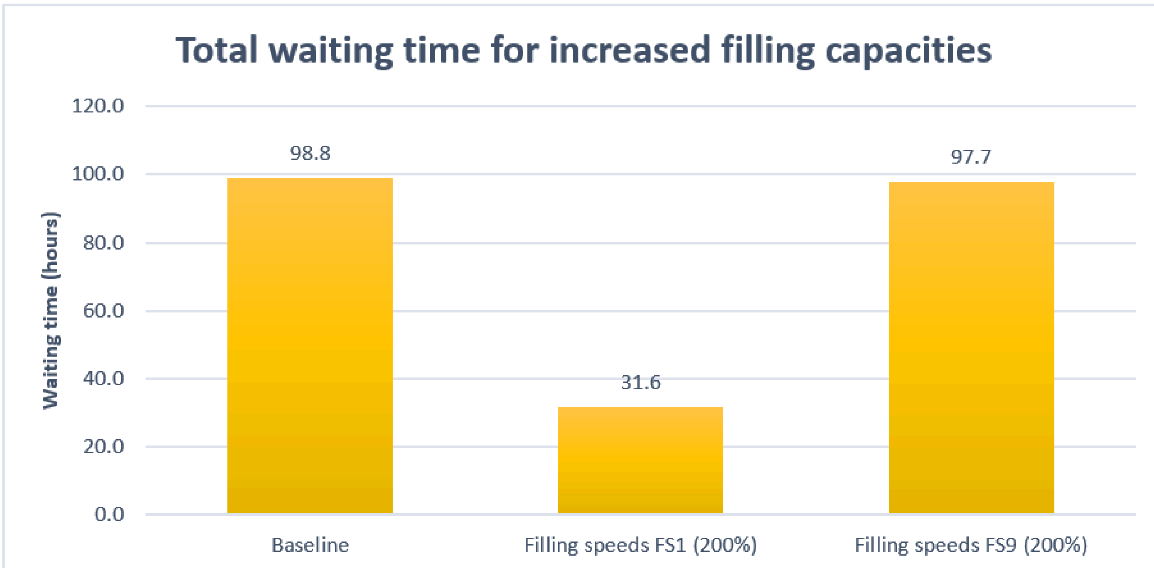


Figure 5.5: Overall waiting time for experiments 9-10 with an increased filling availability

We observe a significant decrease in the total number of waiting hours in case the filling capacity for production line R109 is increased. This is mainly due to the fact that the current filling capacities for this production line are a larger bottleneck than the palletizing robot currently is. With a total reduction of 67.2 hours on the total waiting time in the process (baseline compared to increased filling capacity for FS1), we observe an even larger reduction in comparison to the best experiments found for the increase of the palletizing processing speed to 400% (70 hours) and its best performing availability value 90% (70 hours). As we explained in section 5.1.2, is this reduction realized by a robot that clears the current queues of SKUs at a higher rate. The actual bottleneck that causes the production process to accumulate waiting time is the slow filling speeds in the filling section. Especially the filling process of 18 kg SKUs on fill station 1 (R109) is very slow. This was already highlighted in table 5, with the discrepancy in the realized and the effective filling times for the different SKUs filled at the different filling stations. Adjusting the filling speeds for filling station 9 compares to the situation in the baseline scenario, as this adjustment does not cause additional waiting times in the production process. We conclude for this set of experiments that the installation of a second fill nozzle on filling station 1, which reduces the processing time of filling an 18 kg SKU by a half, reduces the total waiting time in the production process by 67.2 hours.

For these experiments, we also analysed the average daily volume. However, similar to the other experiments performed for the adjustments in the palletizing capacity and availability, we do not observe significant changes. Figure J3 in Appendix J depicts the average daily volume on both production lines for the adjustments made in the filling capacities for the 18 kg filling process.

The last analysis for experiments 9 and 10, is regarding the average cycle times for the filling process. Figure 5.6 depicts the differences in average cycle times for experiments 9 and 10.

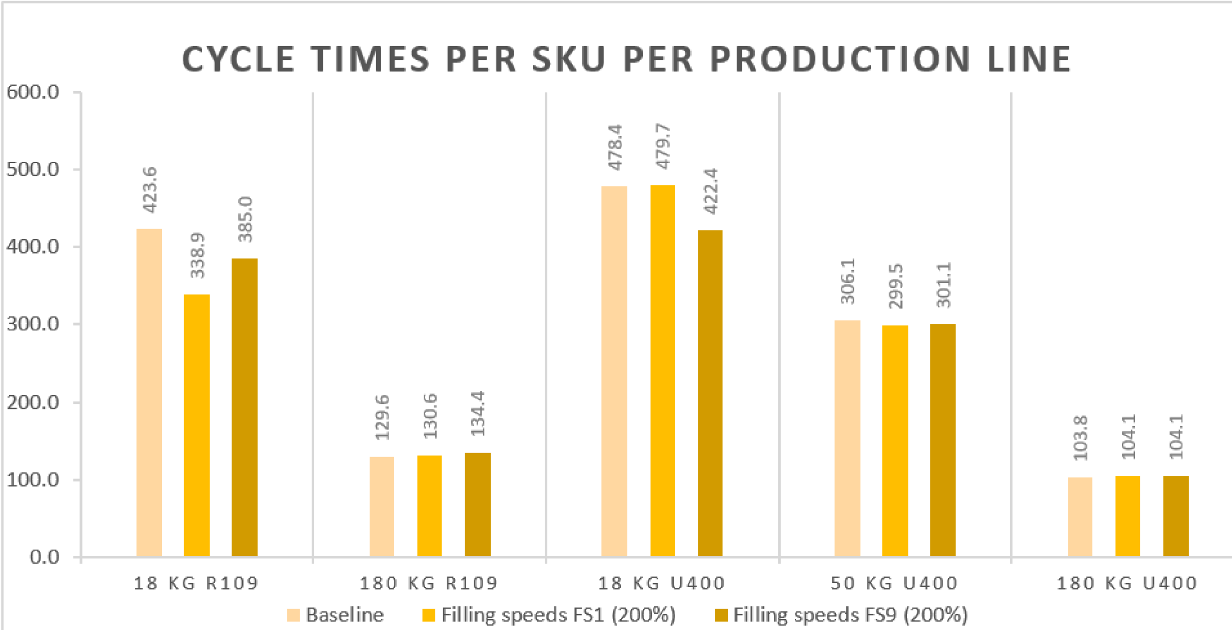


Figure 5.6: Results of the average cycle times per experiment 9 and 10 for the different SKUs filled at production lines R109 and U400

Based on the data presented in Figure 5.6, we observe significant changes in the average cycle times for the 18 kg SKUs produced on the R109 and the U400. For the improved filling capacity from fill station 1 (R109), we observe a similar cycle time reduction as for the implementation of a palletizing robot with an availability of 95%. In the baseline scenario, we produce an 18 kg SKU filling order on average in 423 minutes. With the improved filling capacity this reduces to an average value of 339 minutes. For U400, this changes from 478.4 minutes in the baseline scenario to around 422.4 minutes with the improved filling station capacity. We make the same observation as explained in figure 5.5, in which we claim that the current bottleneck in the filling and EOL sections is found in the filling process. This is due to an inefficient filling process for 18 kg SKUs on the R109, which is caused by batch sizes twice as large as in comparison to U400 and a shorter bottleneck time in the production process. Due to the shorter weighted average batch time, batches are produced faster and filling operators need to fill the SKUs in a higher tempo. The current installation actually fails to meet the desired capacity, which results in accumulated waiting times.

We also observe slight changes in the cycle times for the 18 kg SKUs produced on the R109 in case we increase the filling capacity on the other production line (U400). This is best explained by the fact that there is less accumulation of SKUs on the end-of-line process, which ensures that the slat conveyor buffer will not be fully occupied. Whenever the SKUs from U400 can move faster to the palletizing robot, while maintaining its capacity and availability, there will be more space for the SKUs coming from R109 to arrive at the EOL-section. With more space available, it is less likely that the entire slat conveyor will be occupied and that the filling process of the 18 kg SKUs at R109 is therefore halted.

5.2 Further analysis of interaction effects

Based on the different set of experiments that we performed during the experimental design, we choose three individual experiments that we combine and test with each other. For the improved processing time, we observed that experiment number four (palletizing processing speed of 400%) resulted in the best performance regarding the overall waiting time in the production process. For the robot's availability, we chose to perform additional experiments with experiment number seven (palletizing availability of 90%). A robot availability of 90% is generally easier to obtain in comparison to a value of 95%, therefore we choose this performance value to further test with. Finally, we add experiment nine (increased filling capacity 18 kg SKUs on production line

R109) to test for the interaction effects. This experiment showed the best improvement in terms of average cycle times for the situation regarding the R109 filling process. We perform an additional four experiments, in which we analyse the interaction effects between the improvement scenarios. Table 15 depicts the additional experiments.

Table 15: Further experiments performed to obtain the interaction effects between the best performing improvement scenarios

Experiment	Processing speed robot to 400%	Robot availability to 90%	Increased filling capacity FS1 for 18 kg SKUs
Baseline	Not implemented	Not implemented	Not implemented
11	Implemented	Implemented	Not implemented
12	Implemented	Implemented	Implemented
13	Not implemented	Implemented	Implemented
14	Implemented	Not implemented	Implemented

We first test for the total waiting time in the production process, for each of the different additional experiments. Figure 5.7 depicts the overall waiting time in the production process as observed by the additional experiments.

Figure 5.7: Overall waiting time for experiments 11-14 in comparison to the baseline scenario

Based on figure 5.7, we observe that experiment 11 performs similar to the overall best experiments found for the increased processing time and the increased availability rate for the robot. From this figure, we conclude that the interaction effects of the processing speed and the availability rate do not affect each other, since we obtain in three simulation runs a similar value for this experiment in comparison to experiments four and seven (also around 70 hours of waiting time).

More interesting is the fact that experiments 12 and 14 perform similar. These experiments perform slightly better in comparison to experiment 9 (increased filling capacity for fill station 1), but only by around four hours. When all factors are improved, we obtain the same results when only the processing speed and the fill capacity are improved. This leads to believe that, with these settings, the bottlenecks regarding the palletizing robot are solved, but not for the filling station for 18 kg SKUs on the R109. The waiting time accumulated in the production process is still a matter of the filling capacities on production line R109 which are not up to the desired level.

Experiment 13 is the overall best performing experiment. For this experiment we obtain a total waiting time of 23.7 hours. When analysing the different variances between experiment 12, 13 and 14 (168, 5.3 and 129 hours respectively), we observe that experiment 13 also performs with a very constant waiting time. A higher palletizing availability would therefore out weigh the increased palletizing speed and perform on a more constant level.

With regards to the daily volume produced within the four different experiments, we do not observe any significant changes. An overview of the daily produced volumes per production line for each of the additional experiments, is given in figure J4 of Appendix J.

Finally, we analyse the average cycle times per filling order for each of the SKUs on the different production lines. Figure 5.8 depicts the average filling cycle times for the additional experiments.

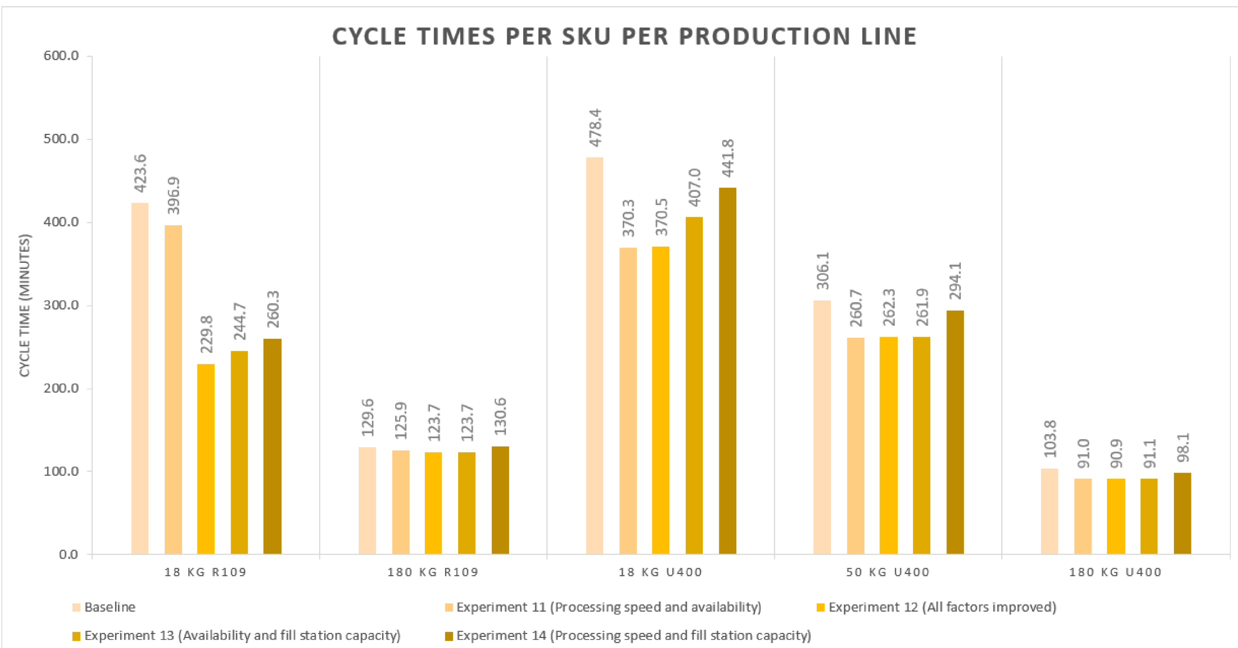


Figure 5.8: Results of the average cycle times per additional experiment 1-4 for the different SKUs filled at production lines R109 and U400

In the figure above, we observe significant improvements to the cycle filling times for 18 kg SKUs on production line R109. The best overall performing experiment is experiment number three, in which all factors are improved. We obtained a total cycle filling time of 230 minutes per 18 kg filling order. We are looking for an average cycle time that falls below the weighted average batch time of 263 minutes, to minimize the overall chance to obtain waiting time. In this case, all of experiments 12, 13 and 14, match this target value. This does not mean that we will not obtain any waiting time in the production process, as observed in figure 5.7, but it minimizes the change of waiting time occurring. Since Ghent has multiple greases that have an even lower bottleneck time of 238 minutes, it is likely that some of these greases will still cause additional waiting time in the production process.

We can also explain the additional waiting time that we have left in the production process for additional experiment 13. This waiting time is caused by the presence of combined filling orders. In majority of the cases, only single filling orders are completed, which are either 18 kg, 50 kg or 180 kg orders. In some cases, orders are combined such as 18 kg and 50 kg orders. We observed that these orders cause generally longer filling times due to the extra set-up times that are incurred. Hence, we experimented with increasing the capacity of filling station 1 from 200%, up to 400% and 800%. We observed that the waiting time in the production process was reduced to 4.4-5.1 hours. This means that further improving the cycle times of FS1 reduces the overall waiting time even further. As this is not a realistic scenario due to the technical limits of the filling equipment, we did not consider further analysing this scenario.

5.3 Best improvement scenario

Based on the additional experiments, we choose experiment 13 as the scenario that improves the current state of the production process, the best. For this experiment, we increase the robot availability to 90% and increase the filling capacity of filling station 1, by implementing a second filling hose. We can translate the number of waiting hours in the production process for the best set of experiments, to a total number of extra batches that could theoretically be produced extra. We obtain the extra batches by dividing the total waiting time by the weighted average bottleneck time for the R109[4]. Table 16 depicts the results regarding the extra batches that could be produced for the best experiments between both the individual and interaction effects.

Table 16: Overview of the extra batches that could be produced after implementation of the best experiments

Best performing experiments	Baseline waiting time (hours)	Scenario waiting time (hours)	Improvement (hours)	Theoretical extra batches produced	Annual extra batches produced	Extra volume (tons)
400% palletizing speed	98.8	70.0	28.8	6	12	97
90% robot availability	98.8	70.0	28.8	6	12	97
Increased FS1 capacity	98.8	31.6	67.2	15	30	242
90% robot availability and increased FS1 capacity	98.8	23.7	75.1	17	34	275

From table 16, we observe that we could produce 34 extra batches in a future state on a full production year. For production line R109, this equals a total extra volume of around 275 tons[5] of greases annually. In comparison to the total volume produced on this production line, that results in a total capacity improvement of 4.7%.

Now, we want to ensure that the experiment in which we increase the robot's availability and the filling capacity for fill station 1 is statistically significant compared to our baseline scenario. We perform a paired t-test in Minitab on the average waiting times in the production process, with an α value of 5%. In the paired t-test, the H0 states that the difference in means of both samples equals 0. In our situation, we reject the H0 as our p-value is 0.012, which is smaller than 0.05. This concludes that we have statistically significant differences between the baseline scenario and the experiment in which we increase the robot's availability and increase the filling capacity of FS1.

5.4 Cost indication of improvement scenarios and payback period

From the engineering department, we obtained cost indications for a new palletizing robot with the desired availability/processing speed and the increased filling capacity for filling station 1. Next to the total cost, we also obtained an fictional value[6] of the net margin per produced kg of grease from the sales department. In table 17, the total investment costs, total cash flow, and the payback period for each of the improvement scenarios, are depicted. The payback period is determined as the total investment costs divided by the annual cash flow.

Table 17: Overview of investment costs, annual cashflow and payback period per investment scenario

Improvement scenario	Investment costs (k€)	Annual cash flow (k€)	Payback period (months)
Palletizing speed 400%	300	102	35.3
Robot availability 90%	300	102	35.3
Increased FS1 capacity	350	254	16.5
Robot availability 90% and increased FS1 capacity	650	289	27.0

[4] Production line R109 only suffers from waiting times in the process
[5] Average batch sizes for the R109 of around 8080 kg
[6] The actual net margin per kg grease will not be used due to confidentiality

Based on table 17, we can conclude that increasing the capacity of FS1, yields the shortest pay back period of 16.5 months. It does not necessarily yield the largest improvement with regards to waiting time reduction (as this is achieved by implementing both a new robot and increasing filling line capacities), but it is cost wise the best option to currently invest in.

5.5 Conclusion

In this chapter, we made use of the DES model to answer the following research question: "Which model configurations result in the most efficient way of removing the current production bottlenecks and obtain more production capacity?".

We first simulated our three individual factors (experimental design), to understand the dynamics of each intervention with regards to the production capacity, the filling cycle times and the total volume produced. With regards to the production capacity, the increase of the filling capacity for 18 kg SKUs on production line R109 (experiment 9), yielded the best reduction in the process waiting times. With regards to the filling cycle times, we noticed that experiment 7 (increase of robot's availability to 90%) and experiment 9 reduced the average cycle filling times, the most. With regards to the total volume produced, we did not observe any significant differences between the experiments.

Combining the best performing experiments and simulating their future states, resulted in 17 extra produced batches per six months, or 34 annually. For production line R109, this yield an additional production capacity of 4.7%. This is realized when the palletizing robot's availability is increased to 90% and the filling capacities of 18 kg SKUs on production line R109, are doubled. We conclude that the filling speeds at filling station 1 (18 kg SKUs) is a bottleneck for production line R109, as this causes excessive waiting times due to the batch sizes being twice the size as for production line U400. In case 18 kg SKUs are filled, it takes longer than the weighted average bottleneck time (263 minutes) to empty the scrape buffer vessel. For production line U400, the palletizing robot is a bottleneck, as it is directly connected to the EOL-section. This production line benefits from the increased availability, but it does not generate waiting times since the weighted average processing time for the batches on this production line are longer (383 minutes) than the filling times. We also obtained statistically significant results in comparing the baseline scenario to the best additional experiment (increased availability and increased palletizing capacity FS1). To conclude, the best strategy for improving the current state of the production process is to invest in increased capacity for filling station 1, as this investment proposal has the lowest pay back period of 16.5 months.

6 Implementation

In this section we answer the final sub-question: "How can Shell Ghent implement the suggested simulation model within their production lines to remove the current bottlenecks?", we briefly describe the priorities for Shell Ghent in order to remove their current production waiting time as observed in the production process of production line R109.

6.1 Bottleneck prioritization

As observed in section 5.5, does Shell's current production process deal with two bottlenecks. In order of the impact each of the bottlenecks has on the production process, we prioritize the bottlenecks. Shell deals with the inefficient and slow filling process and the low OEE of the palletizing robot. In order to remove the current production waiting time, Shell should consider improving the situation regarding the capacities of the filling stations first, as this problem accounts for 68% of the total waiting time as observed in the production process. Also, this improvement scenario has the lowest payback period and hence, is the current best investment in order to reduce process waiting times. This problem is twofold, since it comes down to either improving the capacity of the filling stations or by reducing the overall set-up times and cycle times for filling orders. We only researched the effect of improved filling, therefore we suggest improving the baseline scenario by the implementation of an additional filling hose for the FS1 filling station. Besides the improved filling capacity, we observed that this adjustment does not solely reduce the waiting times to a minimum, since adjustments of 400-800% capacity could only reduce this waiting time to a minimum of 4-5 hours. Therefore, it should be required to further analyse the overall cycle times per process step in the filling process for especially 18 kg SKUs, in order to minimize the potential waiting time in the process.

The most useful tool for reducing the cycle times for the filling process is a traditional variant of Value Stream Mapping VSM. We primarily used VSM to identify the current bottleneck and create insights in the potential benefits for future production states. Within VSM the activities and cycle times for each of the processes is further analysed and wasteful activities that do not add any extra value to the customer, are evaluated and removed. For this method, the activities should primarily be analysed on an operational level. This is especially necessary for 18 kg SKUs due to the extra steps that need to be taken by operators to ensure the right filling process. Next to the 18 kg SKUs, it is also useful to use VSM to further streamline the process of combined production orders.

A short term solution that would decrease the current production waiting time, would be the further focus on Root Cause Analysis RCA from the maintenance department with regards to the palletizing robot. Previous efforts from the maintenance department have already improved the OEE of the robot from around 22% to 60.2%, so it has proven to be a valuable concept within maintenance engineering to further optimize the palletizing robot's availability. This could potentially help Shell increase the palletizing robot's availability to around 80%, hence, reduce the overall waiting time in the production process. Although we could only reduce the number of production hours by 28,8, this would still result in an extra volume of 97 tons annually.

6.2 Conclusion

To answer the sub-question: "How can Shell Ghent implement the suggested simulation model within their production lines to remove the current bottlenecks?", we further discussed the results that we obtained from section 5. Implementation of the suggested adjustments is a long-term strategy, that should be discussed with senior management. Either a new palletizing robot that has the right specifications (at least a 90% availability or 400% processing speeds) or the implementation of increased filling capacities for filling line FS1, are CAPEX investments and need to be approved by both senior management as well as regional general management. Therefore, the short term solution to make further use of RCA and to focus on the so called "low hanging fruit" with regards to the breakdowns of the robot, would be recommended to reduce current waiting times in the production process. On the longer term, we conclude that the investment proposal in increasing filling capacity for fill stations 1, has the lowest payback period and should be prioritized first.

7 Conclusions & recommendation

This chapter provides a conclusion to the main research question as stated in section 1.5. In section 7.1 we present the overall conclusion to the conducted research. Section 7.2 addresses further research for Shell, after which section 7.3 describes several recommendations. We conclude with the contribution to theory and practice in section 7.4.

7.1 Research conclusion

Shell Ghent currently does not have the capacity to counter peak demand or uncertainty in the market or deal with the implementation of R&D requests. To get an understanding on how to improve productivity for their manufacturing plant and deal with the aforementioned factors, Shell Ghent wanted to gain more insights in their current production performance and the potential presence of bottlenecks in their production process. First, we analysed the main research question as stated in section 1.5:

How could Shell increase their production capacity by 8-12% on production lines R109 and U400 in order to deal with rush orders, uncertainty in production demand and R&D test requests?

To understand and identify the bottleneck's of Shell's GMP, we answered sub-question 1: "How are production lines R109 and U400 set up, used and where are current bottlenecks in the production process observed?". Production lines R109 and U400 are the two production lines which account for 78% of the total volume produced annually. We observed that the current filling and EOL-processes are inefficient, and cause multiple breakdowns and complete stoppages of the production lines. For the EOL-section, we observed a bottleneck in which the current palletizing robot is causing on average 20 minutes of breakdowns per hour. Over a 12-week period it also fails to meet the Overall Equipment Effectiveness OEE target of 65%. Without a functioning palletizing robot, the SKUs that need to be palletized will not be processed and remain in the current system. The other bottleneck is therefore the reduced filling capacities on production lines R109 and U400, which are in some cases 54% slower than the capacities used by the scheduling department. This is not only due to the operators being interrupted with their filling activities, but also due to set-up times for different SKUs and the technical limitations of the current filling process. Especially for 18 kg SKUs, the current filling capacities are cumbersome and result in process delays.

In section 3, we answered the second sub-question: "Which methods are available within the literature to address the bottlenecks found in the production process?". We found that Discrete Event Simulation DES is a powerful tool to mimic a production process and its stochastic behaviour. In combination with Value Stream Mapping VSM, in which we analyse a baseline production process with different future states after implementation of certain improvement scenarios, we could create insights in the most inefficiencies of a production process and obtain information with regards to the best performing improvement scenarios.

After the literature review, we answered the third sub-question "What should the simulation model look like for Shell's GMP and what possible strategies could be implemented to remove the current bottlenecks that are observed in the production process?" (section 4). The created simulation model for production lines R109 and U400 focuses on the production of direct batches. This simulation model was validated with production data from March and April 2022, and indicated that it is accurate enough to be used as a representation of the production process (2-5% deviation to the realized production volumes). In this simulation model, we make use of a 17-day warm-up period and use a total run-length of around 183 days. To obtain statistically significant results we make use of three replications per simulation run.

With the use of the simulation model, we answered our fourth sub-question: "Which model configuration results in the most efficient way of removing the current production bottlenecks and obtain more production capacity?" (sextion 5). We observed during the different experiments that a palletizing availability of 90% is indifferent to a palletizing robot with a palletizing speed of 400%. Both adjustments reduced the overall waiting time from 98.8 hours (baseline scenario) to around 70 hours. The implementation of extra filling capacity for 18 kg SKUs for production line R109, yielded the overall best improvements for the individual factors, both in terms of waiting time (31.6 hours) and average filling cycle time (338.9 minutes) per filling order. For the interaction effects, we obtained the best results when we combined an availability of 90% and increased filling capacity for 18 kg SKUs on R109. The overall waiting time was found to be 23.7 hours, which is a total reduction of 75.1 hours in comparison to the baseline scenario. This reduction translate to an additional volume of 275 tons for production line R109 (34 batches annually), which is a total of 4,7% of the total volume produced on this production line. For U400, we did obtain efficiency improvements but this did not translate to productivity improvements since this production line is less affected by the current bottlenecks of the filling and EOL process.

Finally, we answer sub-question 5: "How can Shell Ghent implement the suggested simulation model within their production lines to remove the current bottlenecks?". It currently is possible to remove the bottlenecks regarding the palletizing robot. We observed that a palletizing robot with an availability of 80-90%, with the same capacity of the current robot, is able to reduce the waiting time to 70 hours (reduction of 28.8 hours). However, it currently is not possible to completely remove the bottleneck regarding the filling processes of 18 kg SKUs. This is mostly due to the large batch sizes of production line R109 and the large number of SKUs that we need to fill. The remaining delays were caused by combined filling orders of multiple SKUs, which cause increased complexity in the production process and increases the set-up times for filling orders. Focus should therefore be on the overall reduction of set-up times in the filling process and increase efficiency for this process. Implementation of improved filling capacity for filling station 1 is the best investment option, considering its payback period (16.5 months).

7.2 Further research

In this section, we describe extra research possibilities for Shell's manufacturing plant, to further improve the productivity of their production processes.

7.2.1 Indirect filling process

First, we address the inefficiencies regarding the filling station. As we observed does production line R109 suffer from the direct filling of SKUs, and creates additional waiting time in the production process. Production line U400 does not suffer from this problem, but we observed for the filling process of this production line that indirect fills (filling process from batches that are produced by the hopper buffers) cause another problem. The problem observed is the total time it takes to empty the hopper buffers of around 45 tons in time, before another production run of 45 tons arrives at that same buffer. As we observed earlier in table 5, are the realized filling capacities significantly lower than the scheduled capacities (used by the scheduling department). This problem is slightly worse for indirect fills, as we observed during our data-analysis. With lower filling capacity for indirect fills, the production process can be halted on a more frequent basis. As we did not consider the indirect filling process to our scope, it should be an important problem to solve in Shell's future. Even more so because, as figure H2 depicts in appendix H, the ratio of direct versus indirect filled batches is only declining over the years. For U400 this means that in the future, more batches will be produced and filled by a indirect manner. Therefore, more production stoppages will be encountered in case the filling capacities are not up to the targets used by the scheduling department.

7.2.2 Production lines R103, R105 and R106

Second, we did not take the other three production lines R103, R105 and R106 in to consideration within this research. This means that we left 22% of the total annual volume produced, out of the scope of this research. This was mainly done due to time constraints and the fact that current production issues could already be exposed by only simulating production lines R109 and U400. Including these production lines will give a better estimation of the actual waiting times in the production process, since the filling process of these lines are often done simultaneously when filling from either production line U400 or R109. In practice, the waiting time in the production process could therefore be even more, and simulating this scenario could in potential net even more production capacity. This is in scientific terms often referred to as a "digital twin" of the manufacturing process, but could help Shell with their capital investment decision-making process.

7.2.3 Order complexity combined filling orders

We observed increased filling complexity and increased filling cycle times for combined filling orders (multiple SKU types). As explained in section 5.2, do combined filling orders cause excessive waiting times in the production process. For this problem, we recommend to create more insights with regards to the set-up times and the overall efficiency of switching from SKU types in the filling process. First, VSM or Single-Minute Exchange of Die could be used to identify and eliminate waste in the set-up process and obtain a faster filling process for combined orders. If this is not suitable for this type of problem, a planning and scheduling solution could also reduce the overall waiting time in the process. For this matter,it would be smart to further research the sequence in which Shell Ghent fills their SKUs from the production line and to research if making longer production runs (more batches of the same product), would reduce the overall waiting time in the production process. Also, more produced batches would increase the overall holding and inventory costs for the plant, therefore we are looking for an optimization of the production run length and the inventory holding costs.

7.3 Recommendations

Finally, we give recommendations for Shell in using the developed simulation tool. For Shell, we will briefly discuss the added value and the practical use of the simulation tool. The goal of this thesis is to improve Shell's current production capacity by focusing on certain inefficiencies in its production process. This goal was realized by the creation and implementation of a DES tool, to both quantify the current impact of bottlenecks towards the plant's productivity, and incorporate the process' stochastic behaviour.

With the created tool, Shell is able to identify the current inefficiencies in their production lines R109 and U400. It also helps them to identify wasteful sources within their filling and EOL-section. For the operations department, this tool could be used to verify the implementation of certain process adjustments, such as the impact of reduced bottleneck times within the core process on the overall production capacity, or the implementation of extra buffers in the EOL-section to reduce extra waiting times at different EOL-processes.

Also, the operations department benefits from the created simulation tool as their decision making process regarding batches that are produced on Fridays, will be better streamlined. With the implemented stochastic behaviour of the core process (statistical distributions for all products on the different kettles), the operations department can produce multiple simulation runs to verify whether or not starting a single batch during the Friday's last production shift, could be a realistic scenario. In some cases, batches are not started on the autoclave since there is not enough time to ensure that this batch could reach the finishing kettle before the end of the shift. With the simulation tool and the added stochastic characteristics of the production process, the operations department could therefore increase the current productivity for batches produced on Friday evening, by making use of the simulation model.

Furthermore, the local planning and scheduling department can use the simulation tool to verify one-week ahead schedules, and the impact of accepting rush orders in to the current production schedule. The scheduling department could create a data set of the normal one-week ahead planning. After that, it is possible to add the specific production orders that are marked as "rush orders" to the schedule. With the new and adjusted planning, the scheduling department obtains information on the total waiting time accrued or the extra yielded volume as a result of the implemented rush orders in the new production schedule.

Another benefit for the scheduling department is the experiments that could be performed with variable product runs. During the first months, the scheduling department wondered about the impact of longer production runs (more batches of the same product type) and the effect of this change to the productivity of the plant. Shell's manufacturing plant has always been a manufacturer of specialty greases, which is also the reason why it has a more complex product portfolio in comparison to other grease manufacturing plants. Since most of the planning is done with help of an ERP-system and manual adjustments, the scheduling department could now test for different production run lengths and different sequences.

7.4 Contribution to theory and practice

During literature review, we have noticed that Discrete Event Simulation (DES) is a popular tool in manufacturing, healthcare ad logistic processes. Existing studies have mostly applied DES to the conventional manufacturing industry (metal or automotive industry). Using DES for the chemical industry, has not explicitly been named or been addressed in literature. Grease manufacturing is a process that has been known for decades and falls within the conventional oil and gas/chemical industry. For this sector, it is known that adoption of new technologies and methods of analysing the performance of manufacturing plants, can be extremely challenging. This study shows that new technologies such as DES can be applied for this kind of plants, and can help in improving baseline productivity performances of production plants.

The practical contribution is verified and acknowledged by Shell. With the current efforts in the identified and quantified bottlenecks, Shell has the information on which bottlenecks to address first in order to gain extra production capacity. The simulation model provides the plant with an extra layer to support and verify investment decisions. Also, the simulation model ensures the collection of extra data (production waiting time and cycle time per SKU type) that would otherwise not be logged by either the maintenance or operations department.

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Appendices

A Production process

This section describes the production processes of U100 (R109, R103, R105 and R106) and U400 in more detail.

A.1 Conventional warehouse

The conventional warehouse is a manually operated warehouse that provides storage to all additives used in the grease products, packaging materials for each of the SKUs, storage for special Schwerdtel filling tanks and storage for Intermediate Bulk Containers (IBC). For all products, their components are stored within the conventional warehouse. The on-site logistics department, a third party, provides support to the production activities that happen on-site. Their tasks are amongst others, ensuring that all incoming raw materials, additives, and packaging materials are stored, replenishment of thickening components and additives to the U100 and U400, storage of palletized end-products in the AS/RS warehouse and retrieval of products for outbound logistics to end-customers.

From the production department, a request for thickening components and additives is communicated weekly from the production department to the logistic third-party based on the production schedule for the next week. Here, an overview of the components that are required to produce the difference is stated. The logistic operators collect the pallets with additives and thickening components and store them within the preparation section. In case any of the production units need additives or other components that are required during production, the third party ensures that both units are replenished in a Just in Time (JIT) manner. On several occasions, operators need to manually retrieve material from the warehouses as a result of lack of communication between both the production department and the logistics operator. This results in a loss of effective production time in case the operator is away from its workstation (core process or filling station).

A.2 Preparation section

The preparation section is the second step in the production process for products from both production units. This process step mainly covers the pre-treatment of the batches by preparing the grease thickeners and additives. Each of the production units has their own preparation section. Within this section, different operational activities are performed to ensure that the core process section can be initiated. For every batch, operators collect the thickening components and the additives required to produce one batch. Operators manually weigh the components according to the quantities needed as described in the Method of Manufacturing (MOM). With different thickening types in the greases, different components are needed. For the Gadus S3 V220C, a grease with a Lithium-Complex thickener, the following components are for example needed: Lithium, Boric acid and a LUBAD 638 additive. Each of the three products is originated from the conventional warehouse and needs to be weighted in the preparation section. Figure A.1 depicts a fully weighted pallet with additives and thickening components.

Figure A.1: Fully weighted additives and thickening components for Gadus S2 V220C.

Within the U100, operators can directly add the mixture to the core process after weighing the different components. The U400, where the Polyurea line also shares the preparation section, is located further away from the actual core process. Here, operators need to manually transport the additive and thickening components to the process and use a forklift to eventually get the mixture at the production platform. It occurs that operational mistakes are made during this process, such as retrieving the wrong additives from the conventional warehouse or materials that have not yet been approved by the laboratory.

The preparation section is also marked by the heating of two different vessels on each of the production units. Within the first kettle (V403 for the U400 and the V164 for the U100) a mixture of oil and HCO/HCOFA particles are mixed. The combination of oil and this component provides acidity to the grease and is being heated in the vessels to completely dissolve the granulated particles. Temperature monitoring plays an important role during the heating process, since heating the mixture above 80 degrees Celsius results in degradation of the HCO. Both the contents of the vessels are after preparation pumped through the autoclave reactors in the core process for the typical three kettle processes.

A.3 Core process

After the preparation section, the prepared mixtures are pumped through the core process sections. To understand Shell's production facility for each of the production lines, we need to understand how the production lines are interconnected. The U100 is a production unit which has three different finishing kettles. The R103, R106 and the high-volume R109 kettle. Within this production facility, the Polyurea line is also located but we do not include the Polyurea reactor (R105) since we could not have attended batch productions due to the presence of hazardous materials that require extensive training. For each of the production lines (R103, R106, R109 and R430) different operational activities and processes are performed.

A.3.1 U400

After the preparation section, the prepared mixtures are pumped through the core process sections. The U100 is a production unit which has three different finishing kettles, the R103, R106 and the high-volume R109 kettle. Whereas the U400 only has one finishing kettle. Within this production facility, the Polyurea line is also located but we do not include the Polyurea reactor (R105) since we could not have attended batch productions due to the presence of hazardous materials that require extensive training. The U400s core process is located on a platform next to the conventional warehouse and has the capacity of producing in batches of around 5.8 tons, see figure A.2.

Figure A.2: U400 platform with from left to right the finishing kettle, cooling kettle and autoclave.

U400 mainly focuses on the production of complex greases and two operators are needed to ensure production. One operator is responsible for monitoring the core process whilst the other one is preparing the additives and thickening components for each a new batch. For the three production kettles in the core process (R410, R420 and R430), the Method of Manufacturing (MOM) and the DCS are together responsible for producing the greases. The former is a detailed description of all the actions, states and process parameters that need to be maintained during each phase of the production process. It is the main recipe for producing each of the different products. In the autoclave reactor (R410), the chemical reaction is initiated, and the operators closely monitor the process for parameters such as pressure and temperature. In this first step, the thickening component (such as Lithium, Lithium complex, Lithium Calcium, Lithium Calcium complex, Calcium or an Aluminum complex) are formed. The production of this thickening component is the most important step since the main characteristic of the product is created. After production on the R410, operators manually take a sample from the reactor to check the product for its characteristics.

From the R410 the product is pumped through the R420 where a first mixture of performance additives is added to the product. During the pumping procedures from each of the reactors, a varying quantity of oil is added to clean both the reactors and the piping system. Eventually, the oil is recuperated in the product and no oil losses are created. On the R420, one of the additives is dosed by means of a chute, which is manually supplied by the operators. As the R420 is a stirred tank reactor, each of the additives is homogenized easily.

For operators, the behavior of the stirrer provides them with information on the hardness of the greases. This is usually noted by the amperage of the stirrer and the cooling speed within the reactor. From experience, operators "know" that a higher stirrer amperage and temperature correspond to generally harder greases. A hard grease has higher viscosities and is not always desired if that contradicts its product specifications. After cooling in the R420 cooling kettle, the grease is pumped through the R430. Here, the last set of additives are manually added by the manhole and, in case the grease requires it, a rework is done to obtain the right hardness.

Reworking greases is rather time consuming and could take up to 45 minutes per rework cycle. For hard greases, extra oil and additives are blended with the grease to obtain the right hardness. Greases which are tested and turned out as too soft cannot be reworked and should be approved by the laboratory, for a potential waiver. A waiver is an approval of a batch that could not meet the internal product specifications. One of the Key Performance Indicators (KPI) for production is the First Time Right (FTR). This ratio describes the number of right batches produced the first time divided by the total amount of batches produced. A rework is not affecting whether a batch is produced the first time right. Therefore, this is still counted for as a "right" produced batch. Last year, the plant's FTR was around 91% of all batches produced.

Within the U400, the final product is either pumped to the V440 vessel or to the hopper storage tanks. Both the vessel and the tanks are in direct connection with filling station 9, but their urgency for filling is different. From the V440, the product follows the direct filling route, and these products need to be urgently filled. Whereas the products from the hoppers (V445, V446) are not in direct need of filling into SKUs, the indirect filling route. In the hoppers, which are both dedicated to two products, a total of six different batches are produced to completely fill the hoppers. In order to produce new batches for each of the hoppers, it is mandatory to completely empty its contents. This could either be done by filling from filling station 9 or a separate filling section called the schwerdtel filling, which only fills 0,4 kg cartridges. We do not take the schwerdtel filling during this research into account, since it's a stand-alone filling section.

A.3.2 U100

U100s core process is characterized by the autoclave (R108) and the cooling kettle (R107), along with the R109 finishing kettle. Major differences between both production units are the volume produced per batch and the amount of hopper storages that is used to store products. Volume wise, the R109 can produce twice as many greases as on the R430. It also a total of nine different hoppers, in comparison to the two hoppers from the U400. For these hoppers, the same rules apply as for the hoppers from U400; in order to make another production run for a product that is stored in a hopper, the hopper should be completely emptied.

Finished greases from the R109 also follow either the direct or the indirect filling route. For the direct filling route, any finished product from the R109 is always directly pumped through to the V170 vessel. In this vessel, the product can await to be filled by an operator at filling station one or six, depending on the type of SKU. Filling station six is dedicated to the V170 vessel, and thus, dedicated to the direct filling route for filling products in 50 and 180 kg SKUs. The indirect filling route is marked by filling from the hoppers. Each of the hoppers is connected to so-called collectors, which connects the piping systems from the hoppers to the filling sections. Filling from the hoppers is usually performed by both filling stations one and seven.

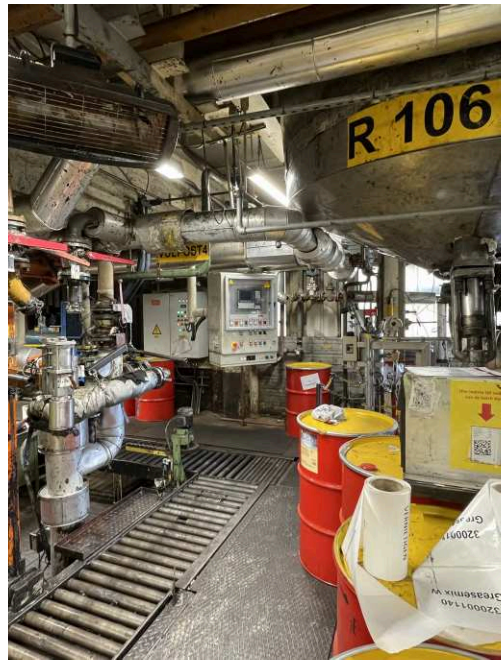
The R103 is a standalone reactor that produces clay greases. Its advantage is the production of clay greases without making use of the R108 (autoclave) or R107 (cooling kettle). The batch sizes produced on the R103 are small in comparison to the other finishing kettles, varying from 1640-1690 kg of grease, depending on the product. In total, four different products are created on the clay reactor. Operating this reactor is usually performed by a single operator and could easily be performed next to operating the R109 or R106 production kettles. Each of the batches takes around 460 minutes each to be finished and after finishing, the end-product is always directly filled. No indirect filling route for this kettle exists. The R103 is equipped with a dedicated filling station filling station 3, to prevent the increased frequency of changeovers when this type of product is filled at other filling stations due to contamination hazards.

The next finishing kettle, the R106, is a finishing kettle that solely produces graphite greases in batches of 4200 up to 4500 kg. Its base grease is produced on either the R109 or R430 finishing kettles, after which it is mixed in the R106 along with graphite particles. From the U400, it is not possible to pump greases directly through to the R106 reactor within the U100 section due to the long distance between the production units and the complexity of pumping grease over such a distance. Therefore, the products are manually filled in 180 kg drums in the U400 filling station, transported to the R106 finishing kettle, and manually emptied by using a Graco pump. For a whole batch of grease from the U400, this corresponds to manually emptying 23 drums and subsequently filling another 23 products with the final product within the dedicated filling station. Due to the contamination effect of graphite on both the kettle and the piping system, the R106 is used as a dedicated and stand-alone finishing kettle.

According to the quality departments, are the kettles for each of the production units used to their full potential. Since the core process follows the MOM, the product recipe which is based on mass percentages for each of the products. Significant capacity improvements are not likely to be found within the kettle sizes, but rather in reducing the operational failures due to retrieving wrong additives. Also, quality departments described that the flushing process is also not subject to major capacity improvements, since this process is key to maintaining product specifications which is achieved by the current flushing sequences.

B Photos of the production process

(a) Filling station 9

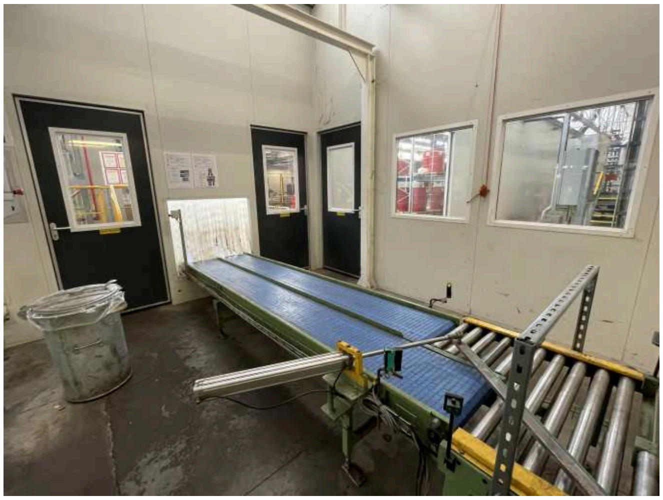


(b) Filling station 4

(c) Filling station 6 at U100

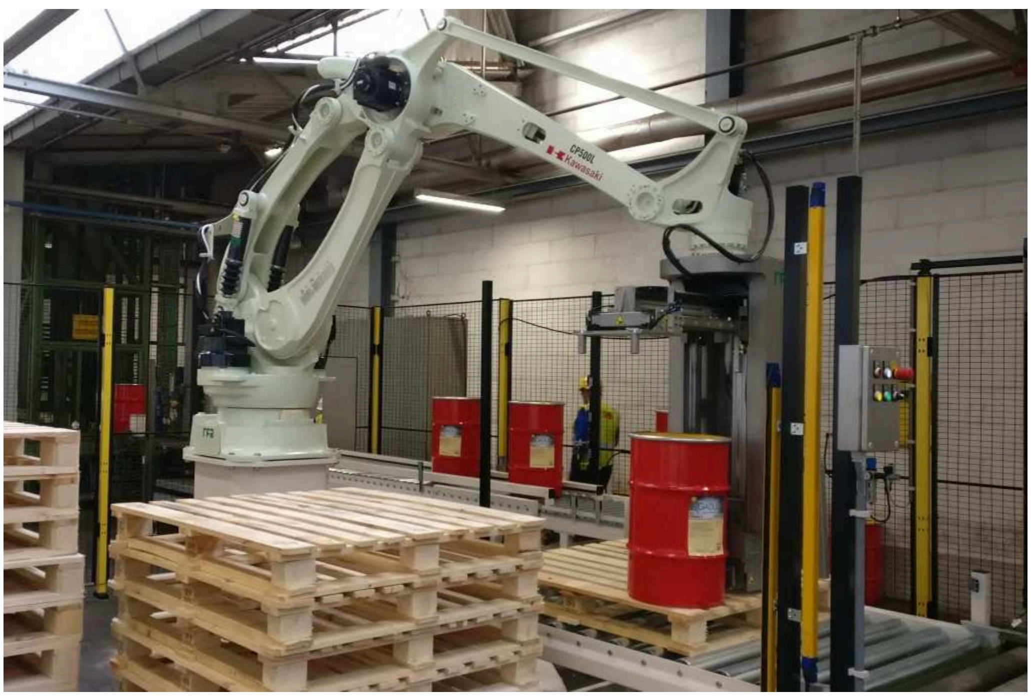
(d) Filling station 7 at U100

Figure B1: Overview of different filling stations within the EOL section, where (a) originates from the U400 and rest of the pictures are located at the U100



(a) Branching section and buffer after FS9

(b) Converyor belts to the palletzing robot from FS9



(c) Palletising robot at the EOL section

Figure B2: Overview of different locations within the EOL section

C Optimal start time of the next batch for the different bottleneck scenarios

Table 18: Bottleneck scenarios and their optimal starting time for entering a new batch in to the production system

Bottleneck scenario	**Bottleneck current batch**	**Bottleneck next batch**	**Optimal start time next batch**
1	Autoclave (1)	Autoclave (1)	$t_{optimal} = t_0 + t_{set-uptime}$
2	Autoclave (1)	Cooling kettle (2)	$t_{optimal} = t_0 + (t_{ck,0} - t_{ac,1}) + t_{set-up\,time}$
3	Autoclave (1)	Finishing kettle (3)	$t_{optimal} = t_0 + (t_{ck,0} - t_{ac,1}) + t_{set-up\,time}$
4	Cooling kettle (2)	Autoclave (1)	$t_{optimal} = t_0 + (t_{ck,0} - t_{ac,1}) + t_{set-up\,time}$
5	Cooling kettle (2)	Cooling kettle (2)	If $(t_{ac,1} > t_{ck,0})$: $t_{optimal} = t_0 + t_{set-up\,time}$
			Else: $t_{optimal} = t_0 + t_{set-uptime} + (t_{ck,0} - t_{ac,1})$
6	Cooling kettle (2)	Finishing kettle (3)	If $(t_{ck,0} - t_{ac,1})$ and $(t_{ck,1} > t_{fc,0})$ $t_{optimal}= t_0 + t_{set-up\,time} + (t_{ck,0} - t_{ac,1})$
			Else if $(t_{ck,0} - t_{ac,1}) < 0$ and $(t_{ck,1} > t_{fc,0})$: $t_{optimal} = t_0 + t_{set-up\,time}$
			Else if $(t_{ck,0} - t_{ac,1}) >= 0$ and $(t_c k_1 < t_f c_0)$: $t_{optimal} = t_0 + t_{set_up\,time} + ((t_{ck,0} - t_{ac,1}) + (t_f c_0 - t_c k_1))$
			Else if $(t_{ck,0} - t_{ac,1}) < 0$ and $(t_{ck,1} - t_{fc,0}) < 0$: $t_{optimal} = t_0 + t_{set-up\,time} + (t_{ck,1} - t_{fc,0})$
7	Finishing kettle (3)	Autoclave (1)	$t_{optimal} = t_0 + t_{set-up\,time}$
8	Finishing kettle (3)	Cooling kettle (2)	$t_{optimal} = t_0 + t_{set-up\,time} + (t_{ck,1} - t_{ac,0})$
9	Finishing kettle (3)	Finishing kettle (3)	$t_{optimal} = t_0 + t_{set-up\,time} + ((t_{ck,0} + t_{fk,0}) - (t_{ac,1} + t_{ck,1}))$

The column "optimal start time next batch" refers to the multiple scenarios for each of the bottlenecks scenarios in which a new product could optimally be started. t_0 refers to the time in which the current batch is finished on the autoclave and $t_{set-uptime}$ refers to the set-up time as incurred by the flushing procedure, which will be discusses in the next section. At last, there are multiple possible scenarios for bottleneck scenarios 5 and 6. These are all dependent on the differences in the starting time of the current batch on the cooling kettle ($t_{ck,0}$), the finishing time of the next batch on the autoclave ($t_{ac,1}$), the finishing time of the current batch on the finishing kettle ($t_{fc,0}$) and the finishing time of the next batch on the cooling kettle ($t_{ck,1}$).

D Set-up times for production line R109 and U400

Table 19: Set-up time for the flushing procedures for production line R109 per product that is produced.

Product	Set-up time	Unit
CALIHAR	3,600.000	Sec
BGr(GHE) Nerita 0768	7,200.000	Sec
BGr(GHE) Rhodina BBZ	14,400.000	Sec
BGr(GHE) GdS2V220 2	18,000.000	Sec
BGR (GHE)GadS2V220AD	3,600.000	Sec
Alvania 1029	7,200.000	Sec
Alvania S 2	600.000	Sec
Rhodina 0616	3,600.000	Sec
Rhodina 0616	86,400.000	Sec
Nerita 0768C	6,000.000	Sec
SKF MT33 (SNF)	1,800.000	Sec
Sterak Grease 1	3,600.000	Sec
Rhodina BBZ	3,600.000	Sec
Rhodina BBZ	86,400.000	Sec
SKF MT47	10,800.000	Sec
Alvania 0854	3,000.000	Sec
Gadus S2 V220 2	3,600.000	Sec
Gadus S2 V220A 1.5	3,600.000	Sec
Gadus S2 V220AC 2	3,600.000	Sec
Gadus S2 V220 00	3,600.000	Sec
Gadus S2 V220AC 0	3,600.000	Sec
Gadus S3 V460 1.5	3,600.000	Sec
Gadus S2 V220 1	3,600.000	Sec
Gadus S2 V100 3	3,600.000	Sec
Gadus S2 V220 0	3,600.000	Sec
Gadus S2 V100 2	3,600.000	Sec
GadusRail S3 EUFR	4,200.000	Sec
GadusRail S3 EUDB	2,700.000	Sec
Gadus S1 V220 2	1,200.000	Sec
GadusRail S3 EU	3,000.000	Sec
Gadus S5 V42P 2.5	4,200.000	Sec
GadusRail S4 HS EUDB	4,200.000	Sec
GadusRail S4 HS EUFR	6,000.000	Sec
Gadus S2 V145KP 2	10,800.000	Sec
Gadus S5 V25Q 2.5	1,200.000	Sec
Gadus S2 V100Q 2	10,800.000	Sec
SL2400	6,000.000	Sec
SL 3239	4,200.000	Sec
SL 3240	6,000.000	Sec

Table 20: Set-up time for the flushing procedures for production line U400 per product that is produced.

Product	Set-up time	Unit
GadusS3V460D 1e fase	3,600.000	Sec
GadusS4 OGK 0/00 1st	3,600.000	Sec
G S3 V460D 1.5	3,600.000	Sec
Gadus S3 V770D 1	28,800.000	Sec
BGr(GHE) GdS3V220C 2	3,600.000	Sec
BGR (GHE) Albida 0617-135C	2,400.000	Sec
BGR (GHE) Albida 0617-170C	0.000	Sec
BGR(GHE)G	43,200.000	Sec
BGR(GHE)GadS3V1002135C	2,400.000	Sec
BGR(GHE)GadS3V1002170C	0.000	Sec
FGr GHE GadS5V460 00	36,000.000	Sec
Retinax LX 2 INA	1,200.000	Sec
SKF GHG	1,200.000	Sec
Albida 0617	18,600.000	Sec
Gadus S2 V220 2	3,600.000	Sec
Gadus S3 V220C 2	7,200.000	Sec
Gadus S3 V460 2	3,600.000	Sec
Gadus S2 V220 1	3,600.000	Sec
Gadus S3 V100 2	3,300.000	Sec
Gadus S4 V150KP 2	43,200.000	Sec
Gadus 1526	21,600.000	Sec
Gadus 1582	43,200.000	Sec
Gadus S5 V460 00	3,600.000	Sec
JD GrGardPrPlus	1,200.000	Sec
Gadus S5 V110KP 1	36,000.000	Sec
Gadus S5 V460KP 1.5	3,600.000	Sec
Retinax LX 2	1,200.000	Sec
Albida 0617A	18,600.000	Sec
SL2262	2,400.000	Sec
Gadus S3 V160CP 2	3,600.000	Sec

E Statistical distributions for the residence times per kettle

	AC				CK				FC			
Product type	Distribution	(stdev/alpha)	(mean/beta)	(level/gamma)	Distribution	(stdev/alpha)	(mean/beta)	(level/gamma)	Distribution	(stdev/alpha)	(mean/beta)	(level/gamma)
Alvania 0854	Weibull	1.8341	17.3850	85.3590	Weibull	1.192	62.598	105.440	Lognormal	0.30045	4.733	0.000
Alvania 1029	Gamma	11.4130	3.6423	81.2760	Lognormal	0.954	3.414	107.760	Lognormal	1.031	2.126	22.277
Alvania S2	Lognormal	0.1489	4.9394	0.000	Lognormal	0.050	6.374	-370.770	Weibull	2.759	58.119	0.000
BGR(GHE) Gadus S2 V220 2	Weibull	6.5140	147.2500	0.000	Lognormal	0.149	4.939	0.000	Gamma	2.702	3.733	19.531
BGR(GHE) Nerita 0768	Gamma	22.0930	10.5600	337.4600	Normal	29.022	279.360	0.000	Lognormal	1.103	1.853	21.512
BGR(GHE) Rhodina BBZ	Weibull	11.3340	388.0600	0.000	Weibull	8.911	437.550	0.000	Weibull	2.515	30.656	0.000
Calihar	Weibull	18.5070	90.4210	0.000	Weibull	6.514	147.250	0.000	Lognormal	0.417	2.676	27.718
Gadus S2 V100 2 LN	Lognormal	0.4450	3.5916	84.6400	Lognormal	0.336	4.685	160.160	Lognormal	1.125	3.683	27.500
Gadus S2 V100 2	Lognormal	0.4147	3.5244	88.1900	Lognormal	0.050	6.374	-370.770	Exponential	0.027	83.000	0.000
Gadus S2 V100 3 LN	Gamma	3.3040	7.9818	92.0780	Lognormal	0.435	3.732	180.820	Lognormal	0.707	3.001	23.187
Gadus S2 V100 3	Lognormal	0.4328	3.4518	99.2520	Lognormal	0.361	4.707	119.400	Lognormal	0.701	2.561	20.203
Gadus S2 V100Q 2	Lognormal	0.1266	5.0088	0.0000	Gamma	3.070	19.803	313.580	Exponential	0.063	25.000	0.000
Gadus S2 V220 0	Weibull	1.6443	29.9790	70.5630	Lognormal	0.421	5.211	0.000	Gamma	3.905	7.020	19.733
Gadus S2 V220 1	Lognormal	0.1430	4.4869	0.0000	Gamma	2.077	41.053	124.670	Lognormal	0.278	5.230	-73.634
Gadus S2 V220 2 LN basisvet	Weibull	2.0537	39.7660	110.5700	Weibull	2.531	105.100	182.840	Weibull	0.824	7.836	27.000
Gadus S2 V220 2 LN	Weibull	1.1984	26.5920	100.7500	Lognormal	0.358	4.668	163.480	Lognormal	0.510	4.744	-8.180
Gadus S2 V220 2	Weibull	1.4649	27.7360	71.4360	Lognormal	0.399	4.414	113.570	Lognormal	0.615	3.903	66.702
Gadus S2 V220 A1.5	Lognormal	0.8905	2.4645	73.9050	Gamma	1.178	41.523	112.690	Lognormal	0.855	2.123	38.357
Gadus S2 V220 AC 2	Weibull	1.6236	22.0720	70.5510	Weibull	6.814	226.320	0.000	Lognormal	0.399	3.208	28.361
Gadus S3 V460 1.5	Normal	24.7510	263.3300	0.0000	Lognormal	0.625	3.917	164.320	Lognormal	0.450	2.829	16.475
Gadus S5 V25Q 2.5	Weibull	1.4926	41.7900	121.6600	Gamma	2.621	20.396	276.100	Weibull	1.177	29.987	28.730
Gadus S5 V42P 2.5	Lognormal	0.4860	3.0997	102.3800	Lognormal	0.428	4.435	133.600	Lognormal	0.546	2.697	23.151
GadusRail S3 EU	Gamma	56.4950	2.5249	0.0000	Weibull	5.160	262.540	-3.730	Gamma	1.745	12.809	34.063
GadusRail S3 EUDB	Lognormal	0.6765	2.9365	116.7000	Normal	18.735	255.210	0.000	Lognormal	0.461	3.079	25.536
GadusRail S3 EUFR	Lognormal	0.3132	3.7367	94.6770	Weibull	1.568	64.601	219.790	Gamma	1.306	19.363	34.735
GadusRail S4 HS EUDB	Weibull	1.2842	21.1160	109.7200	Gamma	6.792	13.849	143.820	Lognormal	0.527	2.817	28.498
GadusRail S4 HS EUFR	Lognormal	0.3665	3.4746	94.8190	Lognormal	0.425	4.103	152.020	Weibull	1.765	27.627	21.955
Nerita 0768C	Lognormal	0.4303	4.5218	426.7100	Gamma	17.689	3.786	199.850	Lognormal	0.762	2.518	27.052
Rhodina 0616	Gamma	5.7363	18.3760	259.8400	Lognormal	0.141	6.041	1.262	Gamma	15.979	7.550	0.000
Rhodina BBZ	Lognormal	0.2524	5.1192	206.9900	Lognormal	0.377	4.644	319.620	Weibull	1.366	24.559	25.473
SKF MT33	Lognormal	0.5381	3.0165	112.6800	Weibull	1.386	52.019	212.750	Lognormal	0.162	5.079	0.000
SKF MT47	Lognormal	0.5201	3.3714	111.5000	Gamma	2.482	29.803	285.380	Lognormal	0.449	3.709	71.058
Sterak 1	Weibull	1.6553	34.3560	101.0900	Normal	34.159	234.730	0.000	Gamma	1.858	21.674	39.426

Figure E1: Statistical distributions for each of the products produced on the R109 and the three specific production kettles

	AC						CK						FC					
Product type	K-S test	Critical value	A-D test	Critical value	Chi-Squared test	Critical value	K-S test	Critical value	A-D test	Critical value	Chi-Squared test	Critical value	K-S test	Critical value	A-D test	Critical value	Chi-Squared test	Critical value
Alvania 0854	0.0566	0.1963	0.3235	2.5018	5.2554	9.4877	0.0821	0.2178	0.6373	2.5018	6.6834	7.8147	0.1054	0.2099	0.3730	2.5018	3.2071	9.4877
Alvania 1029	0.9001	0.2005	0.7659	2.5018	0.9619	7.8147	0.8099	0.2150	0.4949	2.5018	1.9379	9.4877	0.0823	0.2050	0.4881	2.5018	3.5029	9.4877
Alvania S2	0.1190	0.4100	0.2895	2.5018	0.0000	0.0000	0.1210	0.4100	0.4727	2.5018	0.0212	3.8415	0.1340	0.3910	0.6302	2.5018	0.1205	3.8415
BGR(GHE) Gadus S2 V220 2	0.1212	0.4100	0.3606	2.5018	0.0049	3.8415	0.1190	0.4100	0.2894	2.5018	0.0000	0.0000	0.0743	0.1984	0.3872	2.5018	2.6909	11.0700
BGR(GHE) Nerita 0678	0.0825	0.2099	0.4062	2.5018	1.2306	9.4877	0.0775	0.2050	0.3956	2.5018	2.0652	11.0700	0.0841	0.1984	0.4744	2.5018	2.0421	11.0700
BGR(GHE) Rhodina BBZ	0.0675	0.3490	0.3134	2.5018	0.0829	3.8415	0.0873	0.3380	0.3959	2.5018	0.0011	3.8415	0.2701	0.3280	1.8227	2.5018	0.0049	3.8415
Calihar	0.0671	0.2005	0.3377	2.5018	1.7176	11.0700	0.1212	0.4100	0.3606	2.5018	0.0049	3.8415	0.0845	0.1938	0.3799	2.5018	4.9543	11.0700
Gadus S2 V100 2 LN	0.0897	0.2150	0.5503	2.5018	8.4220	7.8147	0.1653	0.2099	1.0928	2.5018	1.4775	7.8147	0.1083	0.2099	0.4941	2.5018	2.5260	9.4877
Gadus S2 V100 2	0.1301	0.2050	0.8893	2.5018	3.8787	9.4877	0.1210	0.4100	0.4727	2.5018	0.2117	3.8415	0.0831	0.3180	2.3231	2.5018	1.6460	5.9915
Gadus S2 V100 3 LN	0.0861	0.2940	0.2088	2.5018	0.9508	5.9915	0.1446	0.3010	0.1924	2.5018	0.6140	5.9915	0.1047	0.3490	0.2168	2.5018	0.0004	3.8415
Gadus S2 V100 3	0.0795	0.2050	0.2316	2.5018	1.3623	11.0700	0.0563	0.2027	0.1512	2.5018	3.3089	11.0700	0.1130	0.1984	1.1390	2.5018	0.8864	7.8147
Gadus S2 V100Q 2	0.1521	0.2940	0.6238	2.5018	1.5426	5.9915	0.1146	0.2900	0.3873	2.5018	1.2246	5.9915	0.0983	0.2776	1.5228	2.5018	3.9474	5.9915
Gadus S2 V220 0	0.0710	0.2074	0.5207	2.5018	1.8267	15.0860	0.0710	0.2099	0.4943	2.5018	1.8267	11.0700	0.0750	0.2099	0.3413	2.5018	3.8715	9.4877
Gadus S2 V220 1	0.1241	0.2005	0.8551	2.5018	5.4628	9.4877	0.0665	0.2005	0.2258	2.5018	1.8373	11.0700	0.0913	0.1963	0.7333	2.5018	6.1137	11.0700
Gadus S2 V220 2 LN basisvet	0.0930	0.2236	0.6370	2.5018	2.1329	7.8147	0.0693	0.2099	0.2146	2.5018	1.3929	11.0700	0.1489	0.2177	1.4751	2.5018	3.1409	9.4877
Gadus S2 V220 2 LN	0.0897	0.2124	0.4985	2.5018	2.4598	9.4877	0.1631	0.2074	1.0724	2.5018	2.0690	7.8147	0.0951	0.2720	0.3820	2.5018	2.5804	7.8147
Gadus S2 V220 2	0.0537	0.1984	0.2048	2.5018	1.7449	11.0700	0.1420	0.2124	0.5616	2.5018	6.8939	7.8147	0.0828	0.2074	0..39211	2.5018	1.4552	9.4877
Gadus S2 V220 A1.5	0.0555	0.1943	0.2883	2.5018	0.7304	11.0700	0.0676	0.2074	0.4219	2.5018	1.5234	11.0700	0.1161	0.2178	0.5786	2.5018	4.5993	9.4877
Gadus S2 V220 AC 0	0.0636	0.2968	0.1933	2.5018	0.2820	5.9915	0.1321	0.4100	0.4283	2.5018	0.0073	3.8415	0.1333	0.2900	0.3796	2.5018	1.0227	5.9915
Gadus S3 V460 1.5	0.0603	0.2099	0.2778	2.5018	1.0730	11.0700	0.0805	0.2050	0.2431	2.5018	0.9497	11.0700	0.0712	0.2005	0.2851	2.5018	2.3137	11.0700
Gadus S5 V25Q 2.5	0.0742	0.2299	9.2284	2.5018	0.8819	7.8147	0.0780	0.2332	0.4181	2.5018	1.3806	9.4877	0.0769	0.2443	0.4045	2.5018	2.7231	7.8147
Gadus S5 V42P 2.5	0.0589	0.2050	0.2322	2.5018	0.6161	11.0700	0.0697	0.2027	0.2766	2.5018	1.7990	11.0700	0.0771	0.2027	0.2720	2.5018	1.9651	11.0700
GadusRail S3 EU	0.0809	0.2443	0.3516	2.5018	1.6602	7.8147	0.1034	0.2236	0.4064	2.5018	3.9347	9.4877	0.0653	0.2332	0.2672	2.5018	8.5952	7.8147
GadusRail S3 EUDB	0.0806	0.2005	0.2103	2.5018	0.7415	11.0700	0.0504	0.1984	0.2632	2.5018	1.2084	11.0700	0.0814	0.2027	0.2755	2.5018	2.0128	11.0700
GadusRail S3 EUFR	0.0852	0.2005	0.3282	2.5018	2.6212	11.0700	0.0496	0.1963	0.2149	2.5018	0.7619	9.4877	0.0673	0.2053	0.3429	2.5018	0.2859	11.0700
GadusRail S4 HS EUDB	0.0727	0.2150	0.3090	2.5018	2.9336	9.4877	0.0848	0.2299	0.3335	2.5018	2.9511	7.8147	0.0851	0.2150	0.2178	2.5018	4.6053	9.4877
GadusRail S4 HS EUFR	0.0792	0.2027	0.3103	2.5018	2.2141	11.0700	0.0563	0.1984	0.1778	2.5018	1.9358	11.0700	0.1062	0.1963	0.4284	2.5018	6.5567	11.0700
Nerita 0768C	0.0623	0.2005	0.2403	2.5018	4.1885	9.4877	0.0874	0.2074	0.3518	2.5018	1.1336	11.0700	0.1205	0.2027	0.5534	2.5018	4.5464	9.4877
Rhodina 0616	0.0786	0.2053	0.3403	2.5018	8.2798	9.4877	0.0664	0.1963	0.2946	2.5018	1.2037	11.0700	0.0944	0.2027	0.5292	2.5018	1.2561	9.4877
Rhodina BBZ	0.0997	0.1963	0.3174	2.5018	3.3553	9.4877	0.0964	0.1963	0.5939	2.5018	3.5978	9.4877	0.0783	0.1963	0.4794	2.5018	3.9434	9.4877
SKF MT33	0.0660	0.1963	0.2819	2.5018	1.8994	11.0700	0.0885	0.1963	0.5723	2.5018	6.8083	9.4877	0.0709	0.2099	0.4090	2.5018	0.8876	9.4877
SKF MT47	0.0994	0.2027	0.3435	2.5018	3.2579	11.0700	0.0991	0.1984	0.5324	2.5018	5.9344	9.4877	0.0503	0.2124	0.2213	2.5018	0.5460	9.4877
Sterak 1	0.0744	0.2150	0.3407	2.5018	10.7910	7.8147	0.0677	0.2027	0.2445	2.5018	0.5104	11.0700	0.0721	0.1963	0.3136	2.5018	1.3680	11.0700

Figure E2: Test statistics for each of the suggested distributions as tested in figure E1

	AC				CK				FC			
Product type	Distribution	(stdev/alpha)	(mean/beta)	(level/gamma)	Distribution	(stdev/alpha)	(mean/beta)	(level/gamma)	Distribution	(stdev/alph	(mean/beta)	(level/gamma)
Albida 0617	-	0.0000	0.0000	0.0000	-	0.0000	0.0000	0.0000	Weibull	2.5001	255.6600	0.0000
BGR Alb617_135C	Lognormal	0.5909	4.4336	485.9500	Lognormal	0.1508	6.1503	0.0000	Lognormal	0.2533	5.4801	0.0000
BGR Alb617_170C	Lognormal	0.4375	4.6719	313.3800	Normal	111.1600	419.6000	0.0000	Gamma	7.3433	38.8820	0.0000
G S3V220C2 BaseG	Lognormal	1.1123	4.5493	292.0600	Lognormal	0.7186	4.5522	90.8920	Logistic	38.1820	166.9400	0.0000
GAD S3 V770D1_F1	Uniform	261.0000	301.0000	0.0000	Uniform	111.0000	124.0000	0.0000	Uniform	166.0000	366.0000	0.0000
GAD S4 V150KP 2	Constant	381	0.0000	0.0000	Constant	131	0.0000	0.0000	Constant	411	0.0000	0.0000
GADS3V4602	Gamma	5.2363	76.1550	0.0000	Gamma	5.2362	76.1550	0.0000	Weibull	2.5001	255.6600	0.0000
Gadus 1582	Lognormal	0.1563	5.9083	0.0000	Lognormal	0.8535	5.0204	134.0000	Weibull	2.7210	315.5600	0.0000
GADUS OGK 0_00F1	Lognormal	0.8021	3.8258	95.1070	Logistic	28.0640	278.9500	0.0000	Lognormal	0.5615	4.5009	131.3500
Gadus S2 V220 1	Weibull	11.9650	191.2200	0.0000	Normal	12.3840	149.4000	0.0000	Weibull	0.8538	101.9500	0.0000
Gadus S2 V220 2	Lognormal	0.4576	5.5592	0.0000	Lognormal	0.6560	4.2670	165.6000	Gamma	0.2309	5.9598	0.0000
Gadus S3 V220C 2	Gamma	37.3250	2.9346	0.0000	Gamma	7.8860	14.4930	252.3500	Gamma	1.3006	50.7510	124.2700
Gadus S5 V110KP	Gamma	15.2060	38.1620	0.0000	Lognormal	0.1226	5.0899	0.0000	Logistic	43.9880	300.6700	0.0000
JD GrGardPrPlus	Weibull	0.9875	49.3950	295.0000	Normal	17.6530	174.6400	0.0000	Lognormal	0.5390	4.9372	123.7700
Retinax_LX2	Weibull	12.5930	326.5000	0.0000	Normal	13.8110	134.3300	0.0000	Normal	0.1199	0.4570	0.0000
Retinax_LX2 INA	Lognormal	0.4532	4.5714	231.5100	Lognormal	0.6313	3.0769	114.2300	Lognormal	0.5256	4.5479	86.8110
S3 V100 2 Afwerk	Constant	0.0000	0.0000	0.0000	Constant	0.0000	0.0000	0.0000	Weibull	4.7806	179.2800	0.0000
SKF GHG	Lognormal	0.8838	3.9174	266.2700	Weibull	1.0577	21.2890	116.9500	Lognormal	0.3670	4.9389	70.6500
SL 2262	Uniform	554.0000	671.0000	0.0000	Uniform	213.0000	333.0000	0.0000	Uniform	307.0000	363.0000	0.0000
FGR GHE GadS5V46	Uniform	355.0000	725.0000	0.0000	Uniform	115.0000	256.0000	0.0000	Uniform	217.0000	247.0000	0.0000
BGR_617_135C_1eb	Uniform	502.0000	693.0000	0.0000	Uniform	231.0000	343.0000	0.0000	Uniform	180.0000	441.0000	0.0000
BGr(GHE)GS4OGK0_	Constant	253.0000	0.0000	0.0000	Constant	300.0000	0.0000	0.0000	Constant	118.0000	0.0000	0.0000
GADS3V460D 1,5F1	Uniform	290.0000	338.0000	0.0000	Uniform	164.0000	267.0000	0.0000	Uniform	307.0000	495.0000	0.0000

Figure E3: Statistical distributions for each of the products produced on the U400 and the three specific production kettles

	AC						CK						FC					
Product type	K-S test	Critical value	A-D test	Critical value	Chi-Squared test	Critical value	K-S test	Critical value	A-D test	Critical value	Chi-Squared test	Critical value	K-S test	Critical value	A-D test	Critical value	Chi-Squared test	Critical value
Albida 0617	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.082	0.150	1.147	2.502	4.457	12.592
BGR (GHE) Albida 0617-135C	0.096	0.227	0.405	2.502	1.279	9.488	0.072	0.233	0.228	2.502	2.719	9.488	0.138	0.224	1.431	2.502	8.913	7.815
BGR (GHE) Albida 0617-170C	0.078	0.215	0.334	2.502	0.826	11.070	0.077	0.215	0.259	2.502	3.257	11.070	0.065	0.210	0.522	2.502	5.621	9.488
BGR(GHE) GdS3V220C 2	0.134	0.318	0.441	2.502	0.097	3.842	0.120	0.309	0.344	2.502	0.834	5.992	0.148	0.318	0.607	2.502	0.008	3.842
GAD S3 V770D1_F1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GAD S4 V150KP 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GADS3V4602	0.110	0.361	0.572	2.502	0.168	3.842	0.164	0.338	1.914	2.502	0.582	3.842	0.082	0.150	1.147	2.502	4.457	12.592
Gadus 1582	0.144	0.272	0.247	2.502	1.418	7.815	0.129	0.262	0.459	2.502	3.433	5.992	0.091	0.262	0.464	2.502	4.983	5.992
GadusS4 OGK 0/00 1st	0.112	0.290	0.263	2.502	0.248	3.842	0.163	0.290	0.872	2.502	1.119	3.842	0.131	0.290	0.568	2.502	9.648	5.992
Gadus S2 V220 1	0.062	0.521	1.565	2.502	0.000	0.000	0.146	0.565	0.231	2.502	0.000	0.000	0.148	0.457	0.622	2.502	0.000	0.000
Gadus S2 V220 2	0.099	0.145	2.183	2.502	19.024	12.592	0.061	0.120	0.736	2.502	6.727	12.592	0.044	0.122	0.844	2.502	1.856	12.592
Gadus S2 V220C 2	0.065	0.126	0.425	2.502	5.290	12.592	0.094	0.122	1.173	2.502	11.719	12.592	0.056	0.125	0.717	2.502	3.083	12.592
Gadus S5 V110KP	0.129	0.349	0.332	2.502	0.065	2.706	0.093	0.328	0.356	2.502	1.598	5.992	0.132	0.338	0.562	2.502	0.585	3.842
JD GrGardPrPlus	0.064	0.224	0.204	2.502	3.470	7.815	0.107	0.221	0.354	2.502	1.413	11.070	0.082	0.230	0.246	2.502	0.182	9.488
Retinax_LX2	0.164	41.000	1.057	2.502	0.000	0.000	0.072	0.432	0.112	2.502	0.000	0.000	0.120	0.457	0.167	2.502	0.000	0.000
Retinax_LX2 INA	0.083	0.157	0.678	2.502	3.264	11.070	0.100	0.156	0.610	2.502	9.858	12.592	0.072	0.159	0.487	2.502	4.179	12.592
Gadus S3 V100 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.164	0.486	1.605	2.502	0.000	0.000
SKF GHG	0.052	0.173	0.192	2.502	3.671	11.070	0.082	0.173	0.742	2.502	8.875	9.488	0.049	0.174	0.243	2.502	1.401	11.070
SI 2262	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FGR GHE GadS5V46	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BGR_617_135C_1eb	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
BGr(GHE)GS4OGK0_	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GADS3V460D 1,5F1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure E4: Test statistics for each of the suggested distributions as tested in figure E3

F Distribution fitting

In order to properly integrate the stochastic behaviour of the production process, we construct statistical distributions for the processing times of each of the products on each of the three kettles. To construct statistical distributions, we make use of software to determine the best statistical distribution. This software, named Easyfit, makes use of three statistical tests to determine a winner (type of statistical distribution) for each dataset. In Tecnomatix' PlantSimulation, a total of 13 distributions can be used as an input parameter for the processing times. The following distributions can be used in PlantSimulation:

- Beta
- Binomial
- Cauchy
- Erlang
- Fréchet
- Gamma
- Gumbel
- Hypergeometric
- Laplace
- (Log)Logistic

- (Log)Normal
- Negative Exponential
- Paralogistic
- Pareto
- Poisson
- Triangular
- Uniform
- Weibull

Testing against every statistical distribution can be a very time-consuming job, especially with Shell's product portfolio. Easyfit tests against three different test statistics, namely the Kolmogorov-Smirnov test, the Anderson-Darling test and at last, the Chi-Square test. Each of these test statistics are unique in their own way, and test for different parameters in the data set. For our distributions, we test according an alpha value of 0.05. In the following sections, we further explain the method used for each test statistic.

F.1 Kolmogorov-Smirnov

According to Law [14], does the Kolmogorov-Smirnov (KS) test statistic compare the empirical distribution function with the distribution function of the hypothesized distribution. The advantage of the KS test statistic is that grouping of data is not necessary, which removes the potential loss of information/data due to data grouping in intervals. Another advantage of the KS test statistic is that it can be applied to any sample size n. Its null hypothesis is rejected if the test statistic value is smaller than the critical value $C_{1-\alpha}$ for a specific value of α. For this test statistic, we make use of the following formula since all our distribution parameters such as the mean and variance are known, to check if the null hypothesis is rejected or not:

$$\left(\sqrt{n} + 0.12 + \frac{0.11}{\sqrt{n}}\right) * D_n < C_{1-\alpha} \tag{9}$$

As for this formula, the test statistic is denoted by D_n and is found by Easyfit. Here, it ranks the test statistics amongst all the other possible distributions that could be chosen from. We make use of an alpha value of 0.05, which translates to a critical value of 1.358 for each of the distributions.

F.2 Anderson-Darling

Another test statistic that is used by Easyfit, is the Anderson-Darling (AD) test statistic. This statistic has more power in the tails of the distribution in comparison to the KS test statistic, but follow the same principle as the KS test. It tests the emperical distribution function with the hypothesized distribution function. Here, the null hypothesis is rejected in case the following condition regarding the test statistic and the critical value holds:

$$A_n^2 \leq C_{1-\alpha} \tag{10}$$

For this test statistic, we make use of an α value of 0.05, which translates to a critical value of 2.492.

F.3 Chi-Square

At last, we make make use of the Chi-Square test statistic. This test statistic focuses on the comparison of the created histogram of a data set and the fitted density or mass function of the distribution. This is done so by creating k adjacent intervals, where we calculate the absolute difference in the number of observations in an adjacent interval N_j and the expected number of observations in the interval np_j. Then, we divide this difference by the expected number of observations in the interval np_j. The sum over all the adjacent intervals results in the Chi-Square test statistic value. The following formula describes the above mentioned:

$$X^2 = \sum_{j=1}^{k} \frac{(N_j - np_j)^2}{np_j} \tag{11}$$

We reject the null hypothesis, in which it does not follow the suggested distribution, in case that the test statistic value is larger than the critical value. Its critical value can be calculated by means of Excel, in which the CHISQ.INV function is used. This functions depends on two parameters, which are the probability of α, which is in our case 0.05 and a degrees of freedom, denoted by df.

G Statistical distributions for the filling stations

Table 21: Statistical distributions for the filling times per SKU type on the different filling lines

Filling station	**SKU type**	**Suggested distribution by Easyfit**	**K-S test statistic**	**Critical value**	**A-D test statistic**	**Critical value**	**Chi^2 statistic**	**Critical value**
FS9	18	Gamma (3p) ($\gamma = 0.341, \alpha = 4.422, \beta = 0.122$)	0.069	0.091	1.123	2.502	10.849	14.067
FS9	50	Gamma (3p) ($\gamma = 0.470, \alpha = 3.587, \beta = 0.316$)	0.053	0.105	0.635	2.502	5.0823	14.067
FS9	180	Gamma (3p) ($\gamma = 1.565, \alpha = 6.127, \beta = 0.082$)	0.071	0.063	1.663	2.502	68.231	15.507
FS1	18	Gamma (3p) ($\gamma = 0.518, \alpha = 1.744, \beta = 0.150$)	0.040	0.038	1.180	2.502	18.680	18.307
FS6	50	Gamma (3p) ($\gamma = 1.034, \alpha = 1.352, \beta = 0.486$)	0.095	0.338	0.352	2.502	0.202	3.842
FS6	180	Gamma (3p) ($\gamma = 1.490, \alpha = 5.119, \beta = 0.193$)	0.128	0.278	0.459	2.502	1.498	5.992

H Development of direct production ratio R109 and U400

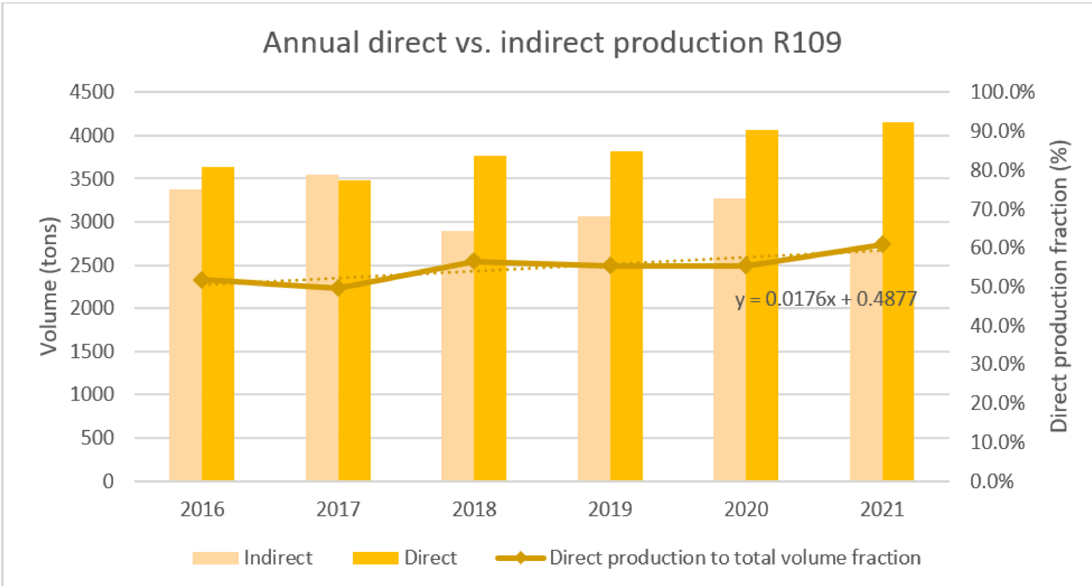


Figure H1: Overview of the annual production of both direct and indirect batches for production line R109. The trend line confirms the upwards trend in the production of direct batches on R109 over the past five years.

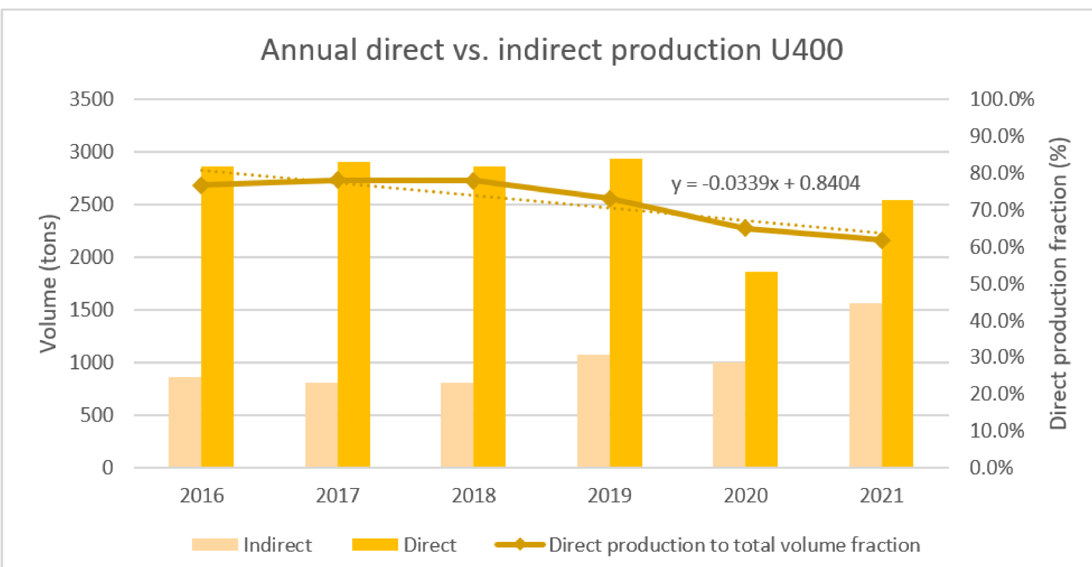


Figure H2: Overview of the annual production of both direct and indirect batches for production line U400. The trend line confirms the upwards trend in the production of direct batches on U400 over the past five years.

I Warm-up period and number of replications

To determine the warm-up period for our non-terminating simulation model, we make use of Welch's graphical method, as described in [29]. Welch's method uses multiple replications, which smooth the variability found in the individual observations. Then, we graph the moving averages over a window $\boldsymbol{w}$. This is done to smooth out the variances and fluctuations in-between the different observations and replications. We experiment with different window sizes, to obtain a smoothed averaged which is stable over time. Figure I1 depicts the smoothed average for the volume produced per day, with three different window sizes of 5, 10 and 20.

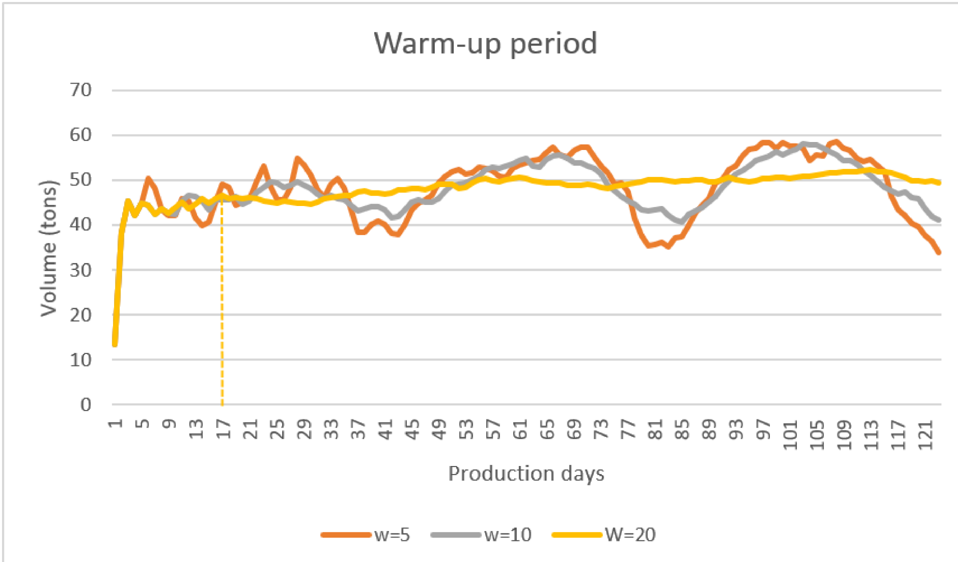


Figure I1: Determining the warm-up period with three different window sizes for the smoothed average

Based on the figure above, we take a warm-up period of 17 days. This is the first moment in which the smoothed average output of the production plant becomes stable. From this point onwards, we begin gathering the output data for the simulation study.

Determining the number of replications is done differently. Here, we also perform different replications of the simulation model with a different seed value for the random numbers. Then, we proceed by performing different replications until the confidence interval, relative to the average of the total volume per day, is sufficiently small. With sufficiently small, we mean an obtained value which is smaller than γ. Gamma is the estimate of the relative error. In practice, we use an adjusted value for gamma, which is denoted as γ'. To obtain the number of replications that satisfies a relative error lower than γ', we make use of the following equations:

$$n_r(\gamma) = min \left\{ i \geq n : \frac{t_{i-1,1-\alpha/2} * \sqrt{S^2(n)/i}}{\bar{X}(n)} \leq \gamma' \right\} \tag{12}$$

$$\gamma' = \frac{\gamma}{(1+\gamma)} \tag{13}$$

In equation 9, we check for the minimum number of replications which equals an gamma prime value smaller or equal to the confidence interval half width, relative to the average of the kpi we measure. As mentioned earlier, is gamma prime the corrected target value for the relative error. In this case, we take an alpha of 0.05 to calculate the confidence interval half width. Table 22 depicts the determination of the number of replications, where we observe that the adjusted error relative to the average output is smaller for three replications.

Table 22: Determination of the number of replications for the total produced volume in the simulation model. The first "Ok" in the last column refers to the first replication where the error is lower or equal to the target error value.

n	**Volume per run (tons)**	**Avg volume per run (tons)**	**Variance**	**Inverse t-test**	**CI half-width**	**Error**	**Check Ok/NotOk**
1	6051.24						
2	5870.38	5960.81	16355.17	12.71	1149.02	0.192	NotOk
3	5949.48	5957.03	8220.38	4.30	225.23	0.038	Ok
4	5832.93	5926.00	9330.66	3.18	153.70	0.026	Ok
5	5951.65	5931.13	7129.50	2.78	104.84	0.018	Ok

J Average daily volumes

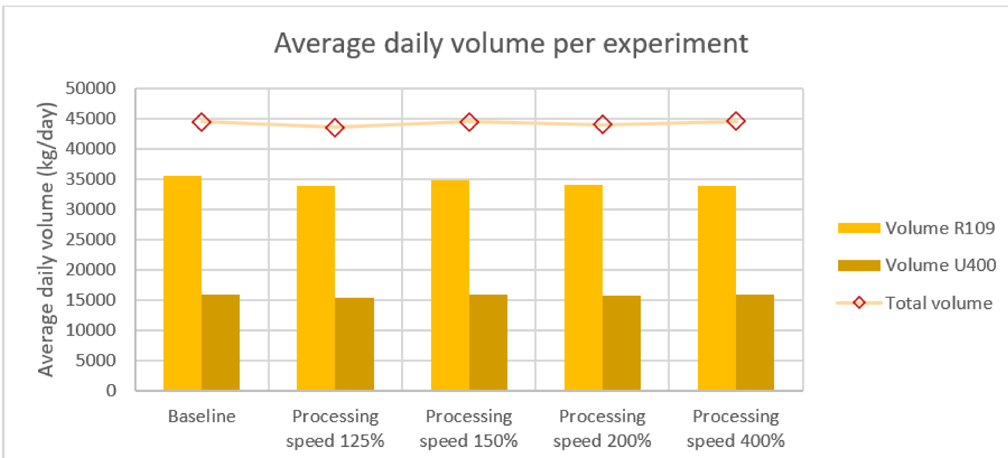


Figure J1: Average daily volume for experiments 1-4 with an increased palletizing capacity

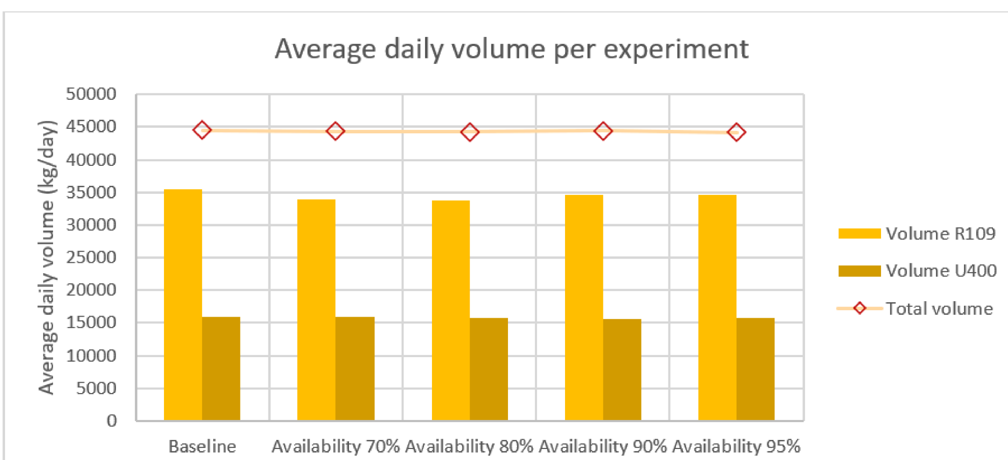


Figure J2: Average daily volume for experiments 5-8 with an increased palletizing capacity

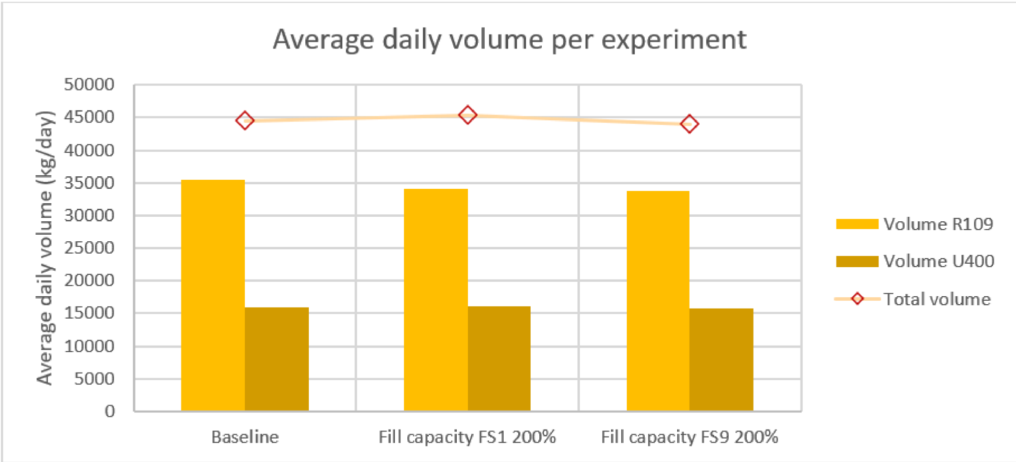


Figure J3: Average daily volume for experiments 9 and 10 with an increased palletizing capacity

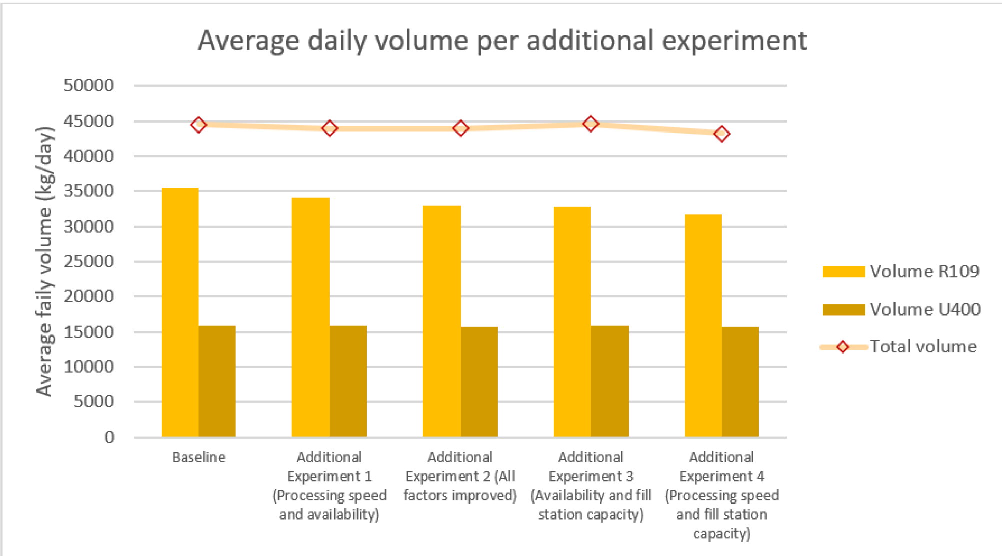


Figure J4: Average daily volume for experiments 9 and 10 with an increased palletizing capacity