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Optimizing the Preparation Stage at Kvadrat Shade: A Simulation Study

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PREFACE

Dear reader,

In front of you lies the bachelor thesis titled ”Optimizing the Preparation Stage at Kvadrat Shade: A Simulation Study”, which results from my research at Kvadrat Shade from September 2023 until April 2024. This thesis will complete my Bachelor of Industrial Engineering and Management at the University of Twente.

I would like to take this opportunity to express my gratitude to everyone who has supported me over the past few months while conducting this research. First of all, I would like to thank Kilian Bennink, my company supervisor, for providing me with the opportunity to conduct my research at Kvadrat Shade and for his guidance throughout the process. Furthermore, I am grateful to my colleagues at Kvadrat Shade for their warm welcome and helping hand in obtaining useful information and data.

Secondly, I would like to thank all the university staff who assisted me with my research. In particular, I want to express my gratitude to my first supervisor from the University of Twente, Dr. S.M. Meisel, for his invaluable help and feedback from the beginning to the end of this research. His expertise and knowledge were instrumental in the writing of this thesis. Furthermore, I want to thank Dr. A. Trivella for being my second supervisor.

Finally, I would like to thank my friends and family for their support during the research. And of course, to you, my reader: I hope you will enjoy reading this thesis.

Ivar Mastwijk
Enschede, April 2, 2024

MANAGEMENT SUMMARY

Introduction

Kvadrat Shade, originally founded as Verosol in 1965 and later acquired by Kvadrat, a Danish textile company, is the inventor and founder of metallized textiles and pleated blinds. Kvadrat Shade specializes in utilizing these metallized textiles to produce roller and pleated blinds that provide glare elimination and effective insulation.

During the preparation stage of roller and pleated blinds production, parts are gathered and prepared before being sent to the assembly stage. To store all parts required during the preparation stage, Kvadrat Shade utilizes a Kanban two-bin system, where for every part there are two bins, each containing a predetermined quantity. This allows one bin to meet current demand, while the other serves as backup. As the primary bin is depleted, the second bin is deployed to ensure a continuous supply. Despite the utilization of this inventory management method, Kvadrat Shade still perceives inefficiencies during the preparation stage of the roller blind production, which contains over 700 unique parts. This results in service levels below the desired goals and order-picking lead times that are not low enough. This research focuses on optimizing the Kanban two-bin system to maintain the continuous availability of parts. Therefore the main research question of this research is formulated as follows:

How can a designated service level be obtained and the average order-picking lead time be decreased at the preparation stage of Kvadrat Shade while maintaining the Kanban method?

Approach

To answer the main research question, a simulation study was conducted following the Seven-Step Approach for Conducting a Successful Simulation Study, as outlined by Law and McComas (2001). The research began with formulating the problem, collecting data, and constructing a conceptual model. This model was then validated with subject-matter experts to ensure its accuracy and relevance. Additionally, to evaluate the overall performance of the proposed experiments KPIs were formulated: service level per part and classification, average daily stockouts and average order-picking lead times.

Following this, the model was programmed in Plant Simulation, a software from Siemens, and a series of experiments were conducted. The first experiment set a benchmark for the current operations, in which two bins per part are available. This is done, since there was no data available on the KPIs. Then experiments were conducted using the Toyota formula (Co & Sharafali, 1997). These experiments aimed to identify the number of required bins within the Kanban system and evaluate their effectiveness in improving service levels and reducing order-picking lead times. The first experiment used the Toyota formula with a maximum number of 4 bins and in the second experiment, the restriction was added that 1 bin was not allowed. To solve this the bin capacity was divided by two and the number of bins increased to two, suggesting the

bin sizes have been halved. Additionally, a third experiment was conducted which consisted of dynamically adjusting bin quantities based on service level targets. This means adding one bin for a part every time the service level target for this specific part is unmet.

Results

Overall, it became apparent that the baseline scenario, along with the utilization of the Toyota formula with a maximum bin constraint to determine the optimal number of bins, is insufficient to meet the desired service levels. However, dynamically adjusting bin quantities based on service level targets showed promise. This resulted in achieving an overall service level target with fewer bins than the current system. Therefore this research does address the operational challenge at the preparation stage and provides the company with data-driven insights that can be utilized to further improve operational efficiency.

Recommendations

The following recommendations have been proposed to tackle the key challenges identified in the research. It aims to help Kvadrat Shade improve the efficiency of its preparation stage and overall operational effectiveness. By implementing these changes, it is expected to obtain better service levels and shorter order-picking lead times.

- Adopt a flexible Kanban numbering system:
  Move away from a one-size-fits-all approach to determining the number of bins per part. Currently for every part two bins are assigned, however, this results in most bins overstocking or understocking. It is important to include more aspects in determining the number of bins.

- Implement alternative inventory management methods:
  For parts that have proven to not fit into the Kanban system, other inventory management methods should be explored. This involves identifying parts that barely meet their service level target and analysing the root causes, such as small bin capacity or high demand fluctuations.

- Improve tracking of parts:
  Enhance the tracking of articles, demand patterns, bin capacity, and stockout occurrences to facilitate better decision-making and model validation.

- Incorporate BOMs of orders more effectively:
  Utilize BOMs more effectively in the future ERP system to improve accuracy and possibilities in demand forecasting and inventory management.

- Periodic reviews for continuous improvement:
  Establish a schedule for regular reviews of the Kanban system and inventory policies to ensure they remain aligned with operational needs and performance targets.

CONTENTS

LIST OF ABBREVIATIONS

BOM	Bill Of Material
KPI	Key Performance Indicator
ERP	Enterprise Resource Planning
SME	Subject Matter Expert
KS	Kvadrat Shade
JIT	Just In Time
ROP	Reorder Point
ROQ	Reorder Quantity
SKU	Stock Keeping Unit
IQR	Inter Quartile Range
MSER	Marginal Standard Error Rule
SL	Service Level

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1 INTRODUCTION

In this chapter, we introduce Kvadrat Shade, identify the problem, present a problem-solving approach and outline the research design. The structure is divided as follows:

- 1.1 Introduction to Kvadrat Shade
- 1.2 Problem identification
- 1.3 Problem-solving approach
- 1.5 Scope of the research
- 1.4 Research design

1.1 Introduction to Kvadrat Shade

Kvadrat Shade, formerly known as Verosol, is the inventor and founder of metallized textiles and pleated blinds. Verosol was founded in 1965 by Cornelis Verolme in Eibergen. Since its founding, Verosol continued to improve the metallization technique and is still to this day the leader in the development of metallized textiles.

After the acquisition in 2019 from Kvadrat, a Danish textile company founded in 1968, the name of Verosol changed to Kvadrat Shade and Kvadrat High Performance Textiles. Kvadrat High Performance Textiles produces metallized textiles, which they partially sell to Kvadrat Shade. Kvadrat Shade produces roller blinds and pleated blinds, with these textiles. The textiles are coated with a thin aluminium layer, which eliminates glare and other annoying light, while providing effective insulation for windows, significantly reducing heat loss in winter and heat build-up in summer.

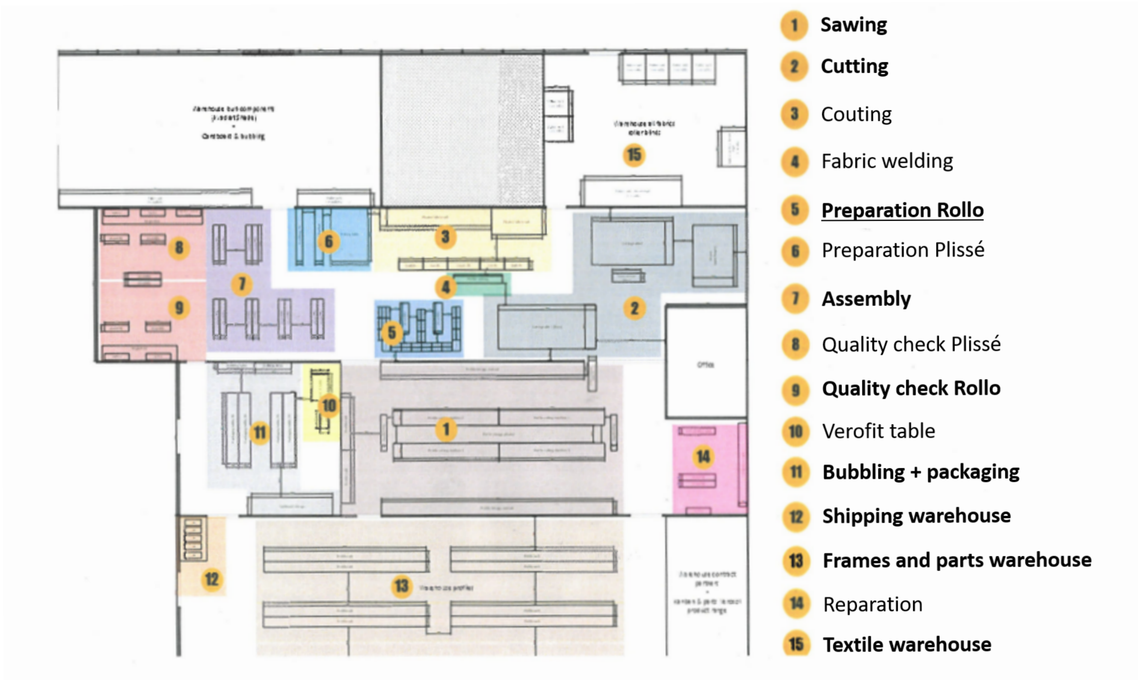
Kvadrat Shade receives the parts for the blinds from multiple suppliers and as mentioned before, the textiles are mainly purchased from Kvadrat High Performance Textiles. All components come together at Kvadrat Shade, where the blinds are produced to the final product.

1.2 Problem identification

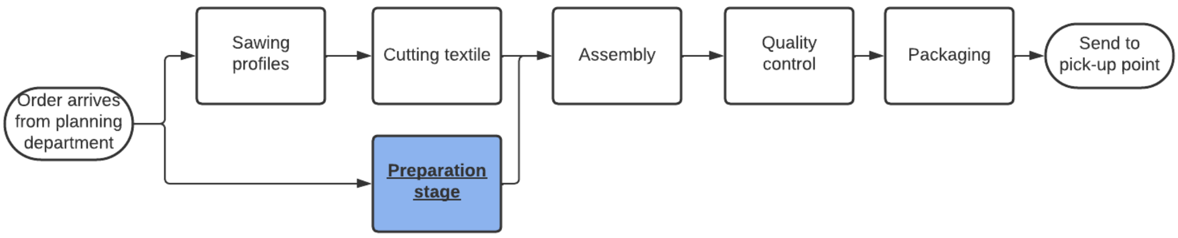
1.2.1 Problem context

All stages in the production hall are divided into left and right sides. On the left part of each stage, the roller blinds are made and on the right side of the stage the pleated blinds. The steps to produce the blinds are therefore comparable to each other, however, the exact techniques that are used are different, as shown in Figure 1.1.

A production order arrives from the production planning department to the first stage. Additionally, a copy of this production order is also sent to the preparation stage which will be explained later on. The first stage in the production process is sawing aluminium profiles, the profiles are sawn to the length that matches the ordered width of the blinds. These profiles are put on a trolley and sent to the next stage. Second, the textile is cut. For roller blinds, the fabric must be rolled off a large storage roll onto a sheet to be cut. For the pleated blinds only, the number of pleats must be counted before it is cut since it is known what the length of one pleat is. Thereafter the trolley with the beam and textile go to the preparation stage. At the preparation stage, a simplified Kanban two-bin system is used to make sure that all necessary parts are added to the trolley. As mentioned before, this stage gets a copy of the production order, which makes it possible to pick up the necessary parts before the trolley arrives. Then the trolley with all the necessary components is sent to the assembly stage to get assembled. After the assembly stage, each blind will be tested and finally packed. An overview of the layout and the production process can be seen in Figure 1.1.



(a) Production hall layout (roller production line in bold)



(b) Production process flowchart

Figure 1.1: Production hall layout and production process flowchart

Kvadrat Shade has multiple collections. There is a Verosol collection and a Kvadrat Shade collection. These collections are divided into multiple models. For each model, there are different options concerning controlling and mounting mechanisms, size and colours. This allows customers to personalize the product to their specific needs. According to Slack and Brandon-Jones (2019) this approach is called mass customization. This high flexibility in produced products and the ability to introduce new or modified products results in a lot of parts in the operation of Kvadrat Shade.

At the preparation stage for both the roller production and pleated production, there are shelves with bins containing all those parts as mentioned in the previous paragraph, that could be needed during the assembly stage. In both lines combined, there are over 1,000 unique parts. At this stage, a Kanban two-bin system is adopted. As elaborated in Section 3.2, the bins are equipped with cards containing information about the part and its quantity. Each part has two bins, with one bin designated for meeting the current demand. When this primary bin is depleted, the second bin comes into play, ensuring a continuous supply. This replenishment strategy is designed to refill the first bin before the second bin runs out of parts.

Kvadrat recognises that there occur problems during the preparation stage, such as stockouts, mis-picks and labour-intensive phases. This results, according to the Kvadrat Shade management, in high order-picking lead times and a low service level of the Kanban system. Lead time refers to the time between when an order is placed and when the order is finished. In general, this is the amount of time a product takes to go through the entire process. For the problem experienced at Kvadrat, the time at the preparation stage is important, therefore it is called order-picking lead time. Additionally, the service level of the Kanban system refers to the rate at which parts are available when demanded during order picking. A service level of 90% means that parts are available 90% of the time when they are needed during the order-picking process. In conclusion, the management problem is formulated as follows:

Management problem: *The perceived service level is lower than desired and the perceived order-picking lead times are not low enough, at the preparation stages of the roller and pleated production lines.*

The reason for using the term ”perceived” to describe the current situation for both service level and order-picking lead time is that it is believed to fall short of the desired level. Currently, there is no evidence to support these perceptions, as there is a lack of data and facts to measure the performance of the preparation stage.

1.2.2 Core problem

Every morning a warehouse employee should make a round to pick up empty bins from the preparation stage. These bins will get filled and put back. This happens directly after the bins are collected and before production starts that day. However, this is the only time this is done. It could happen that an almost empty bin won't get filled that day. Therefore, relying only on the second bin. When the parts from this bin are also empty, the preparation stage will run out of parts. This can result in two effects. They must wait for the warehouse to fill a new bin with the parts, or they will get it themselves, which leads to unnecessary operations. This last effect is also unwanted by the warehouse because it leads to mistakes in inventory management.

Another problem is that no thought has been given to which bin sizes are used and how many parts go into a bin. Currently, these numbers are chosen intuitively, without considering ergonomics or demand expectations. This results in there being too few parts in the bins for the turnover rate there is and therefore bins running out of parts faster than expected.

Furthermore, the bin allocation at the preparation stage is not carefully considered. Items the workers need most are not located closely to their working bench, resulting in more actions than needed. For example, walking further for a part or having to use a step ladder to reach top shelves. Apart from the ergonomics, look-a-like parts are placed next to each other, resulting in missed picks. Which in turn results in the wrong parts going to the assembly line.

Core problem: *The Kanban system used by Kvadrat Shade is not fit to the current production process.*

1.2.3 Problem cluster

The figure below, Figure 1.2, shows the problem cluster that is made to discover all potential causes and effects regarding the action problem. The current Kanban system that is in use during the production process causes a high order-picking lead time and low service level perception. This is due to factors such as bins being filled only in the morning or when empty, randomly allocated bins, and intuitively chosen number of boxes and parts. Resulting in stock-outs, mispicks and labour-intensive work. The core problem is that the currently used Kanban system is not fit for the current production process.

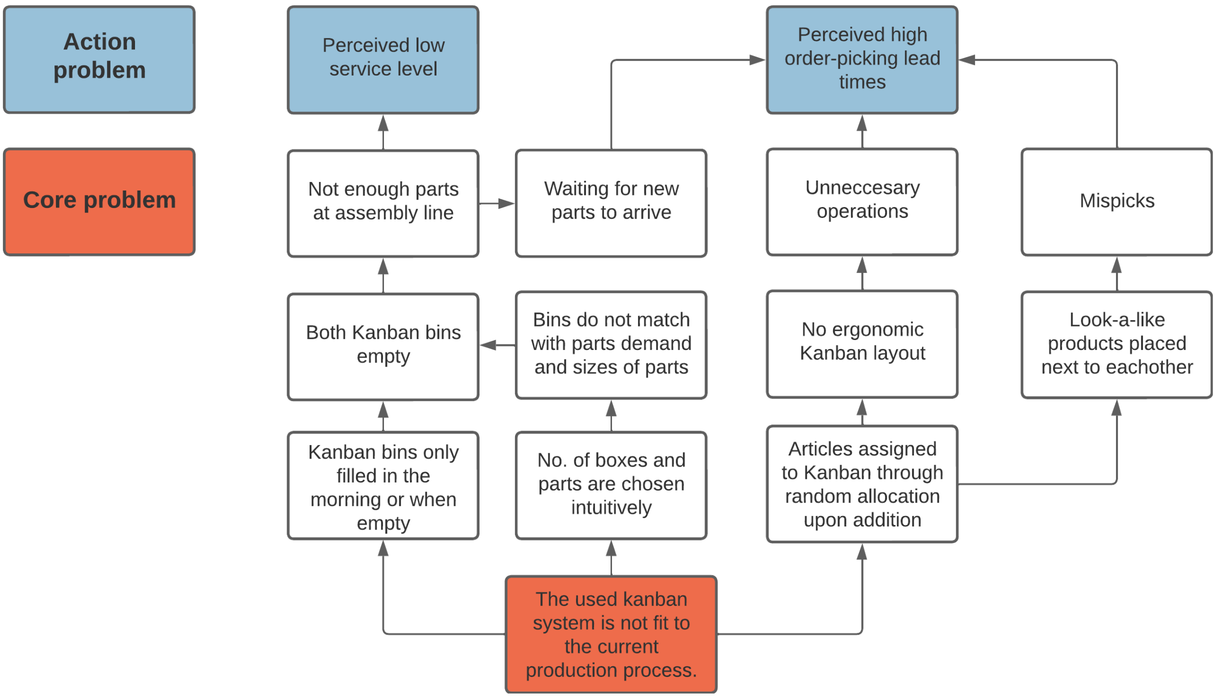


Figure 1.2: Problem cluster

1.2.4 Gap between norm and reality

An action problem is a discrepancy between the norm and the reality, as perceived by the problem owner (Heerkens & van Winden, 2017). In other words, there is a gap between reality and the norm. Quantifying the problem is crucial to determine the gap and norm. It is worth noting that the current service level and lead times for order picking at the preparation stage are not known yet. However, it is crucial to recognize that there is a noticeable gap that needs to be addressed.

The primary objective is to reduce the average order-picking lead time and obtain an acceptable service level during the preparation stage while maintaining the Kanban method. As mentioned previously in Section 1.2.1 there is no evidence to support the perceptions on order-picking lead times and service levels. Together with the management of Kvadrat Shade, the acceptable service levels were discussed. However, for order-picking lead times, no desired levels have been set due to the complexity and uncertainty surrounding what constitutes an optimal time frame. Nevertheless, it is expected to decrease when service levels increase and fewer stockouts occur, since this results in less waiting time. The acceptable service levels are as follows:

- Fast movers: $\geq$98%
- Intermediate movers: $\geq$95%
- Slow movers: $\geq$92%

The reason behind differentiating the parts into three different categories is to allow for more effective management. Fast movers have a high demand and turnover rate. A constant availability must be ensured since stockouts could lead to a significant service level decrease. Intermediate movers have a moderate demand and turnover rate. These articles should be available for periodic demand increases. However, overstocking should be avoided since it leads to an overcrowded Kanban system. Lastly, slow movers are barely used and have a low turnover rate. Their space occupation should be minimal. These categories and their respective goals will be compared with data from the initial simulation model to provide a clear picture of the current conditions and desired improvements.

1.3 Problem-solving approach

To answer the research question a simulation study is conducted. The goal is to find possible solutions to the current problem and implement these as experiments in a simulation, that simulates the current operations. The results of these different experiments are compared to each other. In Montevechi et al. (2015) eight different research methods in Modeling and Simulation were reviewed. The method that is chosen for this research is the Seven-Step Approach for Conducting a Successful Simulation Study from Law and McComas (2001). A flowchart including all the steps can be found in Appendix A

Step 1: Formulating the problem
The first step in developing a simulation model is verbally formulating the problem. The problem context, identification and definition are discussed in chapter one of this research.

Step 2: Collecting information/data and constructing conceptual document
In this step, information on the system layout and operations is gathered. To specify parameters and probability distributions for the model input, necessary data is collected from the ERP system or observed in some cases. Information on the parts at the preparation stage is needed, such as daily demand, bin location, and quantity per bin. Moreover, information on the previous orders along with their Bill of Material is required to generate orders for the simulation. Finally, a conceptual model containing all assumptions is written alongside the collected data..

Step 3: Conceptual model validation
The conceptual document created in the previous step will be validated by subject-matter experts (SMEs) within Kvadrat Shade to ensure that all important aspects are included. This is done by conducting a structured walk-through of the conceptual model together with the SMEs. In case aspects are overlooked that should be included, then it is necessary to go back to step 2 and adjust the conceptual model.

Step 4: Program the model
In this step, the actual model is programmed based on the conceptual model. In this research, the model is programmed in Plant Simulation a software from Siemens, which the University of Twente provides.

Step 5: Programmed model validation
The model validation takes place to ensure a level of confidence so that it proves to the clients that is an aid in decision-making. During this step, there are two types of validation according to Robinson (2014). These will be used in this research and are elaborated on below.

White-box validation is used to determine that the programmed model represents the real world as accurately as possible. First of all the code will be checked and therefore should be explained so that a non-expert in the field of the software could check the model on the data and logic. Next, there should be visual checks by running the model, step by step and forcing events to take place. Additionally, the output reports generated by the experiments should be inspected. This is helpful to compare the results with the expectations.

Next to white-box validation, there is black-box validation. This entails comparing the simulation results with the real world. This is done by using a confidence interval between the model and the real-world output. Next to that statistical tests can be done. An alternative approach is to compare relationships between the input and output. It can be compared with certain changes that are expected that are obtained from the literature.

Step 6: Design, conduct and analyse experiments
This step consists of multiple parts, designing, conducting and analysing the experiments. First, to assure accuracy the run length, warm-up period, and the number of independent model replications are determined for the model, also called experimentation validation.

Then experiments are created and executed to obtain solutions, which are then analyzed. These solutions include current applied and newfound inventory policies, which are designed to ensure that they fall within the scope of the research, as defined in Section 1.4.1.

Step 7: Documenting and presenting the simulation results
The model and study are documented in this step of the simulation process. This means explaining the main idea behind the model, giving a detailed description of how the computer program works, and sharing the results found in the study.

1.4 Research design

In this chapter, the previously identified problem is used to define the research question. Additionally, a problem-solving approach is selected and explained which is used in developing solutions towards the research question. Using the problem-solving approach the research question is divided into multiple sub-questions to make it easier to answer. This also determines the structure of this research.

1.4.1 Research question

The main research question is derived from the problem proposed by Kvadrat Shade. Therefore the goal of this research is to optimize the preparation stage in the production process of the Rollo line. The research question is formulated as follows:

How can a designated service level be obtained and the average order-picking lead time be decreased at the preparation stage of Kvadrat Shade while maintaining the Kanban method?

In this research, experiments are conducted to determine how to improve the service level during Kvadrat Shade's preparation stage while maintaining the fundamental principles of the Kanban method.

Solutions result from experiments that involve improvements in inventory management that are designed to work compatible with the existing Kanban framework. As mentioned in Section 1.2.1 the Kanban system's service level refers to the rate at which parts are available for order picking and the order-picking lead times refer to the time that is needed to gather an order. Furthermore, the Kanban method is a widely adopted lean manufacturing approach. Kanban involves visualizing workflow using cards or signals to indicate when to replenish inventory. This method minimizes waste and enhances efficiency by ensuring materials are restocked when needed. Further insights into the Kanban method can be found in Section 3.2.

1.4.2 Sub-questions

The main research question is divided into sub-questions to make the research more comprehensible. The sub-questions will also function as a segregation of the research.

Sub-question 1: How is the current situation at the preparation stage organized at Kvadrat Shade?

a. How is the current storage allocation sorted?

b. How is the order-picking process organized?

This sub-question aims to get better insights into the current situation at the preparation stage. These insights are needed before improvements can be made to the operation. The sub-question is divided into smaller, easier-to-grasp descriptive questions. These questions are answered by gathering data from Kvadrats' ERP (Enterprise Resource Planning) system, observing the production process, and meetings with employees.

Sub-question 2: What are possible solutions to increase the service level at the preparation stage, within the boundaries of the Kanban method?

According to Kvadrat Shade, lead time increases a lot when parts are unavailable due to stock-outs at the preparation stage. Therefore inventory policies will be reviewed in terms of reorder quantities and reorder points to increase the service level.

Sub-question 3: How does the conceptual model of the preparation stage look like?

a. What assumptions should be made in the model?

b. What input data is necessary for creating a simulation model?

c. What is the output data of the simulation model?

A conceptual model will be constructed, containing assumptions, input variables and output variables. Data that is required for the input variables will be analysed in order to determine the probability distributions for the daily order arrival.

Sub-question 4: How can the operations at the preparation stage be simulated and validated?

To answer this sub-question the conceptual model that is established will be used. Knowledge about the simulation software is required, to make a working simulation model. After the simulation model is created the model will be validated based on historical orders and the used distributions. Next to that, the model is discussed with SMEs, making sure the results are in line with the expectations and experience.

Sub-question 5: Which experiments will be conducted in the simulation study?

a. What experiments are included in the simulation?

b. What are the results of the conducted experiments?

Based on the current situation described in Chapter 2 and the literature review discussed in Chapter 3 experiments will be designed together with the SMEs. Then these required changes for these experiments are implemented in the simulation model. Finally, the outcomes of the conducted experiments are presented.

Sub-question 6: What recommendations can be made with the evaluation of the results from the simulation?

Based on the results of the experiments, conclusions are drawn and recommendations are formed for Kvadrat Shade. This will be explanatory research since the different solutions will be compared regarding the selected KPIs.

1.5 Scope of the research

The scope of the research sets the study's boundaries. There are two areas identified that could help decrease the average order-picking lead time, determining the optimal number of Kanban and implementing efficient bin allocation strategies. However, since Kvadrat Shade is, next to order-picking lead time, primarily interested in the service level of the Kanban, this research concentrates on determining the optimal number of bins within the Kanban system.

The company produces two types of blinds, each with its own production line. However, for this research, only the roller production line is being considered. It is expected that implementing solutions on the roller production line will have a similar effect on the pleated production line. This is because both production lines have a similar preparation stage with a similar design where the required parts are picked.

Additionally, this research provides insights for improving operations during the preparation stage. However, during this research, these improvements will not be implemented in Kvadrat Shade's current operations.

2 CURRENT SITUATION

This chapter provides an overview of the preparation stage at Kvadrat Shade, aiming to shed light on the current performance of its operations. Specifically, it answers the first sub-question: "How is the current situation at the preparation stage organized at Kvadrat Shade?". This is divided into the following sections:

- 2.1 Storage allocation
- 2.2 Order-picking process

2.1 Storage allocation

The preparation stage of the production process can be seen as a small warehouse. It consists of shelves containing all the different parts that might be needed for production orders. The layout consists of multiple parallel lanes each with shelves on the sides containing the parts. Figure 2.1 shows the current layout of the preparation stage. Next to this location, there are also shelves containing parts in the textile warehouse. This is due to the limited room at the preparation stage and because these parts are slow movers, meaning they are not used that often. These shelves are positioned in the same way as the shelves at the preparation stage.

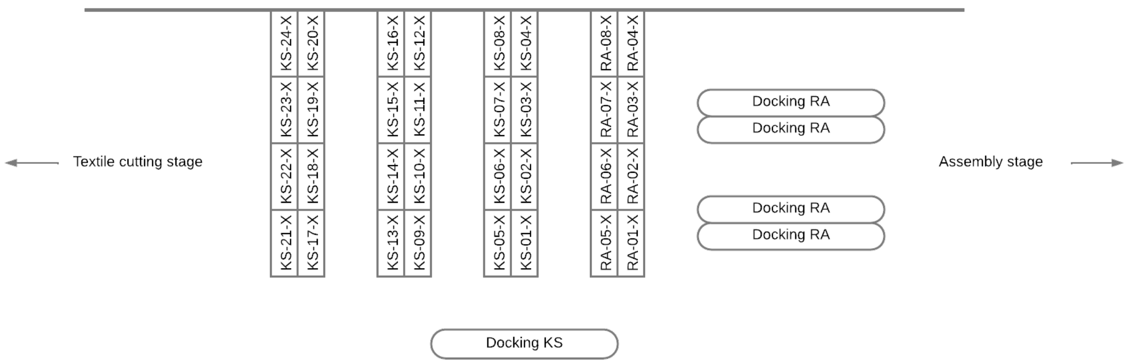


Figure 2.1: Lay-out preparation stage

The four shelves on the left are labelled 'KS' and contain parts exclusively used in the Kvadrat Shade collection. This collection was created after Verosol was acquired by Kvadrat. It consists of roller blinds that, overall, require more parts than the original collection created by Verosol. The remaining two shelves on the right are marked 'RA' and are allocated for the parts needed for the Verosol collection. Shelves RA-05-X to RA-08-X are reserved for parts used in the QS6 series while shelves RA-01-X to RA-04-X are for the QS8 series. As mentioned before some shelves are located in the textile warehouse, these are numbered RA-09-X to RA-22-X. All shelves have the same height and width, with six numbered layers from bottom to top, labelled

01 through 06 for each shelf replacing the ’X’ in the Kanban locations. For reference, an image depicting the preparation stage can be found in Appendix B.1 and an image for the slow movers’ shelves can be found in Appendix B.2.

It’s worth noting that the docking stations serve as assembly stations where certain assembly tasks are carried out before the trolley proceeds to the main assembly stage. At these docking stations, there are bins filled with grab-stock. These small parts are required in most roller blinds and therefore located at the docking stations, so they are easy to grab and no travel time is incurred. These smaller bins are supplied by the two-bin system, which means that they also have a Kanban location at the preparation stage. This, so-called pre-assembly process at the preparation stage is not included in the research as it falls outside the scope and predetermined solutions as outlined in section 1.4.1.

The Kvadrat Shade Collection is still being expanded with new models, consisting of other colors and parts. Whenever a new part is added to the Kanban, it is automatically assigned to the first empty spot available. For instance, currently shelves 22 to 24 are vacant, then when a new Kavdrat Shade part is added to the Kanban, it will be assigned to KS-22-X, where X represents the first available layer on the corresponding shelf. While the Verosol collection will be phased out during the year 2024. The expectation is that the demand for Kvadrat Shade will increase by 70% and for Verosol decrease by 70% throughout 2024.

2.2 Order-picking process

As outlined in Section 1.2.1, the preparation stage involves receiving production orders that include a Bill of Materials (BOM). This is essential to determine the required parts for the production of a specific product. The production orders are a crucial component of the sales order, which contains all the products that a client has ordered. Since clients often purchase multiple roller blinds, the production orders help ensure that all necessary parts are picked for the production process.

A detailed overview of the order-picking process is presented in Appendix C. When customers place an order for multiple units of the same product, each unit is treated as a separate production order. For example, if a customer orders three roller blinds, even if they are identical, three separate production orders are generated.

At the preparation stage, the sales orders are taken consisting of the production orders. For small sales orders, this is done from memory, while for bigger sales orders, a list of the required parts is printed. If an order consists of 20 or more production orders, a list is printed. Instead of picking the parts at the Kanban location, the bin is taken out and brought to the depot. The required number of parts are taken out and the bin is then returned to its Kanban location.

The process of combining the protection order is known as order-batching and it helps to reduce the time taken by order pickers to collect the same part for different production orders. By grouping the production orders, order pickers can collect all the required parts for a sales order in a single picking tour, which saves time and improves efficiency. This process has been proven to reduce travel times and improve overall productivity (de Koster et al., 2007).

After all required parts are collected and the pre-assembly is finished a trolley containing all parts, including the cut textile is sent to the assembly stage. A picture of such a trolley is displayed in Appendix D.

As mentioned before in Section 1.2.1 a Kanban two-bin system is used to hold inventory and display reorder points. When the primary bin is depleted it is put on a specially designated trolley. Each morning an employee from the main warehouse picks up the trolleys containing the empty bins and refills them. During this time the second bin is used to supply parts. It could happen that this bin also depletes. In that case, the order picker has to wait until the troubleshooter solves this issue.

As a rule of thumb, sales orders that consist of >80 identical production orders are excluded from the Kanban order-picking principle. In this case, we speak of transfer orders, also known as large projects, and a pallet containing the necessary parts is placed near the docking stations. This reduces order-picking time and also makes sure the Kanban two-bin system does not incur stockouts.

3 LITERATURE REVIEW

In this chapter, a literature review is conducted to answer sub-questions two. ”What are possible solutions to increase the service level at the preparation stage, within the boundaries of the Kanban method?”. To answer this sub-question this chapter is divided into the following sections:

- 3.1 Simulation theory
- 3.2 Kanban two-bin system
- 3.3 Warehousing theory

3.1 Simulation theory

A simulation is defined as an ”Experimentation with a simplified imitation (on a computer) of an operations system as it progresses through time, for better understanding and/or improving that system” (Robinson, 2014). In the simulation study, the preparation stage at Kvadrat will be the operation system that gets imitated. After the current operations are modelled, multiple experiments will be implemented.

According to Robinson (2014), there are four primary simulation methods, discrete-event simulation, Monte Carlo simulation, system dynamics and agent-based simulation. Discrete-event simulation is used to model queuing systems, which are systems consisting of entities flowing to activities, which are separated by queues. A Monte Carlo simulation models risk in environments where the outcome is subject to change. Following the definition mentioned earlier this method does not model progression over time, but the outcome at some point in the future. System dynamics is an approach that represents the world as a set of stocks and flows. Stocks change continuously in response to the balance of the inflows and outflows from the stock. Agent-based simulation aims to model systems to observe the behaviour, patterns and structures between agents over time.

In this simulation study, the discrete-event simulation method is used. Discrete-event simulation is concerned with modelling stochastic systems, consisting of one or more random variables, as they progress over time in which the system’s status only changes at discrete points in time according to Winston (2004). A state of a system is a collection of state variables, such as the number of busy servers at a certain moment in time. These are used to describe the status of the system. Next to that, there are objects within the system, which are called entities. The entities consist of properties which are called attributes. For example, a necessary part is an entity in the system and the allocation of this part is an attribute.

3.2 The Kanban two-bin system

In this section theory on the Kanban two-bin system is discussed. First of all, the general theory about this system is explained and afterwards, methods of determining the Kanban quantity will be discussed to reduce the average order-picking lead time at Kvadrat Shade's preparation stage.

Kanban is a crucial element of the 'Just in Time' (JIT) approach, which aims to optimize and improve manufacturing efficiency. This lean manufacturing system reduces manufacturing lead time by eliminating waste and utilizing Kanban (Naufal et al., 2012). The Kanban method is a pull system of control, which means that items are only moved to the next stage when this is asked. This type of system, in contrast, to push systems, is far less likely to result in inventory build-up along the production process (Slack & Brandon-Jones, 2019), and therefore it emphasizes obtaining a minimum level of inventory (Naufal et al., 2012).

"Kanban triggers the movement, production or supply of one unit or a standard container of units, such as a bin" (Slack & Brandon-Jones, 2019). Kanban is Japanese for card or signal. In a Kanban system cards that contain information such as the job type, the number of parts to carry, and the Kanban type, are crucial (Huang & Kusiak, 1996). If a Kanban card is received or displayed from a certain article, this triggers the supply of that article in the quantity that is mentioned on the Kanban card. Kanban therefore can be seen as a continuous display of inventory methods. In Figure 3.1, an example of a Kanban card can be found.

Figure 3.1: Kanban card example

A two-bin inventory system is a continuous review inventory policy (Winston, 2004). In a continuous approach, inventory is continuously tracked and an order for a lot size Q is placed when the inventory declines to the reorder point (Chopra, 2019). In Winston (2004) this is called a (r,q) policy. where r stands for the reorder point (ROP) and q for the reorder quantity (ROQ). When the first bin is empty a quantity of q parts is ordered. While waiting for the reorder the second bin is used to pick parts from, which consists of r parts. Therefore the second bin functions as a safety stock and reorder indicator. When the reorder arrives, the second bin will be refilled up to the reorder point and all the parts that are left of the reorder get refilled into the first bin. Slack and Brandon-Jones (2019) indicates that different bins are not always necessary. It could be that the parts are placed differently in a bin, for example upside-down.

At the preparation stage, Kvadrat Shade uses a variation of the two-bin system. Two bins are available, each filled with a pre-determined quantity, for all parts that are in inventory at that stage. As discussed before, the general (r,q)-policy may have different quantities for the ROP and ROQ. However, at Kvadrat Shade, the number of parts initially in the first bin is always equal to the initial number of parts in the second bin. This means that the ROP equals the ROQ (r=q). Instead of filling the second bin up to the ROP with the arriving ROQ and then filling the first bin with the remaining quantity, the first and second bins are simply switched.

By adopting this continuous approach, the organization ensures that there are always parts at the preparation stage, assuming there is sufficient stock available in the main warehouse. It is possible that the main warehouse may not always have sufficient stock due to delivery or order issues. This would result in making it impossible to restock the preparation stage.

3.2.1 Toyota's formula

As previously mentioned, Kanban is a key component of JIT production, which was pioneered by the Toyota Motor Corporation. To determine the appropriate Kanban quantity, Toyota proposed a formula that takes into account the average demand during a production cycle (Co & Sharafali, 1997). This production cycle, or replenishment time, includes waiting time, changeover time, processing time, and shipping time (Mao et al., 2014). The formula for determining the number of parts per Kanban includes the average daily demand, replenishment time, number of parts per Kanban, and safety stock. Safety stock is included as a buffer against fluctuations in demand. In Co and Sharafali (1997); Mao et al. (2014); Tambi and Mashalkar (2023) the safety stock is considered as a factor, whereas Naufal et al. (2012, 2013) use safety stock as a quantity. When using the safety stock as a factor, the resulting equation can be seen below in Equation 3.1.

$$K = \frac{DD \cdot RT}{NPK} \cdot (1 + \alpha) \tag{3.1}$$

$where:$
K = Kanban quantity
DD = daily demand of a part
RT = replenishment time of a bin
NPK = number of parts per Kanban
α = safety factor

3.3 Warehousing theory

Warehouses are typically used for the storage between points of origin and points of consumption of products, like raw materials, goods-in-process and finished products. The term 'warehouse' is used if the main function is buffering and storage (de Koster et al., 2007). In the production process of Kvadrat Shade, the preparation stage can also be seen as a 'warehouse' since it functions as a storage for parts before they are picked for order and sent to the assembly stage. In this section, relevant systems are discussed. Starting with order-picking systems and the design and control of order-picking processes and the two-bin system.

3.3.1 Order-picking

A major activity in warehouses is order picking. It involves the process of retrieving products from storage or buffer areas in response to a specific customer request. The customer orders consist of order lines with each a unique part, a so-called stock-keeping unit (SKU) from the Bill Of Material (BOM) (de Koster et al., 2007).

The majority of warehouses, just like Kvadrat Shade, employ humans for order picking. The most common is the picker-to-parts system, where the order picker moves through the aisles to pick the parts. Within the picker-two-parts system, there are two different types. High-level picking and low-level picking. In high-level picking, lifting trucks or cranes are used. In low-level picking, the order picker travels along the storage aisles and picks the requested items from the storage racks or bins themselves (de Koster et al., 2007). Kvadrat's preparation stage uses a picker-to-part system, where only low-level order picking is applied.

The overall objective of an order-picking system is to maximize the service level under certain constraints and restrictions. For manual order-picking systems, the travel distance is the primary objective for optimization in warehouse design. Since travel distance substantially contributes to order-picking time (de Koster et al., 2007 as cited in Tompkins et al., 2003). The average travel distance of a picking tour and the total travel distance are mainly used when speaking of travel distance within a warehouse. According to de Koster et al. (2007), another important objective is to minimise the throughput time of an order, which is the time for an order to move through a process or in the case of this research the preparation stage (Slack & Brandon-Jones, 2019).

3.4 Summary

In this chapter, the literature is reviewed to answer the sub-question "What are possible solutions to increase the service level at the preparation stage, within the boundaries of the Kanban method?" First of all, simulation theory is elaborated on to explain the method of testing the solutions to the current situation. Next, it was found in the literature that the Toyota formula can determine the optimal number of Kanbans for all parts, based on demand and replenishment times.

4 CONCEPTUAL MODEL

In this chapter the third sub-question will be addressed: "How does the conceptual model of the preparation stage look like?". The sub-question is divided into extra questions, each addressed in its own section. These are as follows:

- 4.1 Assumptions and simplifications
- 4.2 Input variables
- 4.3 Output variables
- 4.4 Flowchart of the conceptual model

4.1 Assumptions and simplifications

This section answers the question "What assumption should be made in the model?". A simulation model aims to represent reality as a simplified imitation of an operations system. Assumptions are made to fill in gaps in our knowledge about the real world and simplifications are incorporated in the model to enable more rapid model development and to improve transparency (Robinson, 2014). Below is a list of the assumptions and simplifications that have been made together with the SMEs from Kvadrat Shade.

1. Carrying capacity
   When the quantity of an order-picking size is ≥ 20 the order pickers take the whole bin with them to the pre-assembly docking stations, instead of picking the parts at the Kanban location, and when the pre-assembly is finished they bring the bin back at the Kanban location.
2. Transfer orders are excluded
   Sales orders with ≥ 80 production orders are seen as transfer orders. In this case, the parts will not be picked from the Kanban, but the main warehouse will deliver the quantities in bulk to the pre-assembly station. Therefore, it does not affect the Kanban inventory or order-picking lead time and is excluded.
3. Sales orders consist of identical production orders
   Sales orders typically involve identical production orders, differing only in dimensions. During the preparation stage, dimensional variations do not matter as only frames and textile sizes are affected, which are processed in other stages. Therefore articles within an order are identical, however, across orders, these can be different. This means that for each order from a customer the production orders including required articles are identical.
4. Refill rounds are in the morning before production starts
   The empty bins placed on the trolley to get refilled are collected and refilled before production starts in the morning. The intention is to do this on time every morning when a refill round is done, even though it might be done later in reality.

4.2 Input data

This section answers the question: "What input data is necessary for creating a simulation model?". It is divided into data that is needed for production generation, ABC classification and order picking time.

4.2.1 Production data

Since production is scheduled in advance, around three days, what orders need to be produced and picked is already known. Therefore the orders arrive at the beginning of the day, however, the size of the orders and which models should be produced need to be determined to generate production data. The sequence in which the orders are processed during a production day does not affect the KPIs, since the replenishment round is done before production starts and not multiple times throughout the day. If the latter was the case, then the daily orders' production sequence should also be determined.

Total production per day

To determine the total number of products produced on a given production day, data from November 2022 up to and including November 2023 is used. For each production date, the total production is calculated. Upon analyzing the current data, no increase or decrease was found in daily production from 2022 to 2023. Figure 4.1 shows a histogram depicting the daily production. After applying the individual distribution identification from Minitab [1], to determine the best-fitting probability distribution, it was concluded that the data follows a normal distribution as shown in Appendix E.1.

Figure 4.1: Histogram on daily production following a normal distribution

[1]Minitab 21 is statistical software, which combines the user-friendliness of Microsoft Excel with the ability to perform complex statistical analysis (*https://www.minitab.com/en-us/*).

Order sizes per sales order

Next to the total production on a day, it needs to be determined how big the sales orders are on a specific day. This means the number of production orders that fall under the same sales order. To determine this, historical data from 2023 is used to match sales and production orders. Sales orders with size $\geq$80 are excluded since these numbers are not taken into account in the Kanban system as discussed in Section 4.1.

The dataset has a bounded range: the lower limit is 1 and the upper limit is 79, as mentioned in the previous paragraph. This means that all data points fall within the range of possibilities. Due to this, traditional outlier treatment of the dataset would not only be challenging but possibly inappropriate, since altering these real-world observations could lead to misrepresentations.

Applying the individual distribution identification from Minitab does not result in a best-fitting distribution, with acceptable Andersson-Darling test and P-value results, as shown in Appendix E.2. However, visually, a log-logistic distribution seems to be a close representation, as depicted in the histogram in Figure 4.2. Additionally, according to the Andersson-Darling test it is, compared to all other distributions, the better fitting distribution as can also be seen in Appendix E.2.

Figure 4.2: Histogram on order sizes

However, to overcome this problem by fitting a distribution to the dataset, another approach could be used. Namely, using the histogram itself as input for the model. To create the histogram of the dataset, it is important to select an appropriate bin width for the data. This is achieved by applying two formulas and taking the average of their results. These are Scott's rule and the Freedman-Diaconis'Rule.

Scott's rule (Scott, 1979), as depicted in Equation 4.1 is based on a constant, 3.49, standard deviation, s, of the observations and, n, the number of observations.

$$Binwidth = \frac{3.49 \cdot s}{\sqrt[3]{n}} \tag{4.1}$$

The Freeman and Diaconis (1981), Equation 4.2, is the second method. It used the Inter Quartile Range (IQR) to determine the bin width, which is the difference between the 25th percentile and the 75th percentile of the observations.

$$Binwidth = 2 \cdot \frac{IQR(x)}{\sqrt[3]{n}} \tag{4.2}$$

The mean of the results from the two formulas results in a bin width of [redacted], however since the observations are integers it is chosen to round this value up, and therefore use a bin size of [redacted]. The histogram can be found in Appendix G. The bin that gets selected is based on its frequency, which is the occurrence rate. When an order is assigned, one of the two possible values from the chosen bin is randomly selected.

Base model distribution

To determine which model should be created, the frequency per model is calculated over historical data from December 2022 to December 2023. Projects with models that had their own model names were deleted from this data since these were backorders from huge projects Kvadrat Shade had to produce between 2021 and 2022. In addition, transfer orders ($\geq$80) are not excluded, since it is of interest what demand was over the whole year for the roller blind models. The table with the models and their respective frequencies can be found in Appendix E.3

Bill of material

As explained in Section 1.2.1, Kvadrat Shade utilizes a mass customization approach, which requires a large number of parts to allow for high flexibility when it comes to customizing the products. This high flexibility results in an unclear Bill of Material for the models, which in turn makes it impractical to determine distributions or frequencies of certain BOMs getting ordered. To overcome this obstacle it is decided to randomly take historic production orders for a certain model.

4.2.2 ABC classification

As stated in Section 1.2.4, the goal of this research is to increase the service level of the Kanban system at the preparation stage. A distinction is made between three categories: fast movers, intermediate movers and slow movers. These categories are based on their turnover rate and are divided under the principle of Pareto analysis, where about 20% of the parts contribute to about 80% of the turnover (Serna-Ampuero et al., 2022). In Table 4.1 below, the distribution of classes can be found.

Table 4.1: Classification table

Code	%volume	# items	%items
A	80%	76	13%
B	10%	57	10%
C	10%	465	78%

4.2.3 Order picking time

To determine the time it takes to pick orders, the preferred method would be to measure the time it takes to collect different orders empirically. However, due to the high variety in orders and while conducting the research and collecting the order-picking data (December 2023/January 2024) there was too little possibility of collecting enough observations. Therefore, it is chosen to approach it using separate measurements, such as the time to grab a bin and grab a part from that bin, and academic literature (Murtagh et al., 2021).

Walking time

The walking time is the time it takes to walk to a specific Kanban location. The literature review from Murtagh et al. (2021) is used to determine the walking times. It is noted that the usual walking speed for an adult is on average 1.31 m/s. The distances between the depot point, all Kanban locations and the main warehouse were measured via blueprints of the production facility. Using these distances and walking speed the walking time can be obtained. The results can be found in Appendix H.1.

Picking time

The picking time is the time it takes to pick the parts from a bin. This can be divided into the time it takes to take the bin from the shelf and the time it takes to collect a certain number of parts. Both are determined via observation and the results can be found in Appendix H.2. The average time it takes to take a bin from the shelf and also put it back is 4.86 seconds. The time to take a part out of the bin takes approximately 1 second per part that has to be taken out of the bin, which can be seen in Appendix H.3.

Stockout time

When a stockout occurs the order picker can not continue collecting the required parts until the parts are available again. In section 2.2 the order-picking process is described. When a stockout occurs a troubleshooter has to solve this, by going to the main warehouse and getting the bin refilled. This refilling process consists of travelling time and refilling time. To determine these times the walking time is observed from the preparation area to the main warehouse. Additionally, the refilling time for a bin is observed. In Appendix H.4 the results of the observations can be found. Using these measurements and those from walking time an average of 454 seconds is used as refill time.

4.3 Output variables

This section answers the question: "What is the output data of the simulation model?". The output variables are the Key Performance Indicators and measure the performance of the simulations. For this research three Key Performance indicators are identified, namely service levels, average daily stockouts and average order picking time.

4.3.1 Service level

The service level is a fraction (usually expressed as a percentage) of all demand that is met on time (Winston, 2004). The formula to determine the service level can be written as follows:

$$\text{Service level} = \frac{\text{Parts available}}{\text{Total part demand}} \cdot 100 \tag{4.3}$$

To analyse the results of the simulation and proposed experiments, especially since parts are categorized into multiple classes (Section 4.2.2), it is decided to differentiate between several types of service levels:

- Daily Service level: It calculates the service level for all parts combined for each day. This gives insights into the daily operational efficiency.
- Service level per part: This metric measures the service level of individual parts throughout the simulation and is crucial in identifying how well each part meets demand on time.
- Service level per classification: The service level per classification calculates the service level for each of the classes (A, B, and C) over the total duration of the simulation. This helps in understanding which classes of parts are meeting the predetermined service level and which ones are underperforming.

4.3.2 Daily stockouts

Next to the service level, the number of daily stockouts is tracked. Daily stockouts represent instances where demand exceeds the available inventory. It is useful for assessing the Kanban two-bin system. Compared to service level it only shows how many times there is a shortage, but not to what degree. However, this KPI is primarily useful for determining the steady state of the simulation model. Since the model starts at zero and gradually reaches a steady state in which, the number of stockouts deviates within a specific range. More on this is explained in Section 6.1.1.

4.3.3 Order-picking lead time

The average order-picking lead time is the average time it takes between the start of gathering required parts and the completion of collection for an order, excluding any pre-assembly tasks. First, the average order-picking lead time is calculated for each day. Eventually, these results are used to calculate the overall average order-picking lead time during the overall simulation run. How these times are determined is explained in Section 4.2.3.

4.4 Flowchart of the conceptual model

A flowchart of the conceptual model is depicted on the next page in Figure 4.3 to describe the decision process. Table 4.2 displays a legend for Figure 4.3. The conceptual model consists of the order generation and refilling process before production starts and order picking during production. Next to that, the model consists of multiple events, indicating the start of the flowchart or process. These events are *New day*, *Next order*, and *Next part*.

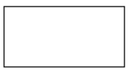
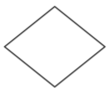
At the beginning of each production day, the event *New day* is triggered, which in turn triggers the order generation and refilling process. To generate the orders for the new day the total production is taken from a normal distribution, discussed in Section 4.2.1. Next, this total production is divided into orders according to a log-logistic distribution, which is also discussed in Section 4.2.1. All these orders get assigned a model type with a matching BOM. This process provides a production schedule, used during the order picking process.

The refilling process is initiated by the *New day* trigger. It uses the Kanban cards on the trolley as input and refills the bins that are on the trolley. This results in the supply of new parts, which updates the inventory as output.

When all orders for the day are generated, production starts, consisting of picking the orders that were generated. The event *Next order* triggers selecting the first order on the production schedule. The decision whether there are still orders on the production schedule determines if the *End day* or the *Next part* event is triggered. When an order is selected, meaning there are still orders on the production schedule, the parts of that order are gathered.

The event *Next part* triggers the process of collecting the parts that are on the BOM. The decision checks if the part is available. When this is not the case the bin has to be refilled before continuing to the process of picking the part. Additionally, the stock out is registered. Next, is the decision *Bin empty?*, which makes sure the Kanban cards of the empty bins are put on the trolley for refill. The next decision, *Order complete?*, checks if there are parts left on the BOM. When all parts of the current order are gathered it is registered and the *Next order* event is called, otherwise, the *Next part* event is called to gather the following part on the BOM of the current order.

Table 4.2: Basemodel distribution table

Symbol	Name	Explanation
	Start/end	Represents start or end of event
	Lines	Shows relationships between symbols
	Dashed lines	Shows information flows
	Input/output	Represents input or output of data
	Process	Represents a process
	Decision	Represents a decision

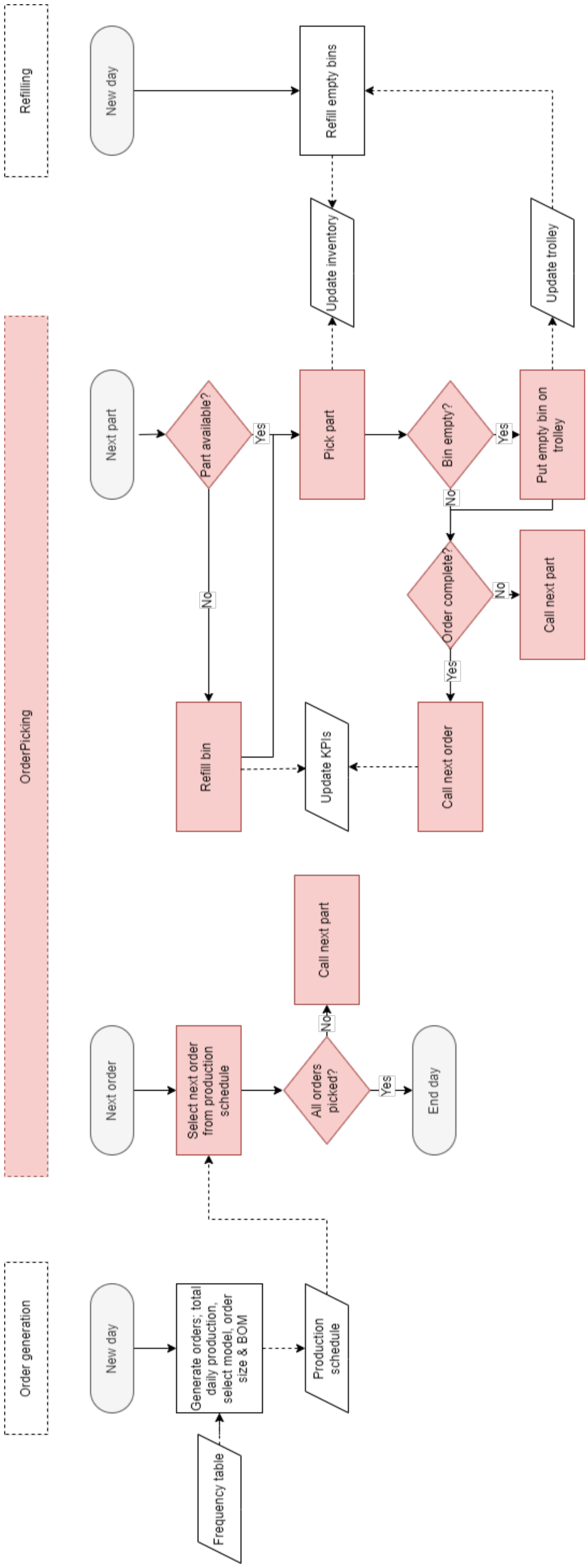


Figure 4.3: Flowchart of the conceptual model.

Note: colours are only used to distinguish between the three processes.

5 IMPLEMENTATION, VERIFICATION AND VALIDATION OF THE SIMULATION MODEL

In this chapter sub-question 4: "How can the operations at the preparation stage be simulated, verified and validated?" will be answered. Based on the conceptual model, that is discussed in Chapter 4, the simulation model is implemented, verified and validated. This chapter has the following structure:

- 5.1 Implementation
- 5.2 Model validation

5.1 Implementation

In this section, the implementation of the simulation model is discussed. This is done by explaining all the different components of the simulation model created in Plant Simulation. Figure 5.1 shows the simulation model of the Kanban operations of Kvadrat Shade partly in its initial state, meaning the simulation has not run yet. For displaying purposes not all base models are included in this figure, however, a full overview of the simulation model can be found in Appendix F.

5.1.1 Information

In the grey box called Information, general information about the model can be found. The variables *OrderId*, *Day_Nr* and *stockouts* are there for display purposes. Additionally the variables *totRequiredAvailable* and *totRequiredArticles* are used to calculate the service level for the daily statistics. *totRequiredAvailable* consists of all parts that were available when there was demand for it on a certain day and *totRequiredArticles* consists of the total demand for the parts on a day.

5.1.2 Input

In the grey box called Input, two tables are displayed. Table *ProductModelTable* contains all base models with their respective frequency, as discussed in subsection 4.2.1, Model distribution. The table *SeedValues*, contains seed values for the distributions that are used in *InitDay*. Seed values are used to generate the same stream of random numbers, ensuring the same control over the experimental conditions. Table *ABCtable* contains all articles with their predetermined classification, which is discussed in Section 4.2.2. It also contains the method *Toyota*, which is used to determine the number of bins according to the Toyota formula, this will be used during experimentation in Section 6.2.2.

5.1.3 Output & KPIs

The grey Output box contains tables with statistics on orders, daily averages and overall averages of a simulation run. These are the tables *OrderStats*, *DayStats* and *ExpStats* respectively. Additionally, it contains a table called *StockoutTable* which contains a list of all parts and displays the number of stockouts, service level and demand per part during a simulation run. Then there is *TotalResults*, which saves the mean service level per part from *StockoutTable* over the six observations for each experiment that is done. This can be used to analyse the results on the part level instead of the total level. At last, the grey box called KPIs contains all KPIs described in Section 4.3, which is for display purposes, since it can also be found in the table *ExpStats*. Additionally, the three KPIs at the bottom are from the average results over multiple observations.

5.1.4 Order generation

In the blue box, the order generation is represented. The generator called *Morning*, triggers the method *InitDay* at the start of the day to create empty orders based on the total production on that day and the order sizes. More on the total production and order sizes can be found in subsections 4.2.1 and 4.2.1 After this is done the order entities are moved to the queue called *OrderQueue*. An order exits this queue by calling the *CreateOrder method*, where an order gets assigned a base model and a BOM, after which it is saved in the *Orders* table and moved to *TempQueue* queue. Both these methods and queues do not take any time on the production day itself. Additionally, the variables *totproduction* and *dailyorders* do not have a function apart from displaying purposes. The *TempOrderSizeTable* table temporarily safes the order sizes that were determined in *InitDay* to make it possible for *CreateOrder* to call these values. The table *TransposeTable* is used to get the BOM from the selected base model table and duplicate it as a nested list in the *Orders* table.

5.1.5 Order picking

In the orange box, simulating the order-picking process takes place. From *TempQueue* an order moves to *Station* where the process of picking the order takes place. Since the model is about processing time per order rather than the whole day there is only one station, since more stations would not affect the picking times. The processing time for *Station* is determined by the method *PickOrders*. This method processes all articles on the BOM of an order, it updates the inventory in *InventoryTable*, possible empty bins in *EmptyBins*, and picking times in *OrderStats*. When an order is complete it is moved to *Assembly* and exits the system.

5.1.6 Refill round

In the green box, the refill round is processed. The generator *Morning1*, just like *Morning*, triggers a method in the morning before production starts. In this case, it triggers the method *RefillBins*. This method reads the articles that were added to the table *EmptyBins* and updates the inventory in *InventoryTable*.

5.1.7 Base models

In the grey box called base models, tables including all historic production orders are displayed per model. Each table contains the production order and the parts, including the quantity, that were required and is used to assign BOMs to selected base models, as explained in subsection 4.2.1.

5.1.8 Event-controller

The white box contains methods that are executed when the simulation resets, initializes and ends. The methods make sure the right results are saved or the model goes back to the initial state, so it can be run again. Next to that, it contains the *ExperimentManager* to obtain and compare multiple runs of the simulation. Additionally, the generator *GeneratorEndDay* triggers the *EndDay* method, which saves the daily statistics in *DayStats* at the end of each production day.

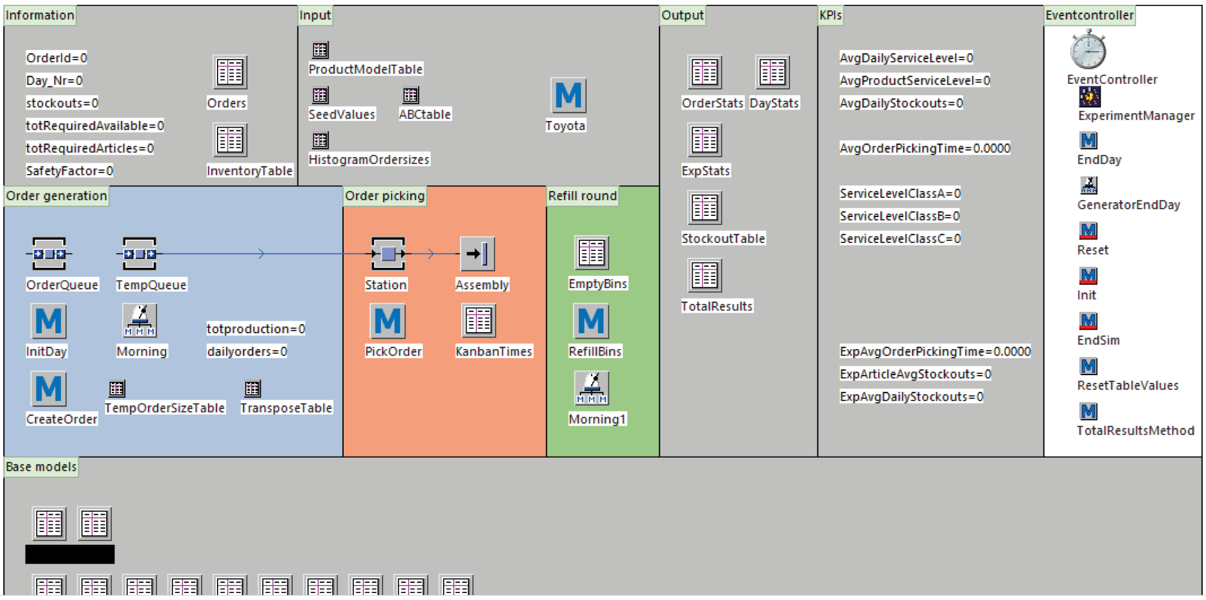


Figure 5.1: The simulation model of the Kanban operations at Kvadrat Shade in the initial state.

Note: Not all base model tables are included in this figure

5.2 Model validation

This section answers the following sub-question: "How can the operations at the preparation stage be simulated and validated?" As discussed in Section 1.3, two methods are applied to validate the model, white-box and black-box validation.

White-box validation ensures that the programmed model represents the real world as accurately as possible. First of all, the code is inspected by doing a structured walk-through, making sure that the model aligns with the conceptual framework. Additionally, the model is explained in a non-technical format, covered in Section 5.1, and reviewed by a subject matter expert of the preparation stage of Kvadrat Shade. Furthermore, visual checks are done to review the different elements of the model, such as inventory changes, bin availability and troubleshooting times. Next to that, scenario analysis is done by testing extreme scenarios, like high bin quantities per part, to see if the system behaves as expected. Lastly, the output reports are inspected to ensure no unexpected results, such as negative service levels, are available.

Black-box validation compares the model's results to real-world data. Real-world data on stock-outs, service levels and order-picking times are unknown, which makes it difficult to validate the simulation output. However, data on the demand for parts can be used to analyse the real world to the simulation output when the simulation is run with settings to the current situation, namely 2 bins per part. The "real world" data refers to the available historical data on the demand for the parts and ”simulated” data refers to the results of the demand for parts that are obtained from running the simulation model. To compare both data samples, demand for parts on historical data and simulation output, a statistical t-test is done, as discussed in Robinson (2014), to determine if there is a statistically significant difference between the two samples. First of all the standard error is calculated using the formula below in Equation 5.1:

$$SE = \sqrt{\frac{S_S^2 + S_R^2}{n}} \tag{5.1}$$

$where:$
S_S = standard deviation of simulated output data
S_R = standard deviation of real world output data
n = sample size

Using the standard error, the confidence interval can be calculated for the difference between the means using the following formula, Equation 5.2:

$$\overline{Xs} - \overline{Xs} \pm t_{1-a/2} * SE \tag{5.2}$$

$where:$
$\overline{X_S}$ = mean of simulated output data
$\overline{X_R}$ = mean of real-world output data
$t_{1-a/2}$ = value from t-distribution with $n-1$ degree of freedom and a significance level of a/2
SE = standard error

In Table 5.1 the descriptive statistics can be found on the simulated output on the demand per article and the historical output, called real-world output.

Table 5.1: Statistical description of the demand of the simulation and real-world output data

	number of observations(n)	mean	standard deviation
Simulated	706	477.63	1948.27
Real world	706	516.56	2051.82

Using the values from table 5.1 to test for a 95% confidence interval for the difference in means is calculated as follows:

$$477.63 - 516.56 \pm 1.647 * \sqrt{\frac{1948.27^2 + 2051.82^2}{706}} \tag{5.3}$$

The calculation in Equation 5.3 results in a 95% confidence interval from -214.31 to 136.46. The confidence interval includes 0, suggesting there is no significant difference at a level of 5% between the simulated output and the real-world data. In other words, the differences that are observed between the simulation outcomes and the historical data are likely due to change than systematic discrepancies between the simulation model and the real system.

6 EXPERIMENTS

This chapter answers the following sub-question: ”Which experiments will be conducted in the simulation study?”. This question is subdivided into the following questions: ”What experiments are included in the simulation?” and ”What are the results of the conducted experiments?”. To answer these questions this chapter is divided into the following sections:

- 6.1 Model initialization and observation protocol
- 6.2 Simulation experiments
- 6.3 Summary

6.1 Model initialization and observation protocol

In the previous chapter, in Section 5.2, the importance of model validation for determining how well the model reflects the real system is covered. Next to this another important issue is obtaining accurate data on the model’s performance. This is done through simulation output analysis. According to Robinson (2014) the main aim is to obtain an accurate estimate of the average, often the mean, performance of the simulation, although measures of variability are also important. There are two key issues in assuring the accuracy of the data obtained from the simulation. The first step to accurate estimation of performance is to remove any initialization bias, followed by obtaining sufficient output data from the simulation (Robinson, 2014). Both of these issues and methods to solve these issues, are covered in this section.

6.1.1 Model initialization

The first issue is the model initialization bias. Robinson (2014) proposed two methods for dealing with this bias: a warm-up period and setting initial conditions. In this research the first method, using a warm-up period, is applied. The reason for this is that although the model must run for a longer period to overcome the warm-up period, it is less prone to errors than setting initial conditions where appropriate conditions need to be specified and additional code for these conditions implemented.

The warm-up period is the initial phase during which the model stabilizes from the initial condition to a state that is representative of its long-term behaviour. In the simulation model of this research, this is measured in production days. There are multiple ways to determine the warm-up period, for this research the heuristic method marginal standard error rule (MSER) is used. According to tests from White Jnr (1997) and White Jnr et al. (2000), this heuristic performs consistently well and requires no assumptions, parameters or complex calculations (Robinson, 2014). MSER aims to identify the point in the sequence when the confidence interval is minimized, after removing initial transient data (White Jnr, 1997). The MSER formula is as follows:

$$MSER(d) = \frac{1}{(m-d)^2} \sum_{i=d+1}^{m} (Y_i - \overline{Y}(m,d))^2 \tag{6.1}$$

$where:$
d = the proposed warm-up period (number of production days)
m = the number of observations in the time-series of output data
$\overline{Y}(m,d)$ = the mean of observations from Y_{d+1} to Y_m

The warm-up period is chosen for the value d that minimises the MSER value. Important to note that the warm-up period should lay within the first half of the time series, which in this research is one production year that equals 235 production days, otherwise it is advised to simulate for a longer time series.

The data output that is used to determine the warm-up period is the number of stockouts per day. Stockouts are a critical measure of the system's performance. It directly affects service levels and picking time, making it an appropriate metric to use. Additionally, as the simulation progresses and the system reaches a steady state, the frequency and pattern of stockouts should stabilize. Lastly, at the start, when all inventory is available, stockouts are less likely to happen.

In Figure 6.1 the results of the warm-up calculation can be found. To reduce the noise in data the simulation model is run for 20 replications for 235 days (approximately the total number of production days per year) each. The MSER value is at a minimum at day 15. Therefore a warm-up period of 15 days is taken.

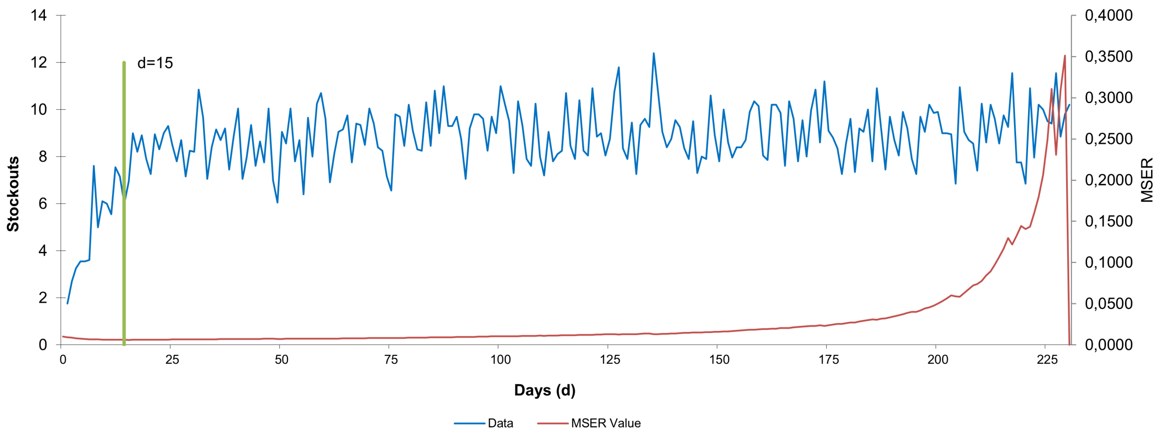


Figure 6.1: Warm-up calculation using MSER heuristic

6.1.2 Sufficient output data

The second issue is obtaining enough output data. This can be separated into the number of replications and the run length of an observation. The aim in both cases is to ensure that enough output data have been obtained from the simulation to estimate the model performance with sufficient accuracy (Robinson, 2014).

In simulations, the use of seed values is crucial for reproducing a consistent stream of random numbers, thus ensuring control over experimental conditions. However, it's important to understand that while the seed value guarantees the same sequence of random numbers, other variables in the simulation can and should be altered to explore different scenarios. For instance, in this research, we vary the number of bins to observe different outcomes under consistent conditions. Relying on a single set of conditions, even with varying bins, may not comprehensively test the model. To overcome this issue, an experiment can be conducted multiple times. In subsequent runs, the simulation progresses further along the random number sequence rather than restarting it, allowing for a broader range of scenarios. This approach of simulating allows for the collection of multiple sets of data, offering a better estimation of the mean performance. This research uses a confidence interval method as proposed in Robinson (2014) to determine the optimal number of runs. This will ensure a reliable sample size for statistical accuracy. The formula used is as follows:

$$CI = \overline{X} \pm t_{n-1,a/2} \frac{S}{\sqrt{n}} \tag{6.2}$$

$where:$
$\overline{X}$ = mean of the output data from the replications
S = standard deviation of the output data from the replications
n = number of replications
$t_{n-1,a/2}$ = value from Students t-distribution with n−1 degree of freedom and a significance level of a/2

To determine the optimal number of runs the model is run for 100 observations. For each run, the daily stockouts and total production are saved. For each of these KPIs, the day averages are taken and these averages are tested on a 99% Confidence interval. Appendix I shows the results of the tests. Eventually, the highest number is taken to ensure a sufficient number of runs, thus the number of replications will be 6.

6.2 Simulation experiments and results

After removing the initialization bias from the simulation model and determining the number of replications, the experiments are designed and performed. Answering the sub-questions: ”What experiments are included in the simulation?” and ”What are the results of the conducted experiments?”. The service level targets are previously mentioned in Section 1.2.4 and the corresponding classification determination can be found in Section 4.2.2.

6.2.1 Baseline scenario

The first experiment that is conducted represents the current situation, as described in Chapter 2. In this experiment, each article has two bins with a set quantity of parts per bin, that is currently in use. Additionally, every morning before production starts, all empty bins on the trolley are refilled in a daily refill round.

Results baseline scenario

Table 6.1: Service levels results baseline scenario.

	Service level
Class A	89%
Class B	84%
Class C	93%

Table 6.2: Results avg. order-picking time, avg. daily stockouts and the total number of bins baseline scenario.

	Results
Average order-picking time	8:41.75
Average daily stockouts	7.95
Total number of bins	1412

6.2.2 Experiment 1: Implementing and assessing the Toyota formula with a 4 bin maximum

Toyota's formula is used to determine the required number of bins per article, which can be seen in Equation 6.3 below as it is discussed in Section 3.2. The parameters that are needed are daily demand, replenishment time, number of parts per Kanban, and optionally a safety factor. For display purposes, the Toyota formula is depicted below in Equation 6.3, for a more detailed overview and explanation see Section 3.2.

$$K = \frac{DD \cdot RT}{NPK} \cdot (1 + \alpha) \tag{6.3}$$

For the daily demand, the average active demand is taken. This means that the average demand is calculated for each day there is (active) demand for a part. Since the parts do not have a consistent daily demand, it would be inaccurate to divide the total annual demand by the number of production days for each part. By doing this it provided a more realistic representation of the demand pattern. Utilizing average active demand ensures a more accurate determination of the number of Kanbans required, thereby reducing the risk of stockouts on days when demand occurs.

The replenishment time is one day since the refill round is once a day before production starts. There is no desire by Kvadrat Shade to change this number since it would mean altering the work responsibilities and workflow dynamics. The number of parts per Kanban is obtained from the current quantities used in the Kanban system. Additionally, the maximum number of bins for each part is 4, which is decided upon by stakeholders. This is decided since using more bins per part would result in a too high space occupation at the preparation stage.

Results experiment 1

After applying the Toyota formula and setting a maximum of four bins per part, the resulting performances can be found in Tables 6.3 and 6.4.

Table 6.3: Service levels results in experiment 1.

	Baseline	Experiment 1	Difference
Class A	88.96%	87.74%	-1.37%
Class B	83.73%	82.17%	-1.86%
Class C	93.22%	88.64%	-4.91%

In Table 6.3 it can be seen that compared with the current situation the service level is lower, for each class. For class A it is % lower, class B % lower and the biggest difference is in class C with a difference of -4.67%.

Table 6.4: Results avg. order-picking time, avg. daily stockouts and the total number of bins experiment 1.

	Baseline	Experiment 1	Difference
Average order-picking time	8:41.75	9:42.49	+11.45%
Average daily stockouts	7.95	9.92	+24.78%
Total number of bins	1412	631	-56.59%

In Table 6.4 the two other Key Performance Indicators (KPIs) that were analyzed during the experiment, namely the average order-picking time and the average daily stockouts, can be found. It is observed that both these KPIs exhibited an increase in comparison to the baseline results. Additionally, as an indicator, the number of bins in the Kanban system is displayed in the table.

The significant reduction in the total number of bins from 1412 to 631 leads to less inventory on hand in the Kanban system. This reduction, in combination with the constraint of a maximum of four bins, may have increased the likelihood of stockouts if demand spiked unexpectedly, directly impacting service levels negatively and increasing order-picking times due to additional replenishment times.

6.2.3 Experiment 2: Assessing the Toyota formula with 1 bin restriction

In the previous experiment, experiment 1, the Toyota formula was used to determine the number of bins per part. The number of bins that could get assigned was between 0 bins and 4, thus also 1 bin can get assigned. However, since a bin only gets refilled in the morning when it is empty, it would mean that there will not be any safety stock (a second bin) during the period the empty bin is on the trolley to get refilled. To solve this problem, when a part gets assigned one bin by the Toyota formula the bin content quantity will be divided over two bins. Resulting in two bins with half the stock. This could serve as a useful buffer.

Results experiment 2

In Tables 6.5 and 6.6 the results and the comparison with the current situation of the experiments can be seen. Just like in experiment 1 the service level is lower than the current situation and does not appear close to the set target. Additionally, the average order-picking time and average daily stockouts increased just like in experiment 1. Even though the one-bin restriction attempted to mitigate risks by splitting bin contents into two smaller bins as a buffer, it did not compensate significantly for demand variability.

Table 6.5: Service levels results in experiment 2.

	Baseline	Experiment 2	Difference
Class A	88.96%	88.03%	-1.04%
Class B	83.73%	82.11%	-1.93%
Class C	93.22%	88.44%	-5.13%

Table 6.6: Results avg. order-picking time, avg. daily stockouts and the total number of bins experiment 2.

	Baseline	Experiment 2	Difference
Average order-picking time	8:41.75	9:43.18	+11.77%
Average daily stockouts	7.95	9.91	+24.65%
Total number of bins	1412	1061	-24.86%

Note: the total number of bins includes smaller bins, half the size of regular bins.

When comparing experiments 1 and 2, there is a slight improvement in service level in experiment 2, for class A parts (from 87.74% to 88.03%) but a marginal decrease for class B and C parts, as can be seen in Table 6.7. This little change indicates that splitting bins for parts initially allocated one bin may have slightly improved availability for class A parts but proved not to be enough to significantly impact classes B and C.

Table 6.7: Service levels results from experiment 1 and experiment 2.

	Experiment 1	Experiment 2	Difference
Class A	87.74%	88.03%	+0.33%
Class B	82.17%	82.11%	-0.07%
Class C	88.64%	88.44%	-0.23%

6.2.4 Expanding upon foundational experiments

Both initial experiments discussed in previous sections showed that only applying the Toyota formula with a maximum of 4 bins did not prove to be sufficient in meeting the set targets. However, it does give valuable insights into the service levels per part and which do and do not meet the requirements. With this information, it is possible to further experiment, to make sure that the service level targets are met. This will be done by adding a bin for each part that does not meet its service level target. Since there is no significant difference between experiments 1 and 2, as shown in Table 6.7 in the previous subsection, further experiments will be based on experiment 1, which will allow for one bin. This is further covered in Section 6.2.5.

Based on the results of experiment 1, the classes can be divided into their bin size and whether or not they met the set target. This can be found in Table 6.8. The table displays the service level compliance by class and number of bins assigned, meaning that each part is assigned to a class (A, B, C and D) and is assigned a certain number of bins from the Toyota formula. The table deviates for each class and bin quantity, whether it met the service level or not (SL-target) or if there was no demand during the simulation run. The quantity in the table is the number of parts that fall under this category. For example, 43 parts belonging to class A were assigned one bin, but the bin did not fulfil their service level target. Only 3 parts met their service level target. Additionally, 2 parts had no demand, and hence their service level was not measured.

Currently, 37.1% of the parts do not meet the service level target. 30.9% of the parts do meet the service level target and 32.0% had no demand during the simulation and therefore are disregarded from the service level calculations. This is done because when there is 0 demand, mathematically, the service level cannot be calculated and stays undefined.

One could argue it is 100% since there are no stockouts. However, it would imply that demand was met, even though there was no demand for that specific part. Including it with a service level of 100%, or 0%, contrarily, would inaccurately depict the overall service level and give misleading impressions of the results. Therefore the parts with zero demand are mentioned separately.

Table 6.8: Service level compliance by class and number of bins from experiment 1.

Class	Bins	<SL-target	$\geq$SL-target	No demand	Total
A	1	43	3	1	47
A	2	7	0	0	7
A	3	7	0	0	7
A	4	4	0	0	4
B	1	19	12	0	31
B	2	10	0	0	10
B	3	2	0	0	2
B	4	6	0	0	6
C	0	0	0	2	2
C	1	134	200	18	352
C	2	17	2	2	21
C	3	2	0	0	2
C	4	11	1	1	13
D	0	0	0	202	202
Total		262	218	226	706

6.2.5 Experiment 3: Scaling bins for service level target

As mentioned in Section 6.2.4, this section expands on the foundational experiments discussed in Sections 6.2.2 and 6.2.3. This is done by adding one bin for a part every time the service level target for this specific part is unmet. Doing this would most probably mean that for some parts the number of Kanbans would exceed the maximum number of 4 bins that were set. Even though this is physically seen as unacceptable, it will give valuable insights on a part-specific level.

Results experiment 3

Adding bins to a part when the service level target was still unmet resulted in the outcomes shown in Table 6.11. Important to note is that there are two parts that with 16+ bins did not reach their service level target. Furthermore, for the same parts as in experiments 1 and 2, the demand is zero and still has a share of 32.0%. Tables 6.9 and 6.10 show the results and the comparison with the baseline scenario (current situation) of experiment 3 after 16 iterations, except for the mentioned two parts.

Table 6.9: Service levels results in experiment 3 after 16 iterations.

	Baseline	Experiment 3	Difference
Class A	88.96%	98.7%	+9.87%
Class B	83.73%	96.9%	+13.59%
Class C	93.22%	97.2%	+4.09%

Table 6.10: Results avg. order-picking time, avg. daily stockouts and the total number of bins experiment 3 after 16 iterations.

	Baseline	Experiment 3	Difference
Average order-picking time	8:41.75	5:51.1	-31.71%
Average daily stockouts	7.95	1.88	-76.41%
Total number of bins	1412	1351	-4.32%

Below the iterative experimentation results are discussed. Table 6.11 shows the service level compliance by class and number of bins after 16 additional iterations, in which all parts reached their targeted service level. Figure 6.2 shows the service level compliance of the parts, excluding the parts with 0 demand. This shows the percentage of parts that meet their required service level target per iteration and what percentage does not. It can be seen that it follows a negative exponential growth, in which it starts stabilizing at around 6 iterations. The comparable increase can be seen for the service level per classification in Figure 6.3. Figure 6.4, which displays the total number of bins at the preparation stage also follows a negative exponential growth, eventually stabilizing around 1300 bins.

Figure 6.5, shows the average order-picking time for an order and Figure 6.6 shows the average number of daily stockouts. Compared to the previous figures discussed above, these figures follow an exponential decay and also start stabilizing around iteration 6. This is consistent with the increase in service level compliance, as fewer stockouts correlate with better service levels.

Table 6.11: Service level compliance by class and number of bins from experiment 3 at iteration 16.

Class	Bins	<SL-target	≥SL-target	No demand	Total
A	1	0	3	1	4
A	2	0	10	0	10
A	3	0	11	0	11
A	4	0	6	0	6
A	5	0	5	0	5
A	6	0	8	0	8
A	7	0	6	0	6
A	8	0	6	0	6
A	9	0	6	0	6
A	10	0	2	0	2
A	16	0	1	0	1
B	1	0	12	0	12
B	2	0	4	0	4
B	3	0	5	0	5
B	4	0	3	0	3
B	5	0	7	0	7
B	6	0	9	0	9
B	7	0	5	0	5
B	8	0	3	0	3
B	9	0	1	0	1
C	0	0	0	2	2
C	1	0	199	18	217
C	2	0	71	2	73
C	3	0	36	0	36
C	4	0	30	1	31
C	5	0	14	0	14
C	6	0	6	0	6
C	7	0	2	0	2
C	10	0	1	0	1
C	11	0	2	0	2
C	12	0	2	0	2
C	13	0	1	0	1
C	16	0	1	0	1
C	21	2	0	0	2
D	0	0	0	202	202
Total		2	478	226	706

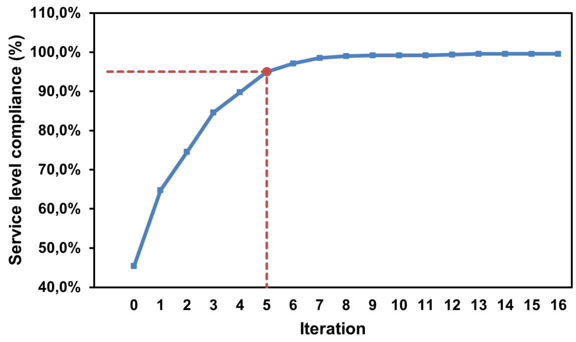


Figure 6.2: Service level compliance percentage (excluding parts with 0 demand).

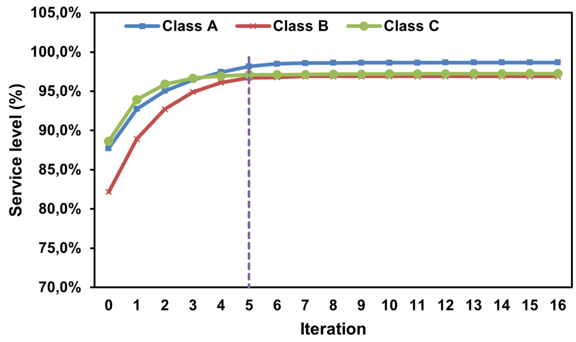


Figure 6.3: Service level per classification.

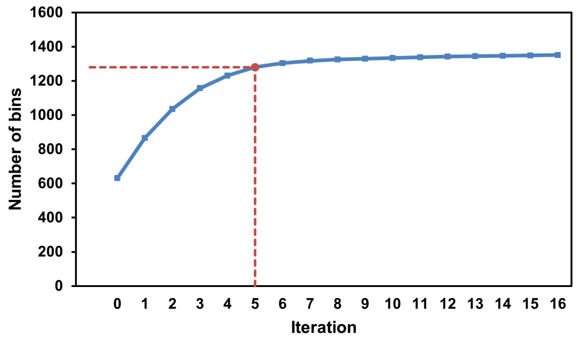


Figure 6.4: Total number of bins at the preparation stage

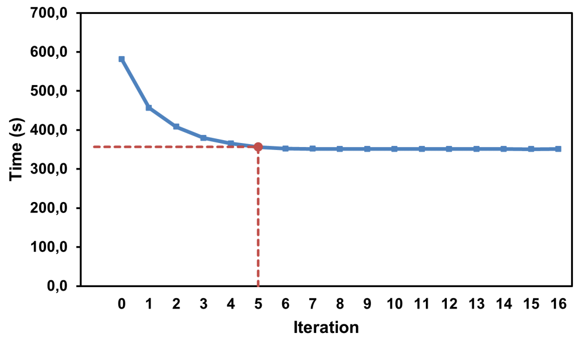


Figure 6.5: Average order-picking time.

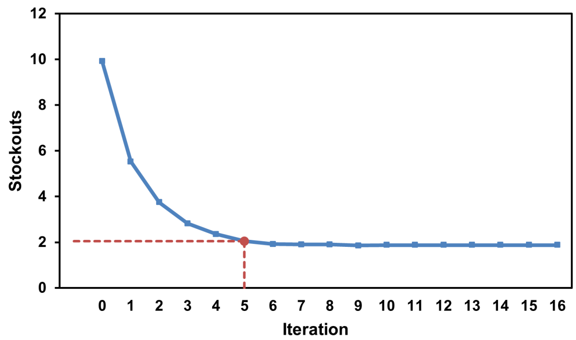


Figure 6.6: Average daily stockouts.

At iteration 5 the service levels discussed in Section 1.2.4 are met for all classes, 98.2%, 96.7% and 97.1%, respectively. After eliminating parts with no demand, 456 parts meet the service level target, representing 95% of the demanded parts. In Table 6.12, on the next page, the state at iteration 5 is shown in terms of the service level compliance by class and number of bins, comparable to Table 6.11.

Table 6.12: Service level compliance by class and number of bins from experiment 3 at iteration 5.

Class	Bins	<SL-target	≥SL-target	No demand	Total
A	1	0	3	1	4
A	2	0	10	0	10
A	3	0	11	0	11
A	4	0	6	0	6
A	5	0	5	0	5
A	6	3	8	0	11
A	7	4	4	0	8
A	8	5	2	0	7
A	9	1	2	0	3
B	1	0	12	0	12
B	2	0	4	0	4
B	3	0	5	0	5
B	4	0	3	0	3
B	5	0	7	0	7
B	6	2	9	0	11
B	7	0	5	0	5
B	8	0	1	0	1
B	9	0	1	0	1
C	0	0	0	2	2
C	1	0	199	18	217
C	2	0	71	2	73
C	3	0	36	0	36
C	4	0	30	1	31
C	5	0	14	0	14
C	6	0	6	0	6
C	7	0	2	0	2
C	9	9	0	0	9
D	0	0	0	202	202
Total		24	456	226	706

6.3 Summary

This section summarizes the findings of the simulation experiments, focusing on improving the service level and reducing the order-picking lead times while maintaining the Kanban system. First, the context for the experiments was discussed, including obtaining enough output data and removing the initialization bias. Then various experiments were described, starting with a baseline functioning as a benchmark and eventually, the Toyota formula was utilized to optimize the number of bins per part in the Kanban system.

The first experiment evaluated the baseline scenario and after that, the solution to evaluate the impact of applying the Toyota formula with maximum bin restrictions was conducted. This showed that applying the Toyota formula with a restriction to a maximum of four bins did not result in the desired service levels across all classes, with service levels decreasing compared to the baseline. The next experiment explored splitting bins for parts initially allocated one bin by halving the bin capacity and using two bins. This, compared to the first experiment applying the Toyota formula, slightly improved availability for class A parts but proved not to be enough to significantly impact classes B and C. However, this too failed to improve service levels or reduce order-picking times compared to the baseline.

In response to these findings, additional experiments were designed to iterate over the bin numbers for parts that did not meet their service level targets. This approach aimed to identify a more flexible solution that works better with the varied demand patterns and operational constraints at Kvadrat Shade. Through these experiments, insights were gained into how bin allocations could be optimized beyond the initial Toyota formula application.

7 CONCLUSIONS, RECOMMENDATIONS AND DISCUSSION

In this final chapter, the conducted research performed at Kvadrat Shade is concluded. This is divided into multiple sections. Section 7.1, answers the main research question that was formulated in Section 1.4.1. Section 7.2 discusses the recommendations, that were retrieved via the research, for Kvadrat Shade. In Section 7.3 the limitations of the research and the simulation model will be discussed. And finally in Section 7.4 further research directions are discussed.

- 7.1 Conclusions
- 7.2 Recommendations
- 7.3 Limitations
- 7.4 Further research directions

7.1 Conclusions

This section will answer the main research question, which was derived in Chapter 1 after the problem identification. The problem researched for Kvadrat Shade, the management problem, is: *The perceived service level is lower than desired and the perceived order-picking lead times are not low enough, at the preparation stages of the roller and pleated production lines.* To research this problem and propose solutions, the main research is formulated as follows:

How can a designated service level be obtained and the average order-picking lead time be decreased at the preparation stage of Kvadrat Shade while maintaining the Kanban method?

To answer the main research question the question is divided into sub-questions covered in Chapters 2-6. Chapter 2 provides an overview of the performances and processes at the preparation stage at Kvadrat Shade to gather information on the storage allocation and the order-picking process.

In Chapter 3, literature research is conducted to find solutions, to increase the service level, that can be implemented at the preparation stage of Kvadrat Shade. First of all, research has been done into the Kanban two-bin system to find out the principles and operational mechanics of such a system. From this literature research, the Toyota formula, proposed by Toyota Motor Corporation and covered in Co and Sharafali (1997); Mao et al. (2014); Tambi and Mashalkar (2023); Naufal et al. (2012, 2013), had been demonstrated to be useful in determining the appropriate number of Kanban bins.

Chapters 4 and 5 deal with the conceptual and simulation models, respectively. Chapter 4 discusses the assumptions and simplifications made for the model. Additionally, it discusses the required input data and output variables. Finally, this is summarized in a flowchart of the conceptual model. This then was used in Chapter 5 to program the simulation model and to validate the model.

In Chapter 6, simulation experiments are conducted to explore strategies for adjusting the Kanban system to meet service level targets and decrease average order picking time. The experiments utilized the Toyota formula, obtained from the literature review in Section 3. First of all, the current scenario is simulated to create insights into the current Kanban system and to compare the results from the proposed experiments. The baseline experiment, with two bins for each part, felt short of the desired service levels.

Then experiments were conducted using the Toyota formula to determine the optimal number of bins per part. Two different options were tested: one where one bin per part is allowed, and another where two smaller bins are interchanged to maintain two bins, in case of having only one bin. Between these two experiments, no significant effect is found. However, it became evident that both experiments performed worse than the current situation, where the service levels decreased by 1.37-1.04%, 1.86-1.93% and 4.91-5.13%, and the average order picking times increased by 11.45-11.77%. Only the number of bins from experiment 1 compared with the baseline experiment, showed improvement by a decrease of 56.59%.

Overall, applying the Toyota formula with the constraint of a maximum number of bins does not lead to improvements, suggesting that using the Toyota formula alone is insufficient to meet the goals. This limitation is due to the formula's dependence on data on daily demand, which doesn't account for sudden demand spikes. Especially in the high-variety (mass customization) market Kvadrat Shade operates in this is difficult to predict.

However, the subsequent experiments in which the bin quantities are dynamically adjusted based on service level targets reveal an adequate strategy capable of achieving desired service levels. After the fifth iteration, where a maximum of 9 bins are allowed, the strategy met and even exceeded the overall service level targets for the different classes, while also reducing the total number of bins by 9.35% compared to the current Kanban system. Despite the maximum 4 bins part constraint, this is still lower than the current space utilization, demonstrating the potential for dynamically adjusted bin quantities.

Overall, it can be concluded that by implementing a flexible, data-driven approach to the Kanban system, Kvadrat Shade can improve its service levels, reduce order-picking times and optimize inventory space usage at the preparation stage. This approach and the simulation model provide solutions that can adapt to future changes in demand, which is especially useful for Kvadrat Shades upcoming year. This is because the Verosol collection, consisting of 43 base models, equalling up to 67% will be phased out and completely taken over by the Kvadrat Shade collection, consisting of 39 base models, which currently equal up to 33% of Kvadrat Shades production.

In conclusion, this research delivers critical insights into existing practices of the Kanban system used at the preparation phase and provides the company with data-driven insights and action points that can be utilized to improve operational efficiency further. Recommendations to further improve and utilize the data insights for the preparation stage will be discussed in the next section, Section 7.2.

7.2 Recommendations

This section discusses recommendations that are devised after conducting the research. The aim is to address identified solutions and challenges and to provide Kvadrat Shade with actionable strategies to improve Kvadrat Shade's preparation stage regarding stock management.

The first recommendation is to adopt a flexible Kanban numbering system. Moving away from a one-size-fits-all approach to determining the number of bins per part. Currently for every part two bins are assigned, however this results in most bins in overstocking or understocking. It is important to include more aspects in determining the number of bins. Additionally, alternative inventory management methods should be implemented for parts that do not fit into the Kanban system. This involves identifying parts that barely meet their service level target and analysing the root causes, such as small bin capacity or high demand fluctuations.

This flows over to the next recommendation, which is keeping track of the articles and the effects the changes have, including but not limited to their demand, bin capacity and stockouts. Currently, stockouts are barely kept track of and no document contains the articles and their respective bin capacity. Implementing this essential information will provide better insights and allow for easier analysis possibilities in the preparation stage. Next to that, it allows also for better model validation of the created simulation model for this research. Furthermore, it is recommended to incorporate the BOMs more effectively in the future ERP system. This would facilitate more accurate demand prediction for parts and allow for demand forecasting.

Combining proposed recommendations would allow for continuous improvement and experimentation to find the most effective bin configurations. Therefore, it is recommended to schedule periodic review moments to analyse the current Kanban.

7.3 Discussion

In this section, the limitations of this research are discussed. The limitations are divided into the following subsections: data limitations and assumptions.

7.3.1 Data limitations

First of all the data on daily demand for articles was retrieved from the ERP system and relied on the demand over one year. Due to the high variety of products that are offered, not all parts are needed daily. Therefore the choice was made to use the average active demand. However, this approach does not include seasonal fluctuation.

Additionally, there are no clear BOMs, which led to inaccurate demand forecasting on a part-specific level. The frequency of the models was known, however, the BOM within this model is chosen randomly by selecting a random configuration that was produced in the last year.

There is no accurate data available on stockouts and processing times. This makes it difficult to validate the simulation model on its accuracy compared to the real-world conditions.

The simulation model does not consider an exact distribution for the order sizes. Even though this issue is addressed, in Section E.2, and solved by using the histogram over last year it limits the variability in order sizes.

7.3.2 Assumptions and simplifications

Orders with a size of $\geq$80 were excluded from the simulation. This may not completely represent the impact of large orders on daily production, even though the model is not created for this purpose, it should be acknowledged that the model does not take this into account and does not show the simulation of the complete preparation stage nor the whole production process.

The bin capacities per part are subject to human error since there was no file, and it had to be collected by reading the Kanban cards. Additionally, it was observed that some bins were filled beyond their capacity as mentioned on the Kanban card in real life. This research and simulation did not account for this. Next to this, it is assumed that a refill round always takes place before production starts, however, this is not always the case. Sometimes it takes place when production has already started.

The current Kanban system allocates the two bins for a part on top of each other, which fits perfectly. However during experimentation, when >2 bins were allocated the bin locations were not adjusted to accommodate the additional bins. This would mean that the order picking time in regards to walking is not accurate unless these bins are placed there if a spot becomes empty after the first bin placed there becomes empty.

7.4 Further research directions

The research utilized the Toyota formula to increase the service level, however, this alone appeared to be insufficient. The research did however give insights into the behaviour of parts in the Kanban system. Using these insights suggestions regarding further research directions can be given. This will be discussed in this section.

Firstly, research showed that for a lot of parts, a maximum of four bins is insufficient to obtain the desired service levels. Therefore it is recommended to search for alternative inventory methods, for these specific parts, that can be implemented alongside the Kanban system. Taking into consideration the effects on parts with high demand, irregular demand, and low bin capacities.

Secondly, the daily demand used in determining the number of Kanbans with the Toyota formula was the average active demand of a part over a year. It would be interesting to research the effects of determining the daily demand over shorter periods, average order sizes and forecasting methods.

Thirdly, experimenting with the replenishment times would be of interest. Currently, this is done once a day, before production starts. The preparation might benefit from adding a replenishment moment when production is on hold during lunch break for example. Interesting to see if this affects daily stockouts. For this research, it was excluded since it would also mean altering work responsibilities. However, it may be interesting to weigh one replenishment moment against an additional moment.

Fourth, investigating the potential benefits of implementing a more effective BOM into the ERP systems, for improving demand forecasting accuracy, is of interest. During my time at Kvadrat Shade, it was observed that the current way of configuring and extracting a BOM was quite difficult and error-prone. Additionally, the current ERP system runs on Microsoft AX and is expected to need replacement over a year. The transition of the ERP platform should be started on time and also looked at with current staff what they would like to see changed.

Furthermore, finding a more structured way to determine the number of bins required per part should be investigated. For example by implementing clustering algorithms to group parts based on their characteristics, such as demand patterns and bin capacities. For each group, different optimization techniques, such as linear programming or simulated annealing, could be applied to determine the optimal bin configuration.

Lastly, it would be interesting to study how bin allocation affects order picking times, taking into account walking distances, shelf heights and bin sizes. This would mainly focus on ergonomics rather than service levels. However, organizing bins and parts in a way that maximizes the number of parts that can be stored in each bin would increase bin capacity and likely result in improved service levels.

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A PROBLEM-SOLVING APPROACH

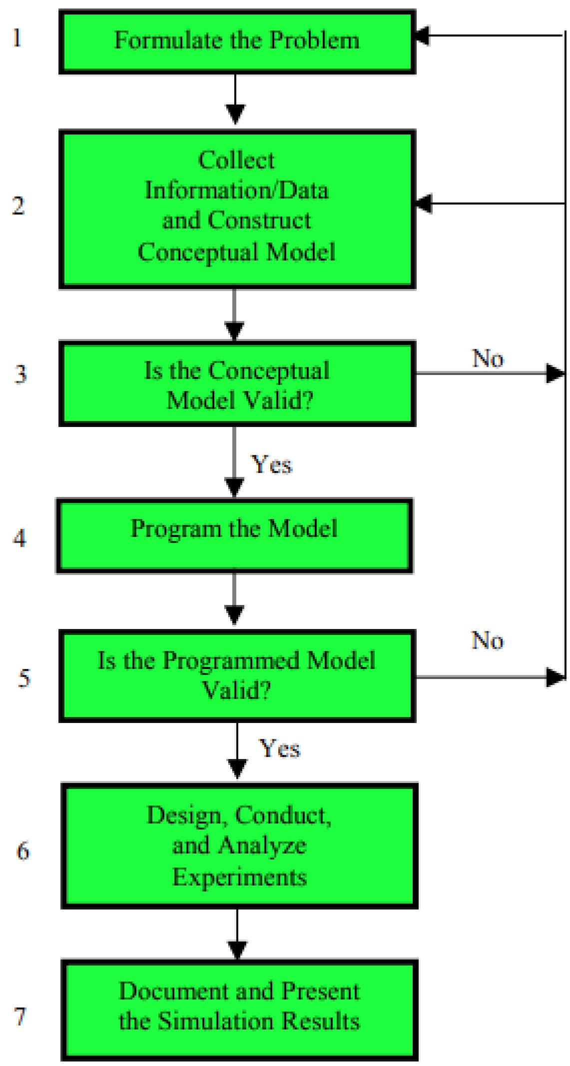

Figure A.1: Seven-Step Approach for Conducting a Successful Simulation Study (Law & McComas, 2001)

B PREPARATION STAGE

B.1 Picture of preparation stage

Figure B.1: Picture of preparation stage

B.2 Picture of slow movers location

Figure B.2: Picture of slow movers location

C ORDER-PICKING FLOWCHART

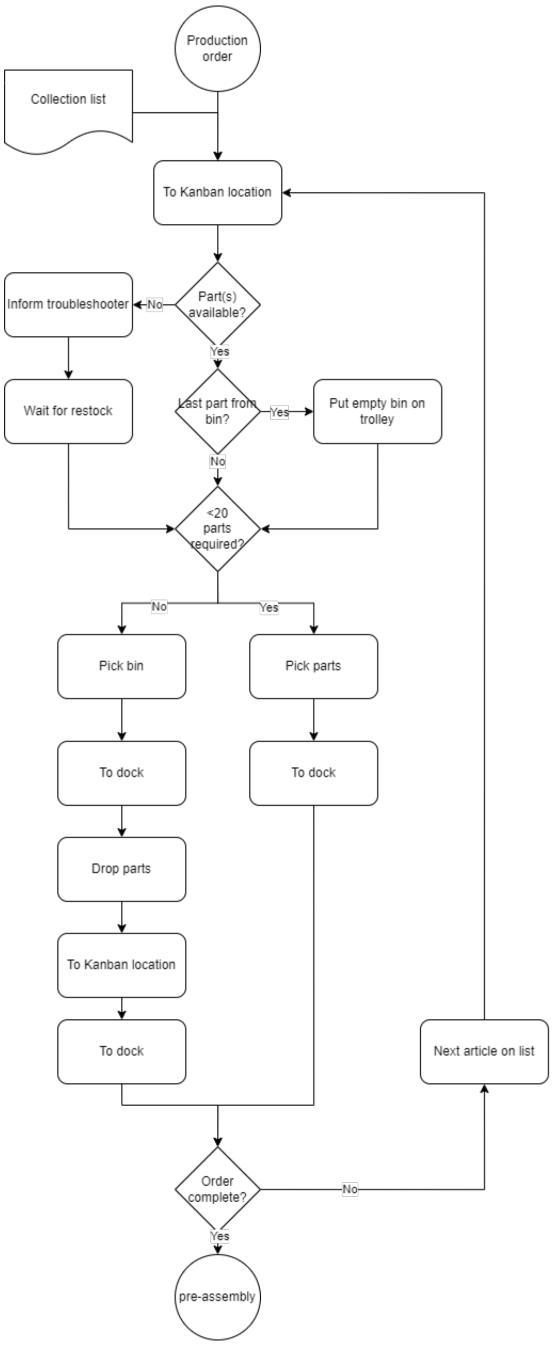

Figure C.1: Order-picking process flowchart

D TROLLEY

Figure D.1: Trolley used to move orders through the production process

E DISTRIBUTIONS IN THE PROCESS

E.1 Distribution identification daily production

As can be seen below, the data follows a normal distribution. First, the p-value that is calculated in Minitab is high enough to fit a distribution. Next to that, the data points follow the normal distribution well with a 95% Confidence Interval.

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	0,167	0,938	
Box-Cox Transformation	0,167	0,938	
Lognormal	11,295	<0,005	
3-Parameter Lognormal	0,179	*	0,000
Exponential	37,889	<0,003	
2-Parameter Exponential	36,956	<0,010	0,006
Weibull	0,954	0,017	
3-Parameter Weibull	0,183	>0,500	0,000
Smallest Extreme Value	2,544	<0,010	
Largest Extreme Value	2,893	<0,010	
Gamma	4,662	<0,005	
3-Parameter Gamma	0,268	*	0,000
Logistic	0,370	>0,250	
Loglogistic	3,740	<0,005	
3-Parameter Loglogistic	0,373	*	0,000

Figure E.1: Goodness of Fit test daily production

Figure E.2: Probability Plots for daily production

Figure E.2: Probability Plots for daily production (cont.)

E.2 Distribution identification order sizes

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	401,559	<0,005	
Box-Cox Transformation	69,603	<0,005	
Lognormal	79,062	<0,005	
3-Parameter Lognormal	482,002	*	0,000
Exponential	214,447	<0,003	
2-Parameter Exponential	1368,669	<0,010	0,000
Weibull	129,510	<0,010	
3-Parameter Weibull	510,973	<0,005	0,000
Smallest Extreme Value	518,670	<0,010	
Largest Extreme Value	258,998	<0,010	
Gamma	162,086	<0,005	
3-Parameter Gamma	582,904	*	0,000
Logistic	279,473	<0,005	
Loglogistic	67,807	<0,005	
3-Parameter Loglogistic	452,883	*	0,000

Figure E.3: Goodness of Fit test order sizes

Figure E.4: Probability Plots for order sizes

Figure E.4: Probability Plots for order sizes (cont.)

E.3 Model distribution frequency table

Table E.1: Distribution roller blind models

Model	Frequency
Model 1	0.00155%
Model 2	0.00095%
Model 3	0.04653%
Model 4	0.00262%
Model 5	0.01648%
Model 6	0.00105%
Model 7	0.00087%
Model 8	0.02635%
Model 9	0.00217%
Model 10	0.00315%
Model 11	0.00013%
Model 12	0.00005%
Model 13	0.13759%
Model 14	0.04758%
Model 15	0.00401%
Model 16	0.01315%
Model 17	0.07075%
Model 18	0.01595%
Model 19	0.00199%
Model 20	0.00307%
Model 21	0.02463%
Model 22	0.01438%
Model 23	0.00474%
Model 24	0.00004%
Model 25	0.00775%
Model 26	0.00081%
Model 27	0.00781%
Model 28	0.0025%
Model 29	0.00013%
Model 30	0.00112%
Model 31	0.00036%
Model 32	0.00029%
Model 33	0.10442%
Model 34	0.00025%
Model 35	0.00039%
Model 36	0.00464%
Model 37	0.00005%
Model 38	0.00253%
Model 39	0.00042%
Model 40	0.00394%
Model 41	0.00007%
Model 42	0.00189%
Model 43	0.08734%
Model 44	0.02122%
Model 45	0.00868%
Model 46	0.02612%

Model 47	0.00008%
Model 48	0.00774%
Model 49	0.00051%
Model 50	0.00332%
Model 51	0.00081%
Model 52	0.00003%
Model 53	0.00031%
Model 54	0.00147%
Model 55	0.00346%
Model 56	0.00383%
Model 57	0.08389%
Model 58	0.00018%
Model 59	0.00049%
Model 60	0.08567%
Model 61	0.01008%
Model 62	0.00011%
Model 63	0.01857%
Model 64	0.00196%
Model 65	0.00228%
Model 66	0.02558%
Model 67	0.00299%
Model 68	0.00016%
Model 69	0.00027%
Model 70	0.00012%
Model 71	0.00004%
Model 72	0.00034%
Model 73	0.00178%
Model 74	0.00009%
Model 75	0.00658%
Model 76	0.00706%
Model 77	0.00498%
Model 78	0.00007%
Model 79	0.00085%
Model 80	0.00079%
Model 81	0.00082%
Model 82	0.00013%
Total	**100%**

F THE SIMULATION MODEL

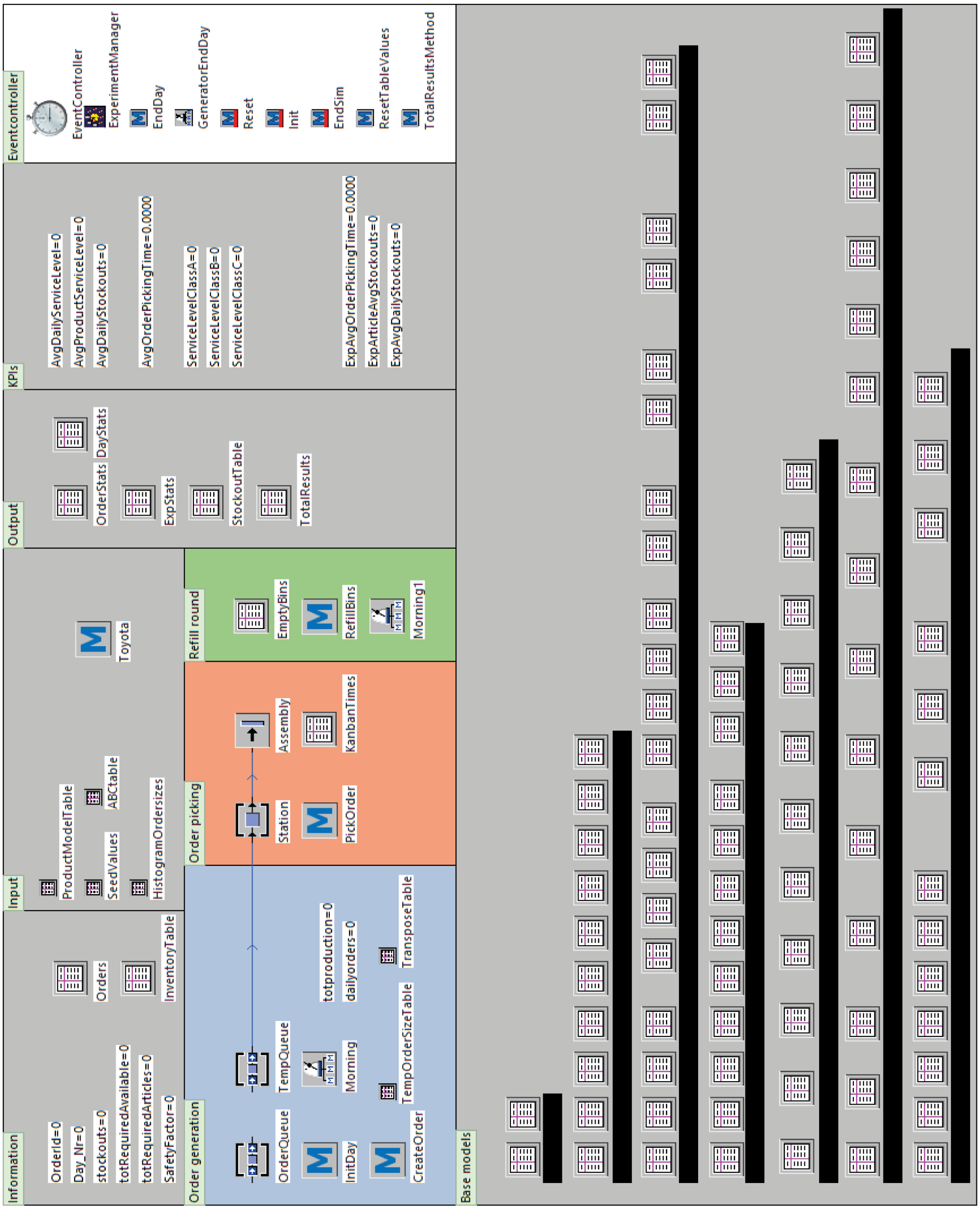

Figure F.1: The complete simulation model of the preparation stage

G ORDER SIZE HISTOGRAM

Figure G.1: Order size historgram

H ORDER PICKING TIMES

H.1 Walking times

Location	Distance (m)	Walking time (s)
Warehouse	114	87
KS-01-01	10	8
KS-01-02	10	8
KS-01-03	10	8
KS-01-04	10	8
KS-01-05	10	8
KS-01-06	10	8
KS-02-01	8	6
KS-02-02	8	6
KS-02-03	8	6
KS-02-04	8	6
KS-02-05	8	6
KS-02-06	8	6
KS-03-01	6	5
KS-03-02	6	5
KS-03-03	6	5
KS-03-04	6	5
KS-03-05	6	5
KS-03-06	6	5
KS-04-01	4	3
KS-04-02	4	3
KS-04-03	4	3
KS-04-04	4	3
KS-04-05	4	3
KS-05-01	6	5
KS-05-02	6	5
KS-05-03	6	5

Location	Distance (m)	Walking time (s)
KS-24-05	16	12
RA-01-01	8	6
RA-01-02	8	6
RA-01-03	8	6
RA-01-04	8	6
RA-01-05	8	6
RA-01-06	8	6
RA-02-01	6	5
RA-02-02	6	5
RA-02-03	6	5
RA-02-04	6	5
RA-02-05	6	5
RA-02-06	6	5
RA-03-02	4	3
RA-03-03	4	3
RA-03-04	4	3
RA-03-05	4	3
RA-03-06	4	3
RA-04-02	2	2
RA-04-04	2	2
RA-04-05	2	2
RA-04-06	2	2
RA-05-02	6	5
RA-05-03	6	5
RA-05-04	6	5
RA-05-05	6	5
RA-06-02	8	6

Continued on next page

(Continued)

KS-05-04	6	5	RA-06-03	8	6
KS-05-05	6	5	RA-06-04	8	6
KS-05-06	6	5	RA-06-05	8	6
KS-06-01	8	6	RA-06-06	8	6
KS-06-02	8	6	RA-07-01	10	8
KS-06-03	8	6	RA-07-02	10	8
KS-06-04	8	6	RA-07-03	10	8
KS-06-05	8	6	RA-07-04	10	8
KS-06-06	8	6	RA-07-05	10	8
KS-07-01	10	8	RA-07-06	10	8
KS-07-02	10	8	RA-08-01	120	92
KS-07-03	10	8	RA-08-02	120	92
KS-07-04	10	8	RA-08-03	120	92
KS-07-05	10	8	RA-08-04	120	92
KS-07-06	10	8	RA-08-05	120	92
KS-08-01	12	9	RA-08-06	120	92
KS-08-02	12	9	RA-09-02	122	93
KS-08-03	12	9	RA-09-03	122	93
KS-08-04	12	9	RA-09-04	122	93
KS-08-05	12	9	RA-09-05	122	93
KS-08-06	12	9	RA-09-06	122	93
KS-09-01	12	9	RA-10-01	124	95
KS-09-02	12	9	RA-10-02	124	95
KS-09-03	12	9	RA-10-03	124	95
KS-09-04	12	9	RA-10-04	124	95
KS-09-05	12	9	RA-10-05	124	95
KS-09-06	12	9	RA-10-06	124	95
KS-10-01	10	8	RA-11-01	124	95
KS-10-02	10	8	RA-11-02	124	95
KS-10-03	10	8	RA-11-03	124	95
KS-10-04	10	8	RA-11-04	124	95
KS-10-05	10	8	RA-11-05	124	95
KS-10-06	10	8	RA-11-06	124	95
KS-11-01	8	6	RA-12-01	122	93
KS-11-02	8	6	RA-12-02	122	93
KS-11-03	8	6	RA-12-03	122	93
KS-11-04	8	6	RA-12-04	122	93
KS-11-05	8	6	RA-12-05	122	93

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KS-11-06	8	6	RA-12-06	122	93
KS-12-01	6	5	RA-13-01	120	92
KS-13-05	8	6	RA-13-02	120	92
KS-14-01	10	8	RA-13-03	120	92
KS-14-02	10	8	RA-13-04	120	92
KS-14-03	10	8	RA-13-05	120	92
KS-14-04	10	8	RA-13-06	120	92
KS-14-05	10	8	RA-14-01	118	90
KS-14-06	10	8	RA-14-02	118	90
KS-15-01	12	9	RA-14-03	118	90
KS-15-02	12	9	RA-14-04	118	90
KS-15-03	12	9	RA-14-05	118	90
KS-15-04	12	9	RA-14-06	118	90
KS-15-05	12	9	RA-15-01	120	92
KS-15-06	12	9	RA-15-02	120	92
KS-16-02	14	11	RA-15-03	120	92
KS-16-03	14	11	RA-15-04	120	92
KS-16-04	14	11	RA-15-05	120	92
KS-16-05	14	11	RA-15-06	120	92
KS-16-06	14	11	RA-16-01	122	93
KS-17-01	14	11	RA-16-02	122	93
KS-17-02	14	11	RA-16-03	122	93
KS-17-03	14	11	RA-16-04	122	93
KS-17-04	14	11	RA-16-05	122	93
KS-17-05	14	11	RA-16-06	122	93
KS-18-01	12	9	RA-17-01	122	93
KS-18-03	12	9	RA-17-02	122	93
KS-18-04	12	9	RA-17-03	122	93
KS-18-05	12	9	RA-17-04	122	93
KS-19-01	10	8	RA-17-05	122	93
KS-19-02-A	10	8	RA-17-06	122	93
KS-19-03-A	10	8	RA-18-01	120	92
KS-20-02-A	8	6	RA-18-02	120	92
KS-20-02-B	8	6	RA-18-03	120	92
KS-20-02-C	8	6	RA-18-04	120	92
KS-20-03-A	8	6	RA-18-05	120	92
KS-20-03-B	8	6	RA-18-06	120	92
KS-20-03-C	8	6	RA-20-02	116	89

Continued on next page

(Continued)

KS-20-04	8	6	RA-20-03	116	89
KS-21-04	10	8	RA-20-04	116	89
KS-21-05	10	8	RA-20-06	116	89
KS-21-06	10	8	RA-21-02	118	90
KS-22-02	12	9	RA-21-03	118	90
KS-22-03	12	9	RA-21-04	118	90
KS-22-04	12	9	RA-21-05	118	90
KS-22-05	12	9	RA-21-06	118	90
KS-23-02	14	11	RA-22-02	120	92
KS-23-03	14	11	RA-22-03	120	92
KS-23-04	14	11	RA-22-04	120	92
KS-23-05	14	11	RA-22-05	120	92
KS-24-02	16	12	RA-22-06	120	92
KS-24-03	16	12			

H.2 Bin picking time

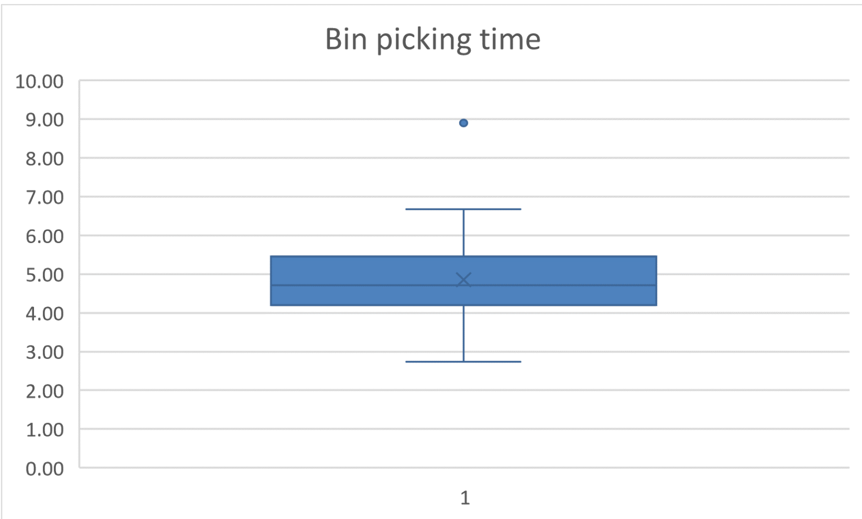

Figure H.1: Bin taking and placing back time.

H.3 Picking time per part

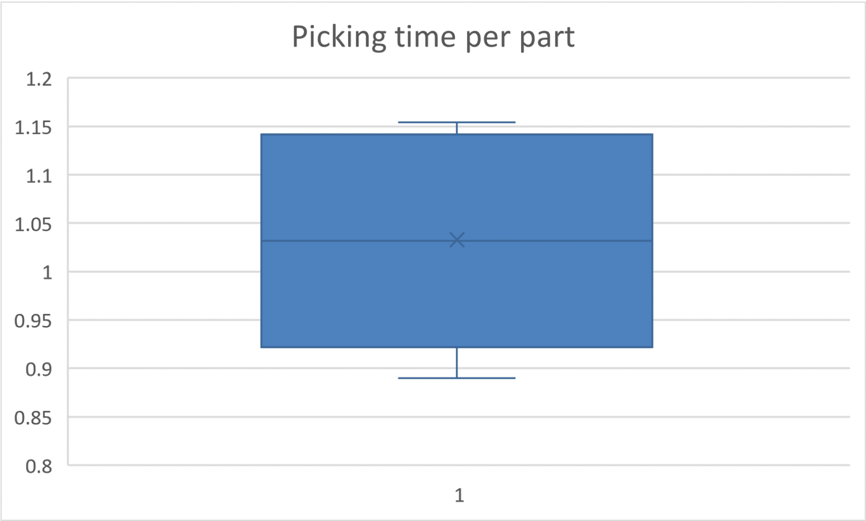

Figure H.2: Picking time per part.

H.4 Refilling time

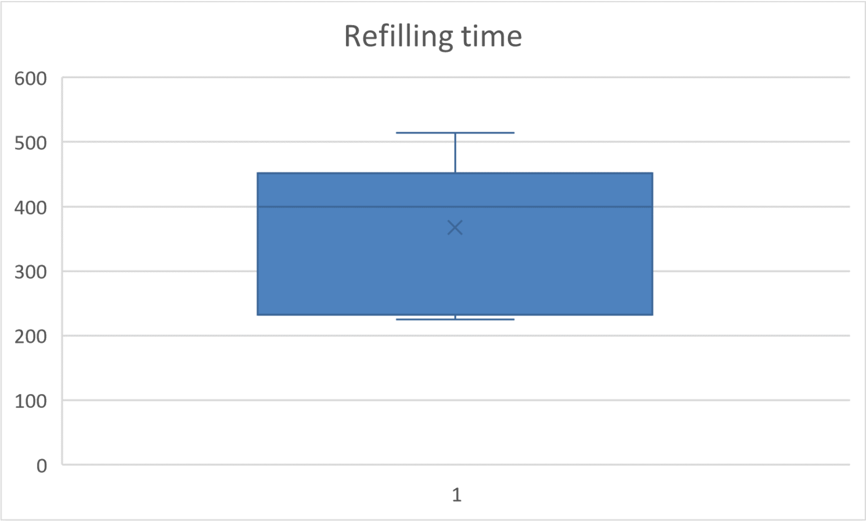

Figure H.3: Bin refilling time excluding travel time.

I NUMBER OF REPLICATIONS

n (=100)	AVG repl	Mean	Var	t-value	CIHW (**)	Error	Test		
1	8.855319	8.85531915							
2	8.578723	8.71702128	0.0382526	63.65674	12.45016	1.009931	FALSE	<---	2 replications
3	9.06383	8.83262411	0.05921835	9.924843	1.707799	0.157871	FALSE	<---	3 replications
4	8.782979	8.82021277	0.04009507	5.840909	0.675251	0.066301	FALSE	<---	4 replications
5	8.897872	8.83574468	0.0312775	4.604095	0.407127	0.041213	TRUE	<---	5 replications
6	8.782979	8.82695035	0.02548604	4.032143	0.287874	0.029772	TRUE		
7	8.876596	8.83404255	0.02159046	3.707428	0.222397	0.023307	TRUE		
8	8.8	8.82978723	0.01865097	3.499483	0.180637	0.019136	TRUE		

Figure I.1: Results of the 99% Confidence Interval Method on the stockout output data

Figure I.2: Results of the 99% Confidence Interval Method on the total production output data