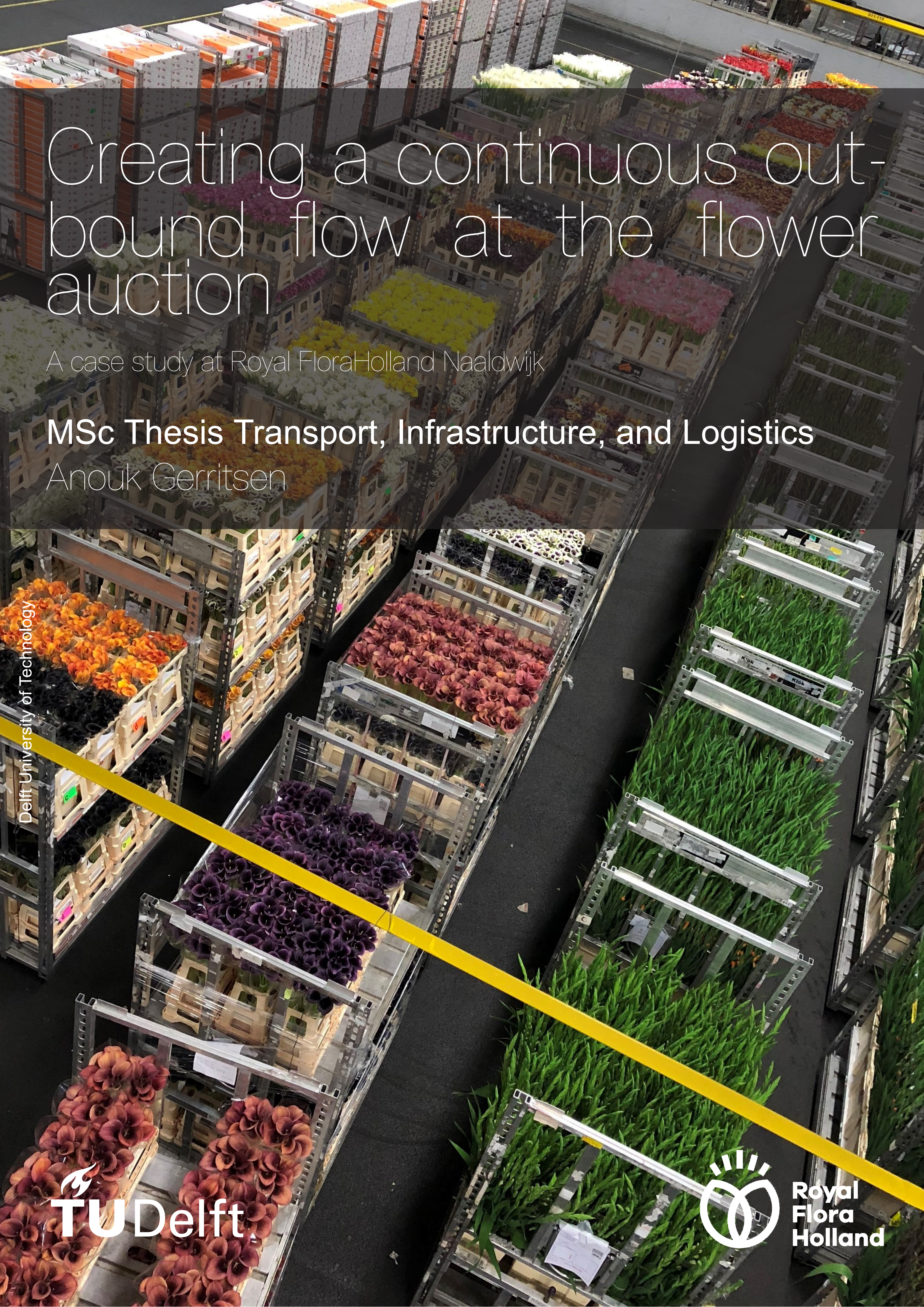
Creating a continuous outbound flow at the flower auction

A case study at Royal FloraHolland Naaldwijk

MSc Thesis Transport, Infrastructure, and Logistics

Anouk Gerritsen



Delft University of Technology

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Royal Flora Holland

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by

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Preface

This research takes you into the world of flower auctions. This report will explain how the world's largest flower auction runs daily. Several bottlenecks in the outbound flow are addressed, and a new design is created. This research has been conducted to complete my master's degree in Transport, Infrastructure and Logistics at the Delft University of Technology.

First, I would like to thank Royal FloraHolland and, specifically, the LS&BD department for the warm welcome and for allowing me to conduct this research. Under the supervision of Ingrid Abels and Oscar Binneveld, I got the chance to explore the company and also what working for such a company can be like. The company allowed me to investigate the problem in my way, and all other employees were very welcoming if I had any questions or to get to know each other.

In addition, I would like to express my gratitude to my graduation committee from TU Delft. My daily supervisors, Dr. Jaap Vleugel and Ir. Mark Duinkerken, have always been available for feedback and extra guidance when needed. Prof. dr. Rudy Negenborn, chair of the committee, has provided me with additional insights during the mandatory meetings.

Finally, I would like to acknowledge the support of my family and friends. Even though my family has no substantive knowledge of what I have been doing for the last 6.5 years in Delft, they have always encouraged me to keep going and make the best of my time as a student. My friends have provided many fun activities during my thesis to keep my mind fresh and helped me whenever I was stuck. A special thanks here to Jenne and Fabian for all their Python knowledge.

Anouk Gerritsen
Delft, March 2024

Executive Summary

A growing number of products at the Dutch flower auction and changing expectations from growers and buyers ensure that the flower auction needs to adjust its outbound process. The outbound process consists of preparing the goods that must be put through the outbound process, processing and delivering orders. With over 100,000 transactions per day company-wide, Royal FloraHolland (RFH), the largest flower auction in the Netherlands, is changing part of its process to an order-picking process to serve its customers better. While doing so, they ran into some trouble organising the overall outbound process and managing this. Much information is available in the literature regarding the different sub-processes and preparations. However, there is still a gap regarding consecutive sub-processes and how to align them well to execute the overall process more efficiently. These problems combined have resulted in research being conducted with a case study at RFH Naaldwijk to see how two consecutive processes can be aligned well to execute the overall process efficiently. The main research question is the following:

How can the order-picking and in-house delivery processes at a flower auction be aligned well to execute the overall auction process efficiently?

First, the aspects, requirements, and KPIs involved in both sub-processes have been investigated. The KPIs with which the performance of the current process and the proposed design will be measured are:

- Percentage of orders that are delivered on time
- Lead time of the overall process
- Total distribution cost

The second step of this research is to find out what the current processes look like, how they are executed, and what kind of management is involved. This has been done in two ways. First of all, a physical analysis has been done. This has been done by joining the process and talking with process experts. In addition, a data analysis has been done with available data at RFH. During the analysis phase, several issues have been found:

- The current output of the order-picking process is too low to deliver all carts before their latest delivery time.
- The in-house delivery process cannot handle the current output of the order-picking process.
- The main issues in the in-house delivery process are the spread in waiting time and the large average share of waiting time in the total lead time.
- Management is done manually, with managers walking around within the process and only adjusting the part where they are physically present based on what they see happening.

Several solutions to improve the current process have been introduced in a morphological chart. Based on a multi-criteria analysis, four alterations have been found which must be

implemented in the new design. One of those implementations is a limited waiting time. When creating a model (Python) that calculates outcomes such as required employees and train lengths, it was found that the limited waiting time would result in a large number of extra employees. Thus, extra ideas have been tested to see if the number of required employees could be reduced to make the proposed idea more feasible. The final result from testing with the calculation model is that the following alterations have to be done:

- **Limited waiting time on track** Limiting the waiting times ensures that the spread in waiting time decreases.
- **Capacity of each step in the overall process** The capacity of the process must be high enough to deliver all products on time.
- **Limiting number of tracks in work area** With limited waiting times, trains are shorter without altering the track division, and more employees are needed to move all those trains. Limiting the number of tracks should fill the tracks sooner, and the limited waiting time should no longer be responsible for short trains.
- **Direct delivery to the large buyers** Instead of moving trains for large buyers from the tracks after order picking to the dedicated buyer tracks, trains for large buyers are now directly delivered to the buyers. This way, the waiting time on a track for carts for large buyers can be increased.
- **Cluster of the delivery tracks** By forming clusters, again longer trains are created.

The proposed alterations will have to be implemented together with directed management, and the employees need a device on which the warehouse management system can communicate the next task.

The model created works in the following manner:

- **Input:** The model uses the output of the order-picking process from a day in the past, and different parameters have been set.
- **Step 1. New division tracks:** The current tracks are overwritten by the track according to the new division.
- **Step 2. Capacity:** The required order-picking output uses the same output sequence as the current situation. Per 15 minutes, the required number of lines is taken for that time interval and evenly distributed over that time interval. Then, the output time of the order-picking process is changed to the new time according to the distribution over the time intervals.
- **Step 3. Preparing for tugging:** With the new track division and order-picking output, waiting on the track for a train is limited by either a maximum waiting time of 15 minutes for the first cart of that train or by reaching the maximum train length. As soon as one of these constraints is met, the train is taken away by a tugger.
- **Step 4. Direct delivery to dedicated buyers:** Direct delivery takes place by assigning a deliverer to the dedicated buyer track in the track area. Instead of waiting 15 minutes, the maximum waiting time is set to 30 minutes.
- **Step 5. Creating clusters:** In the sorting area, clusters are created by grouping the tracks in one cluster.
- **Step 6. Delivering from the sorting area:** Each cluster is checked if the first cart entered is not waiting longer than 15 minutes and if the tracks combined do not exceed the train length of 14 carts. When one of these limits is reached, a deliverer takes the cluster away to the buyers.

- **Output:** The model calculates the required number of employees per half an hour, the lead time, and the number of carts delivered too late.

When running the model, it has been found that the total lead time for the in-house delivery process remains under 60 minutes for all carts. At the same time, it was already found that the order-picking process is reliable and predictable. This combination ensures a reliable and predictable overall process. In addition, the percentage of carts delivered on time increases significantly.

The required number of work hours is calculated to measure the total distribution cost. It was found that a significant extra number of work hours are required with the first set of parameters. However, some parameters have been set conservatively. The delivery time has been set to the 75th percentile of all current deliveries. When changing this to the 50th percentile, fewer work hours are needed. Another aspect is that the productivity in the sorting area could be increased, resulting in fewer employees. The actual outcome is between the current and a hundred extra work hours. This outcome is calculated with a higher order-picking output than currently. This means that the changes to the process should be feasible with the current output and the current number of employees.

The proposed alterations have been proven with the model to be sufficient to improve the efficiency of the overall process. Some elements of the alterations can be used by other industries as well, such as the limited waiting time. However, it is recommended that further research is done into other options, such as a more detailed investigation into driving times or mechanisation for perishable and vulnerable goods.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
CSA	current state analysis
dbt	dedicated buyer tracks
FIFO	first in, first out
KPI	key performance indicator
MCA	multi-criteria analysis
RFH	Royal FloraHolland
SWOT	strengths, weaknesses, opportunities, threats
WMS	warehouse management system

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1 Introduction

Before diving into the details, the research topic will be introduced together with the approach. The first section will give general background information on the topic and introduce the problem. Then, the scope of the research and the description of the problem is given. Following are the objective and the research questions. The chapter will end with the outline of the rest of this report.

1.1. Research context

Royal FloraHolland (RFH) is a flower auction that has customers and growers from all over the world as members. The company accommodates over 100,000 transactions per day (Lucas, 2023). Growers provide the auction with all types of flowers and plants. Buyers, in their turn, can buy these products directly from the grower or via the auction. RFH is the connecting factor between the growers and buyers and must ensure that the process from grower to buyer runs smoothly.

The Dutch flower auction has been growing for years in revenue and number of products (Het Parool, 2011, 2015; Vermeer, 2022). A growing number of products to handle daily means the logistics become more complicated. This, in combination with the expectations of buyers to receive their products quickly after they purchased them (Aagerup et al., 2022), makes it extra challenging for the company to keep control of all their processes. The decision has been made to change from a distribution process to an order-picking process so buyers are better served in their needs (Royal FloraHolland, 2023). With the shift to an order-picking process, delivery can be done within a certain timeframe so buyers can better know when to expect their purchased products. This way, they can better coordinate their own processes. However, transitioning from a distribution process to an order-picking process is not easy and many day-to-day problems still need to be solved.

The overall process in such a company consists of multiple parts. One important part is order picking. This is where customers have placed orders, and the products for each order need to be gathered. According to the literature, order picking is responsible for about 55% of the warehouse operating costs (Bartholdi & Hackman, 2019). This is based on warehouses of distributors such as Amazon. Approximately 55% of the order-picking time is spent travelling by the person (Frazelle, 2016). Since there is a high number of orders per day at RFH and, therefore, a lot of them simultaneously, the order picking and delivery must be done efficiently. One of the easiest ways to improve the process is by reducing travel time while collecting an order (Lu et al., 2016). There are different types of order-picking methods which can be applied to a warehouse (Petersen & Aase, 2004). A Warehouse Management System (WMS) can support the order-picking process by producing pick lines and pick lists (Bartholdi & Hackman, 2019).

At auctions, the logistical part is more complicated than in an average warehouse. The demand changes dynamically, as does the supply (Qin et al., 2014). This means that there is a completely new situation every day. In addition, items are still being auctioned while the order-picking process has already begun. In a 'normal' warehouse (e.g. Amazon), a customer finishes the order, and then the order picker starts. At the flower auction, order pickers gather products for a buyer while that buyer can still add products to their order. Therefore, it could be that an order picker has an assignment for which they do not use the full capacity of the cart on which they transport flowers and that later, another cart has to be partially filled for that same buyer. Another aspect that makes order picking more difficult at an auction is storing products at different temperatures. As a result, there are different work areas at RFH Naaldwijk in which carts are order-picked.

After the order-picking process, the gathered goods have to be delivered to customer areas on the property of RFH. This means that all the gathered goods placed on carts have to be sorted per customer and then delivered to the right location. Because the picked goods come from different work areas, there is a central sorting area from where the carts are delivered.

The unpredictability in supply and demand and the abnormal layout of this warehouse make the process at an auction very different than in the average warehouse. One of the few studies that has been done about this subject is by X. T. Kong et al. (2023). This research proposes order postponement based on a model's estimations to ensure that carts are fuller before starting to order pick them. However, this is a first setup with very rough model assumptions and does not consider that orders must be delivered before the latest delivery time, which can differ per customer. Apart from this, there is some general research about distribution management about which KPIs (Key Performance Indicators) to focus on (Pajić et al., 2021) and issues to be aware of (Binos et al., 2021). Nevertheless, there is nothing specific about auctions on this topic and other topics (Chapter 3). Thus, there is a gap in the literature regarding the post-auction process. The main issue is that very limited research is done on aligning two consecutive sub-processes at an auction.

Trying to fill this gap will be done with a combination of literature research and a case study at RFH in Naaldwijk. One location has been selected since other locations use different approaches. First, it is necessary to understand in detail what the current processes look like at RFH. At the same time, knowing what types of systems and data are already available and what could be possible is important. After gathering the data and understanding the possibilities, several possible improvements will be evaluated. Ultimately, advice will be given about how they can change their processes to align them better and keep them as efficient as possible. The focus will be on the day-to-day execution of the process.

1.2. Problem statement and scope

A general overview of the complete auction process is shown in Figure 1.1. The process starts with the supply from growers. Products are delivered on every auction day via road, air, or rail. When products arrive, they must be unloaded, checked, and split to be moved to the correct storage location. After storage, orders are gathered. Next, the in-house delivery of the orders starts. Buyers have an area somewhere on the premises of RFH where their bought products need to be delivered. From here, buyers can take the products to another location or process the flowers there. This research will focus on the order picking and in-house delivery of products, particularly the alignment between the two processes. The scope is indicated in the figure by the orange rectangle. The scope will be from the moment all the products are in position for the start of the auction until they have been delivered to an area. The main focus will be on the day-to-day execution of the overall process.

It has to be mentioned that flowers and plants are sold during the auction. Since RFH has only implemented the order-picking process for flowers and not for plants yet at the location Naaldwijk, this research will only focus on the distribution of flowers. Therefore, when terms such as 'the overall process' are used, it implicates the processes of order picking and in-house delivery of flowers.

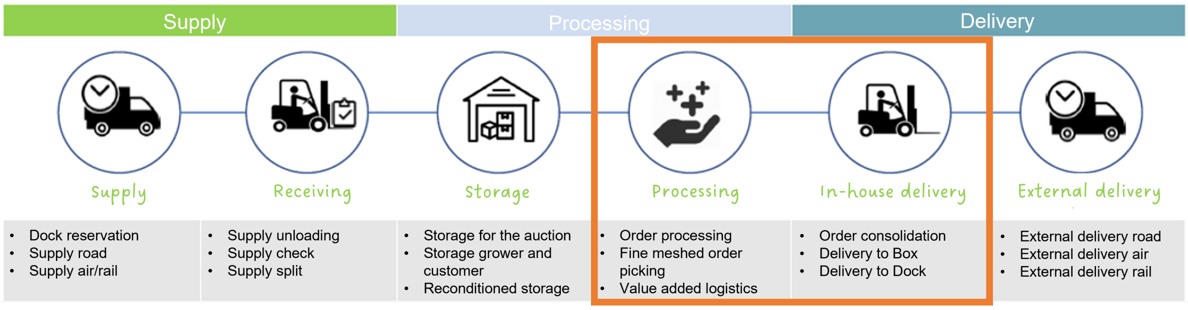


Figure 1.1: Complete auction process and indicated scope (LS&BD Royal FloraHolland, 2021)

1.3. Objective and research questions

Based on the defined scope, the objective for this project is set. The objective is to find a way to better align two consecutive processes at a flower auction while executing the overall auction process efficiently. The two processes that will be used to investigate this problem are the order-picking process and the in-house delivery process. A main research question and several sub-research questions have been formulated to guide the research. The main research question covers the project's objective, while the sub-research questions combined should answer the main research question.

Research question

How can the order-picking and in-house delivery processes at a flower auction be aligned well to execute the overall auction process efficiently?

Sub-research questions

1. What are the aspects, requirements, and KPIs involved in well-aligned order-picking and in-house delivery processes?
2. What is the step-for-step execution of the current processes at RFH, how are they connected, and what are their main strengths and bottlenecks?
3. What are different alternatives to better align the order-picking and in-house delivery processes?
4. How will the proposed improvement(s) perform compared to the current situation at RFH?

1.4. Outline

This report will start with the methodology of how to approach the problem. The methods used during the project will be named and explained in this chapter. Some literature is used here to support specific decisions made. In addition, a section will be written about data requirements. Next is an elaborated literature study in Chapter 3. This literature study will discuss several topics: warehouse design, order picking, distribution management, and auction order fulfilment. In Chapter 4, the current state of the order-picking and in-house delivery processes will be described in detail. The focus will be, amongst others, on all steps taken during the processes, the people involved, and the information shared. The chapter will finish with an overview of aspects going well and bottlenecks found. After the current state analysis (CSA), a chapter will be devoted to new design ideas. This chapter will include the requirements, functions, a conceptual design, the evaluation of this design, and the final design. Then, in Chapter 6, advice about implementing the new design will be given. Next, a conclusion will be given concerning the original research question. Finally, some recommendations will be given regarding future research.

2
Research methodology

This chapter will first discuss the methods used to answer each sub-research question and explain the proposed methods. In addition, a section about the data requirements containing the data analysis approach is provided.

2.1. Methodology

Being able to improve such a process means understanding the possibilities, requirements and key performance indicators (KPIs) involved. This must be done for both the order-picking and in-house delivery process and again for the alignment of the two. This information will be retrieved via literature study and discussions with process experts.

After a literature study, it is essential to understand precisely what happens at RFH during the execution of the processes. The second research question will be answered by physically joining the process and interviewing employees who have worked in or with the process for longer. There is also some information available via documents. However, the documents could be outdated or incomplete. Processes often work differently in practice than in theory. Thus, the decision has been made not to rely on process documentation entirely. After gathering all the information, it is necessary to present it in a structured manner. This will be done with visualisations (e.g. flow chart, value stream map). In addition to visualising the actions taken during the process, a statistical analysis is added to discover more about the flow of products and other matters. More about data analysis can be found in Section 2.2. A summary of the current process will be given in the form of a SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis.

Based on all the information gathered, conceptual improvements can be made to the process. Ideas can be presented in a morphological chart. A multi-criteria analysis (MCA) can be done to create different solutions. It has to be kept in mind that the weight of criteria used in an MCA is objective and can differ per person or department. Thus, enough input is required to find a reliable solution.

Finally, the new design has to be evaluated to see if it is an advancement compared to the current situation. This will be done in three ways. First, the process experts will be approached to ask how feasible the proposed design is and if they think it is an improvement. Second, a new analysis will be done (e.g. flow chart, value stream map) to compare the new and current situations. Finally, calculations will be done with the future scenarios to see the effect of the changes based on set KPIs. Table 2.1 shows an overview of the methods per sub-research question.

Table 2.1: Method per sub-research question

Sub-research question	Method	Chapter
1	Literature study and process experts	3
2	Joining process, interviewing employees and existing documentation, analysis (e.g. flow chart, value stream map), statistical data analysis and SWOT analysis	4
3	Morphological chart and multi-criteria analysis (or similar)	5
4	Discussions with people who have experience with the current processes, calculations of possible future states about what the expected performance will be, and analysis comparison between new and current situations (e.g. flow chart, value stream map)	5.7.4

Answering sub-research question 2 can be done with the help of different methods. First, a stakeholder analysis of company members connected to the process can be done. A stakeholder map gives an overview of network relations (Stickdorn & Schneider, 2012) and shows their influence on the process (Walker et al., 2008). In addition, an IDEF-0 diagram can be created to map the process (Figure 2.1). Such a diagram gives a structured overview of the process steps with its required input, output, constraints and mechanisms (Presley & Liles, 1995). An IDEF-0 diagram is a good technique for finding the information transfer between two steps. To go into more detail, a Swimlane analysis could be done to see which process step is executed by whom. Ezeonwumelu et al. (2015) used such an analysis to identify bottlenecks in the process and improve the process. Together with all these methods, a SWOT analysis can be used to conclude the current state analysis. According to Benzaghta et al. (2021), a SWOT analysis is ”an effective strategic tool that can be used efficiently and resourcefully to assess the strengths, weaknesses, opportunities, and threats of businesses”.

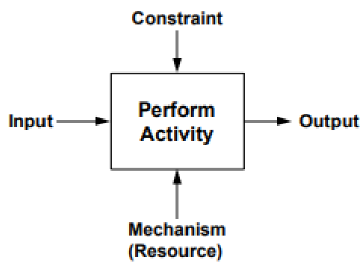


Figure 2.1: Representation of IDEF-0 diagram (Presley & Liles, 1995)

Dym et al. (2014) proposed a design process model. A visual is presented in Figure 2.2. The rectangular boxes are the stages, and the ovals represent the input/output of those stages. Feedback will come within the process during the stages from, for example, the client. External feedback is also possible after the design is put into practice. It has been indicated in the figure for which step, which sub-research question will be answered. The original five stages are presented in the list below (Dym et al., 2014). A sixth state, Preparations, has been added for this research.

- **Problem definition:** The problem is framed by requirements, objectives, constraints, and functions.
- **Conceptual design:** Different concepts are created with all objectives, constraints and functions in mind. The concepts are evaluated based on certain objectives.
- **Preliminary design:** The evaluated concepts are combined into a preliminary design, and more details are added.
- **Detailed design:** The preliminary design is developed in greater detail, and choices made in the previous step are refined.
- **Design communication:** The design process and final design are presented in a document.

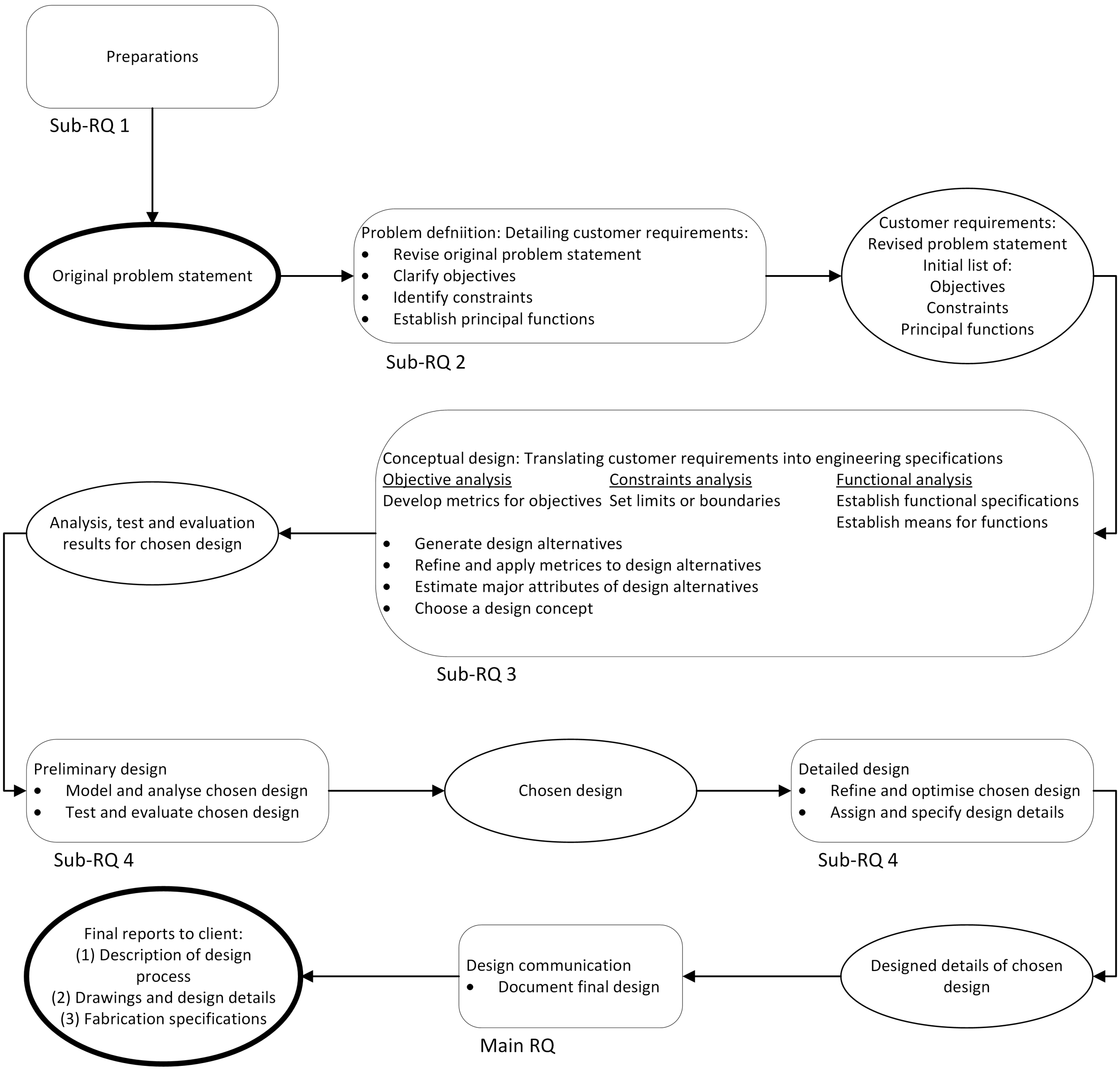


Figure 2.2: Five-stage design process (Dym et al., 2014)

To create conceptual designs, a morphological chart can be created with the functions set in the first stage. A morphological chart is a matrix where the functions or other key features are in the leftmost column (Dym et al., 2014). It is important that all of them are on the same level of detail. Across from the first column, the possible means to realise that function or feature are placed. When all ideas are put into the matrix, feasible and non-feasible designs can be highlighted to show the possibilities based on the requirements. As a result, conceptual designs are created. To move from multiple designs to one final, a decision has to be made on which conceptual design is the best. Yoon and Hwang (1995) proposed different versions of MCA to make the best decision. The ’simple additive weighting method’ is suggested as the easiest method for an MCA. This method may only be used if the preference independence or separability assumption is met (Yoon & Hwang, 1995). For now, the assumption will be made that this is the case, if not, further research on the other methods proposed by Yoon and Hwang (1995) has to be done. An overview of the proposed methodology for the whole duration of the project is given in Figure 2.3. In the upper corners, the (sub-)research question indicates to which step taken it will contribute.

2.2. Data requirements

RFH has a substantial amount of data available. The data range from the type and number of flowers that enter the auction every day to the performance of its employees. For this research, two data types are particularly important and are linked to each other. The two types are shown below but are not the only data that will be used:

1. Location of product
2. Time

To understand the flow of products and how everything moves through the system, it is necessary to know where each product is at what time. Data showing the number of vehicles available at each moment could also be useful later. RFH has all this data and more stored in Power BI.

Power BI is a Microsoft software for data visualisation. The program can import data sets to create different graphs and overviews (Microsoft, 2023). Excel or Python could also be used if an extra analysis is preferred. RFH can use these programs as well. It might be beneficial to use one program for all analyses so that all information is in one place. Any final outcomes that consist of data are preferably in Power BI so that RFH can use the outcome immediately and does not have to transfer it from another software type.

According to Sprent (2003), false conclusions may be drawn when using improper statistical methods. Ali and Bhaskar (2016) stated that a researcher must know basic statistical methods’ concepts. Therefore, they explained numerous basic principles, such as the difference between descriptive and inferential statistics, mean, variance, standard deviation, normal distribution, and (testing) hypothesis. Some methods described can be used for data analysis during this research.

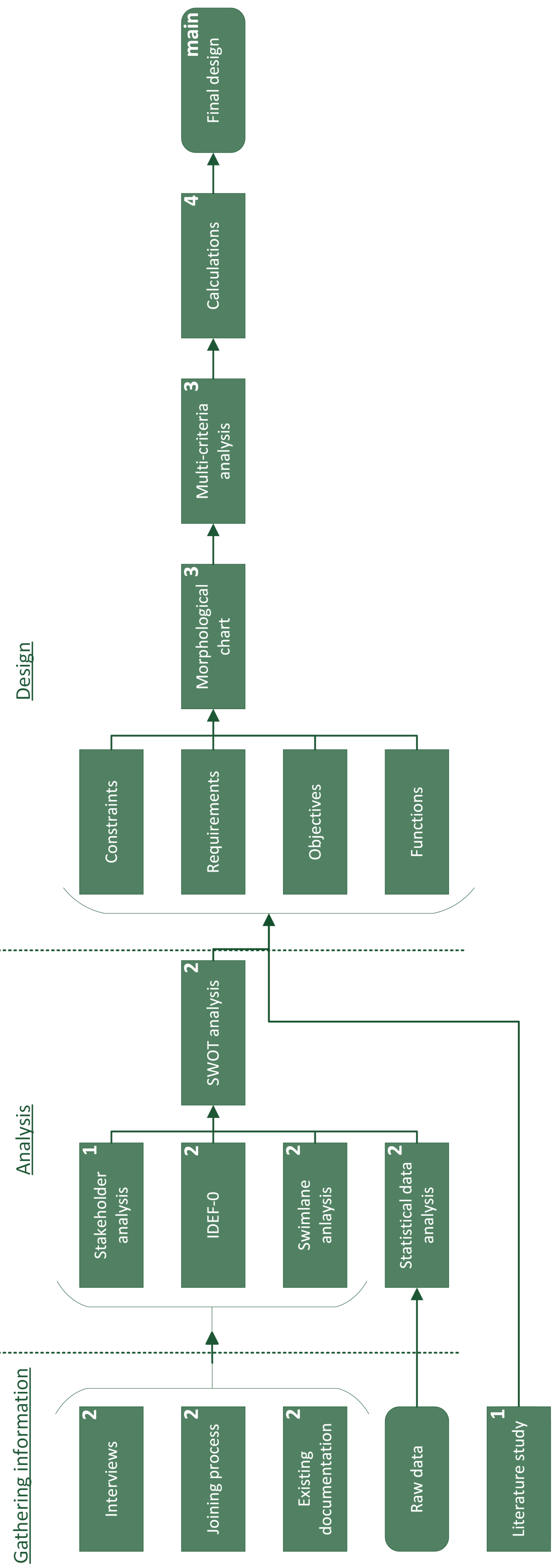


Figure 2.3: Proposed research methodology

3
Literature study

Literature research has been done to understand the project topic better and to find out what is already done and known. Multiple topics could be useful for this project. The topics that have been searched for are: ”warehouse design”, ”order-picking”, ”distribution management”, and ”auction order fulfilment”. The search engines that have been used are Scopus and Google Scholar. All papers were found by using the topics mentioned as search topics and searching references used in the papers that came up during the search. It has been tried to find papers about order-picking of perishable goods and in-house delivery specifically. However, no relevant papers about those topics were found. This chapter will provide an answer to the first sub-research question.

3.1. Warehouse design

Designing a warehouse is a very complex task where different stages are executed for a final design. Commonly, the different stages are functional description, technical specification, equipment selection and determination of the layout (Rouwenhorst et al., 2000). Different criteria, such as costs, throughput, storage capacity, and response time, have to be met at every stage. Often, there is a large number of feasible designs. Finding the best one for a particular application can be complicated (Brito & Basto, 2006; Rouwenhorst et al., 2000).

Rouwenhorst et al. (2000) have done literature research about what type of information is available on warehouse design. The intention is to provide a warehouse design framework and to review the existing literature. The paper focuses on the internal warehouse structure and internal operations. It is stressed that implementation is excluded from the research. Unfortunately, implementation is key to how your design will work in practice (Mitra, 2023). However, the paper does give clear descriptions and fine characterisations to use as an anchor during a design process. First, they introduced three different angles: processes (steps), resources (means), and organisation (planning and control procedures). Making decisions about a subject can be difficult since a different outcome is possible from a different angle. It is helpful that they showed it so you know making decisions could be more difficult than anticipated. In addition, the paper also describes the processes for the flow of items through a warehouse (Rouwenhorst et al., 2000):

1. **Receiving:** Products arrive by a certain type of transport (depending on the warehouse). Products are checked, and they have to wait for transportation to the next step.
2. **Storing:** Items are placed in a storage location. The paper makes a distinction between two types. First is the reserve area, where products are stored very close to each other (economical way). Second is the forward area from where the orders are picked. Thus, in this area, the products must be accessed easily.

3. **Order picking:** Items are retrieved from storage. This can be done manually or automated.
4. **Shipping:** Orders are first checked, packed and then loaded into trucks or another type of transport.

How the three different angles are connected to the process steps just described is shown in Figure 3.1. This figure is about long-term decisions. The paper also proposed figures for medium-term decisions and short-term decisions.

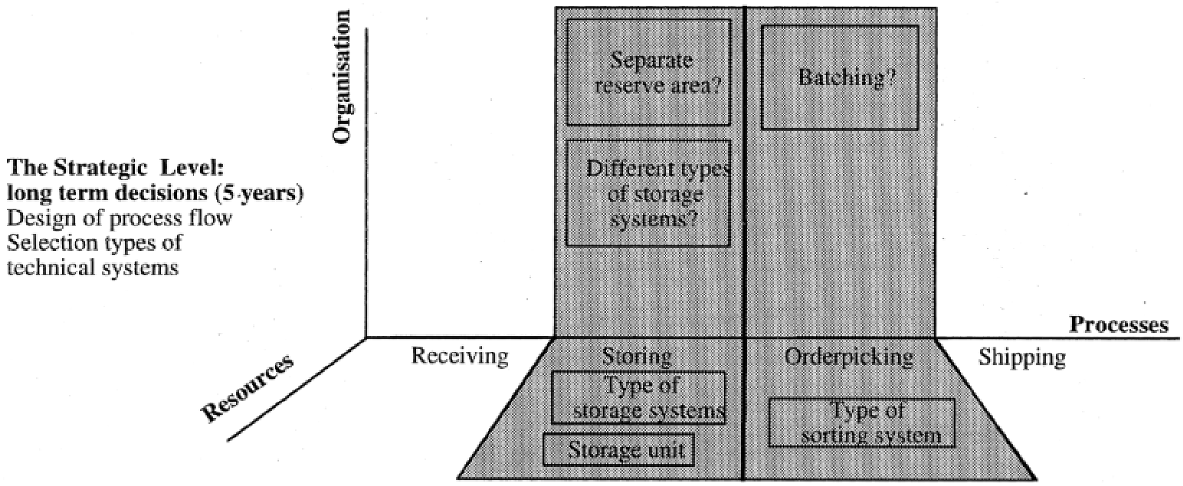


Figure 3.1: Decisions warehouse design (Rouwenhorst et al., 2000)

The paper further introduces some criteria for a design, such as investment and operational costs, throughput, response time, and order fulfilment quality (Rouwenhorst et al., 2000). Regrettably, the paper often mentions that more research has to be done about certain topics, but there are no recommendations about how to approach the problem. This leaves the conclusion with information that was already available in pre-existing papers.

Baker and Canessa (2009) did something similar to Rouwenhorst et al. (2000). In addition to the literature review, the writers contacted several companies in the UK to verify their proposed framework for warehouse design. This gave the writers extra insight into how warehouses are designed in practice. The paper proposes an eleven-step framework for warehouse design. The steps are (Baker & Canessa, 2009):

1. Define system requirements
2. Define and obtain data
3. Analyse data
4. Establish unit loads to be used
5. Determine operating procedures and methods
6. Consider possible equipment types and characteristics
7. Calculate equipment capacities and quantities
8. Define services and ancillary operations
9. Prepare possible layouts
10. Evaluate and assess
11. Identify the preferred design

For each step, some tools are proposed. However, those tools are not further analysed or assessed. Even though Baker and Canessa (2009) were able to verify their framework with companies, there is still no optimisation solution for warehouse design.

McGinnis et al. (2014) have a different approach for their paper than the previous two. They show the added value of software tools supporting warehouse design. Different possibilities and tools are discussed. Using the proposed tools during a case study and evaluating it would have added value to the paper. Currently, the paper is a sort of manual to use the tools. However, their literature part agrees with the other papers that there is no standard protocol for warehouse design. Essential steps were indicated by this paper, which corresponds with the steps as proposed by Baker and Canessa (2009).

Much research has been done about the layout design of a warehouse. Some layouts proposed are Fishbone, Flying-V or Diamond and numerous variations (Mesa & Akhilesh, 2016). Bortolini et al. (2020) extended the existing research by proposing a model and doing a case study about layout with parallel vertical racks combined with straight diagonal cross-aisles. These aisles depart from the central pickup and delivery point. The research proposed an optimal angle for the cross-aisles depending on the type of operations. The case study showed that a lot of travelled distance can be reduced. However, the study was done in a 2-dimensional world, so the vertical distances were not included.

Brito and Basto (2006) discussed the possibilities of warehouse simulation to optimise operations. There are numerous options for simulation, but there are some drawbacks. Simulation takes a lot of time, and the right person for the job has to be available when needed. This can cause serious delays in the design, which costs money. In addition, every aspect has to be communicated to the simulation professional without mistakes. Misunderstandings can otherwise result in wrong outcomes. On the other hand, Mourtzis et al. (2019) proposed a model that minimises inventory costs. Using data from the past as input, they designed and simulated a warehouse. This has been done until an optimal solution was found. They had to deal with different sizes of products, FIFO (First-In-First-Out) storage, and minimising the surface. However, fluctuating demands are not considered.

It was stated by Lepori et al. (2013) that visualisation of the physical flows in a warehouse could support understanding how the network of logistical activities is structured. In addition to this, it is stressed that the chosen timeframe is important. A horizon that is too long can result in a complicated overview with a large number of arrows. In such a visualisation, it is important that there is a separation of physical and information flows. For warehousing, an analysis of product flows can also help to identify unnecessary moves or storage time. They state, however, that people's movements are more important to focus on because they cost more money than a longer storage time.

A case study that used steps similar to the ones proposed by Baker and Canessa (2009) has been described in the paper of Sapry et al. (2020). The case study was done in the warehouse of a manufacturer of AC electric motors and variable-speed drivers. These are non-perishable goods but still need to be handled with care. The benefit of a case study is that it can be concluded if the course of action was successful or not. This is also one of the first papers that mentions the importance of the connection between certain processes. Unfortunately, apart from mentioning it, not much was said about how to improve the connection.

The case study of Mahroof (2019) took everything a step further by investigating the possibility of implementing AI (Artificial Intelligence) in a warehouse. He found that multiple matters are important. First of all, there is the technology in a warehouse that needs to be ready. There has to be some infrastructure, such as forecasting. Another thing that he found was that often, the IT department argues that everything is ready for AI to be implemented, while the operational staff says they are not. In addition, the IT department can be sure that it is possible, but the senior management must also be on board. Mahroof (2019) also argued that current studies lack ”relevance and application in real organisational settings”. By pointing out numerous subjects to focus on, the researcher tried to reduce this gap. This research has only done a case study at one warehouse, so it cannot be said that this approach will always work.

3.2. Order picking

As briefly mentioned in Chapter 1, order-picking is responsible for about 55% of the warehouse operating costs (Bartholdi & Hackman, 2019). Besides, designing an order-picking system is very complex. It depends on multiple elements such as the products, customer orders, types of functional areas, combination of equipment types, and operating policies for each functional area (Dallari et al., 2009). Dallari et al. (2009) proposed five main groups of order-picking systems:

1. **Picker-to-parts:** Pickers walk or drive to the parts to complete one order or a batch of orders.
2. **Pick-to-box:** The picking area is divided into zones. In each zone, there are one or multiple pickers to retrieve the product(s) from that zone and place it on a conveyor that is connected with all other zones.
3. **Pick-and-sort:** Pickers take one type of product for multiple orders and put it on a conveyor to a sorting area. The products are then sorted to the right destination.
4. **Parts-to-picker:** Unit loads are brought to picking stations where employees take the product(s) for their order of the unit.
5. **Completely automated picking:** Everything is done by machines.

Based on an in-depth survey sent to 68 warehouses, the paper also proposed a new design methodology consisting of four stages: input stage, selection stage, evaluation stage, and detail stage. In the input stage, the kind of input the system needs must be decided. For the selection stage, the most suitable system is chosen for each subsystem, the needed equipment is specified, and the areas are designed. All these decisions are then evaluated during the next stage. The final stage is to give more detail to the characteristics of each subsystem (Dallari et al., 2009). The key parameters in such a design are the number of order lines picked per day, the number of items and the average order size. It must be mentioned that this research was done in one industry and is not validated if it would work in other industries as well.

According to Chan and Chan (2011), there are four decision problems in an order-picking design: layout design, picking policies, storage assignment policies, and routing policies. They also state that the efficiency of the chosen policies for each problem is interdependent. Regarding order-picking, Chan and Chan (2011) concluded that 50% of the order-picker’s time is spent travelling. The paper aimed to improve the performance of an order-picking system by experimenting with different combinations of storage assignment policies, routing policies, and pick densities. Some of their findings were that the best storage assignment policy depends on the type of storage; the best system depends much on what has been set as the most important performance indicator; combined routing worked best in their case. However, this research did not consider some factors, such as congestion. Also, the way orders are placed was not considered.

The focus of Lu et al. (2016) was creating a routing algorithm for an order-picking problem where new orders can arrive randomly. The algorithm used most of the time is the Steiner Travelling Salesman Problem. The paper mentions that there are some settings to take into account. One of them is that a trade-off has to be made when it is beneficial to add an extra pick to the list or when it is better to do it with a new picklist because of extra travel distance.

Klodawski et al. (2018), on the other hand, focused on congestion during order-picking. According to Klodawski et al. (2018) is congestion in manual order picking ”related to the situation when tasks of the order picker are interrupted by another picker while all requirements for a regular picking process are met”. The research again pointed out the importance of storage assignment and that storage assignment influences congestion. One assumption is that people cannot pass each other in an aisle. However, numerous warehouses have aisles where passing each other is possible. The research results are that, first of all, the process efficiency increases with a growing number of pickers. At the same time, the increasing number of pickers causes lower growth in efficiency and an increase in congestion.

Congestion was included in the study of Kovac and Djurdjevic (2020). A simulation study was done with data from a real warehouse to see which order-picking method was the most efficient. The best combination of decisions is using order-oriented slotting storage assignment with optimal routing policy and the sort-while-pick method. The sort-while-pick method means that employees pick multiple orders but sort them immediately in boxes. Order-oriented slotting storage assignment might be difficult at an auction since orders differ daily. The most important conclusion of the research was that separate problem-solving can only lead to suboptimal solutions (Kovac & Djurdjevic, 2020).

One of the first papers to prove relations among storage location assignment, order batching, zone picking and picking routing in manual order-picking warehouses is the one written by van Gils et al. (2018). They first did a simulation study with real-life data to determine which problems in the planning are related and should be considered. Then, they researched how the problems are related to finally improving the order-picking performance. The warehouse used for the study has three types of stock-keeping units: fast-moving, moderate-ordered, and slow-moving. The outcome showed that combining the different decisions is of great importance.

3.3. Distribution management

The distribution process is one of the basic processes in logistics (Pajić et al., 2021). The process starts with the customer’s order and ends with the delivery. A company can use KPIs as a measurement tool to monitor its performance and achieve cost savings and efficiency. Pajić et al. (2021) used two methods to find the five most important KPIs in the distribution process. The five most important KPIs that followed from the study are (Pajić et al., 2021):

1. Total distribution cost (cost to deliver the product from origin to end user)
2. On-time shipping ratio (# order lines shipped on-time / total # order lines)
3. Flexibility of distribution (ability to change distribution processes efficiently to adjust to requirements of customers (Yu et al., 2012))
4. Timeliness of goods delivery (# of units delivered within the set time period defined by the customer)
5. Profitability by item (amount of profit that a certain product makes within a set time period)

The same study also found that distribution planning is even more important than transport, inventory, and demand planning.

Hompel and Schmidt (2007) agreed with the KPIs described and emphasised the importance of continuously tracking the material flow. They proposed implementing identification points within the process. This way, these measurement points give you information about the flow of ordered goods. Not only gathering information is of great importance, but also providing information to the employees working within the process is necessary during their shift (Hompel & Schmidt, 2007). Everything discussed so far in this chapter is about long-term and mid-term planning. Hompel and Schmidt (2007) also pointed out the importance of operative planning (just before and during the process). They mentioned the importance of resource assignment, which employee or machine needs to be used, where at what time, scheduling, and pre-planning.

According to Rascão (2021), information is indeed important, but the structure of an information system is very complex. An information system cannot be designed as a separate system but has to be connected to many other systems within a company. Reliable and accurate information is needed so that operational managers can use this information to solve day-to-day problems (Rascão, 2021).

Binos et al. (2021) explained that different issues can occur in a dynamic environment that can impact the performance as a whole if not corrected on time. Some examples given are (Binos et al., 2021):

- Congestion
- Picking from an incorrect location
- Incorrect stock location
- Over-picking
- Under-picking
- ...

When such an issue appears, it influences the product flow. Then, prevention or detection and correction are needed in real-time. This is often still done by humans (Binos et al., 2021). The paper first analysed which agents are involved and what their responsibility is. Thereafter, a communication protocol was designed. Based on this, a system with autonomous adaptive agents was built. Simulations showed that occurring bottlenecks can be solved by such agents. However, in warehouses that have specific requirements, it might be difficult to implement the automated agents fully (Binos et al., 2021). This means people are still needed, but such a system can support them.

3.4. Auction order fulfilment

X. T. Kong et al. (2015) discusses the importance of a cloud-enabled platform in auction logistic centres. Since logistics are so extensive nowadays, keeping track of everything on paper is impossible. The paper also stresses that an auction is very complex and dynamic. This makes adaptive planning necessary, which such a platform can assist. Auction logistic centres rely heavily on planners to minimise costs and lead times (X. T. Kong et al., 2015). The planners forecast average and peak sales, which mechanisms should be used for the auction, capacity planning for both machines and workforce and logistics of auction trolleys. The paper also describes some management issues and keeps the research general. A case study has been done at a flower auction in China. The outcome of the case study mainly describes the auction process and provides some insights into how to use the technology. However, since the paper is a few years old, the technology discussed is no longer relevant, only its principle.

X. Kong et al. (2017) took it a step further and discussed the possibilities of a robot-enabled execution system for perishables auction. They proposed a system where robots were responsible for picking up the goods. The cars could follow a line and via that line, they could visit every location in the warehouse. The robot then took the product and drove it to the drop-off zone. The situation was tested and the test was a success. However, the paper also states that robot-enabled warehouse automation is uncommon when handling perishable goods. Additionally, an auction is very complicated and time-sensitive.

X. T. Kong et al. (2022) continued to build upon the previous works and introduced demand forecasting to increase revenue at an auction. The experiment was based on real-life data from a flower trading centre. The proposed method is limited to one type of auction, meaning it must be expanded before being used in every auction. There are other problems as well. Nonetheless, the evaluation with real-life data showed that the proposed method is effective.

Another method that has been proposed by X. T. Kong et al. (2023) is order postponement. In this case, orders of a certain buyer are held until the buyer is finished ordering. The moment a buyer is finished is estimated with the help of a model. The idea is that more full carts will go to the buyer instead of half-full carts. This was tested at an auction where everything is delivered when the auction closes. This method will become more complicated for an auction that works with certain delivery times. X. T. Kong et al. (2023) also stated that most studies separate auction or logistics activities. This means no study exists on the connection between two or more activities.

3.5. Conclusion

The literature shows that a lot of general information about warehousing is already available. Frameworks are presented for the design of a warehouse, and tools are proposed. The main problem found during literature research is that all the design steps and the different processes are not connected. Everything is looked at separately. Another issue is that frameworks have been designed but not always tested in real life. This makes it challenging to know which framework is the best for a particular situation. Another problem with this is that implementation is not included in the research, while this is sometimes more important than the framework itself.

To zoom in more, research has also been done about the order-picking process. Much information about different types of order-picking systems, case studies, and design ideas is available. It has been found that congestion greatly influences order-picking efficiency, and numerous solutions have been offered for this problem. However, none of the studies connected with the process after order-picking: delivery.

On a day-to-day basis, a lot can happen during the distribution of products. A slight interruption can affect the complete product flow. Such an interruption must be corrected as soon as possible based on real-time information. This information must be available. Automation is possible by detecting interruptions, but humans are still needed.

When focussing more on auctions instead of warehouses in general, the importance of software was shown. This has become more important with the expansion of the business. It was also proposed to use a robot-enabled system, but that is very difficult with the combination of perishable goods and the complicated process of an auction. Therefore, it is not common yet. Other possibilities to increase revenue are demand forecasting and order postponement. It remains essential that all steps in the complete process are well aligned.

This chapter described all aspects involved in an order-picking and in-house delivery process according to existing literature. The requirements and KPIs for such processes have been presented, and therefore, the first sub-research question, as stated in Section 1.3, has been answered.

An overview of all studied literature can be found in Table 3.1. A reoccurring gap in all studied topics is that no research has been done about the detailed functioning of two sequential processes. Much research has been done about most processes separately, and researchers often mention the importance of aligning the processes. Still, no studies have been found where the alignment is investigated. This leaves an opportunity to add information to the literature by doing a case study about aligning two processes in a day-to-day situation.

Table 3.1: Overview of findings in literature

Reference	Topic				Method					Notes
	WD	OP	DM	AO	LS	Si	CS	SA	MA	
Rouwenhorst et al. (2000)	✓	✓			✓					Characterizations within a warehouse
Brito and Basto (2006)	✓					✓				Possible options for simulation
Baker and Canessa (2009)	✓				✓			✓		Eleven-step framework
McGinnis et al. (2014)	✓				✓	✓				
Lepori et al. (2013)	✓				✓					Separation of physical and information flows
Mesa and Akhilesh (2016)	✓	✓			✓					Different types of warehouse layouts
Mourtzis et al. (2019)	✓						✓	✓		Simulation options
Mahroof (2019)	✓	✓			✓		✓			Connection between theory and implementation must be further investigated
Bortolini et al. (2020)	✓						✓		✓	Layout designs
Sapry et al. (2020)	✓						✓			Connections between processes are important
Dallari et al. (2009)		✓					✓			Design methodology and key parameters for designing an order-picking process
Chan and Chan (2011)	✓	✓				✓				Decision problems in order-picking design and the efficiency of chosen policies for each problem is interdependent
Lu et al. (2016)		✓							✓	Trade-offs that have to be made before implementation
van Gils et al. (2018)		✓				✓				Relations among location assignment, order batching, zone picking and picking route
Klodawski et al. (2018)		✓				✓				Process efficiency increases with a growing number of pickers but an increasing number of pickers causes a lower growth in efficiency and an increase in congestion
Kovac and Djurdjevic (2020)		✓				✓				Separate problem-solving can only lead to sub-optimal solutions
Hompel and Schmidt (2007)	✓	✓	✓		✓					Importance of tracking flows, providing information to everyone involved and operative planning
Rascão (2021)			✓		✓					Reliable and accurate information is needed for day-to-day problems
Pajić et al. (2021)			✓						✓	Most important KPIs for the distribution process
Binos et al. (2021)			✓		✓					Small interruptions can affect the whole flow and autonomous agents can support the people working in the system by solving these interruptions

X. T. Kong et al. (2015)				✓			✓			Importance of technology in auction logistics
X. Kong et al. (2017)		✓		✓			✓			Limited application of robots in perishable auctions
X. T. Kong et al. (2022)				✓		✓				Demand forecasting can be helpful to increase revenue
X. T. Kong et al. (2023)				✓					✓	Order postponement; most studies separate auction or logistics activities
This research		✓		✓	✓		✓			

WD = Warehouse Design, OP = Order-Picking, DM = Distribution Management, AO = Auction Order fulfilment

LS = Literature Study, Si = Simulation, CS = Case Study, SA = Software Analysis, MA = Mathematical Analysis

4 Current state analysis

To find improvement points, it is essential to understand what currently happens within the overall process. Retrieving such an understanding will be accomplished in twofold. First, a physical analysis will be done. This will include all employees' actions during the order-picking and in-house delivery process. The planning and control of the physical process will be discussed separately. In addition, a more in-depth data analysis will be done to measure the performance of the current state and find any particularities. The two separate analyses will be combined in a final SWOT analysis to find the strengths, weaknesses, opportunities, and threats. The chapter will end with a short conclusion about the current state and will answer the second sub-research question as stated in Section 1.3.

4.1. Physical analysis

First, a short introduction will be given to the layout of RFH Naaldwijk so that there is a better understanding when explaining the process. Next, an IDEF-0 diagram will show the input and output of specific steps within the processes and all other mechanisms needed. Then, an explanation will be given about the actors involved. The order-picking and in-house delivery processes will be described in further detail separately. This will be done with Swimlane diagrams, which also show which actor is responsible for each step.

4.1.1. Layout RFH Naaldwijk

The layout presented in Figure 4.1 is only where the order-picking process and the tugging and sorting of the in-house delivery process occur, thus not the delivery. There are ten work areas in total where order pickers are working. The light purple square next to the green rectangle is the work area for flowers, which may not be stored in a cooling cell. The large green rectangle is the place where empty carts are kept, which order pickers will use to collect orders. Other work areas are on the other side of the empty cart buffer. There are two work areas above each other, each with its tracks. Across from those areas are the rest of the work areas. The work areas on the ground floor have a larger total surface than the ones upstairs. The light purple rectangle belongs to the ones on the ground floor. Downstairs are four work areas and two track areas. Above these are three work areas and also two track areas. All the cells, except for the small area with flowers that cannot be cooled, have a low temperature (between 2°C and 8°C). It depends on the number of carts sold and whether all work areas are used.

The large blue area is where plants are processed, but as already mentioned, this is out of this project's scope. Carts are moved in the grey and orange regions after order picking. The grey area is for carts that need to go through the sorting process, and the orange area is for carts for dedicated or large buyers. This will be explained later in this chapter. The rest of the space that is visible in the figure is where customers want their products to be delivered.

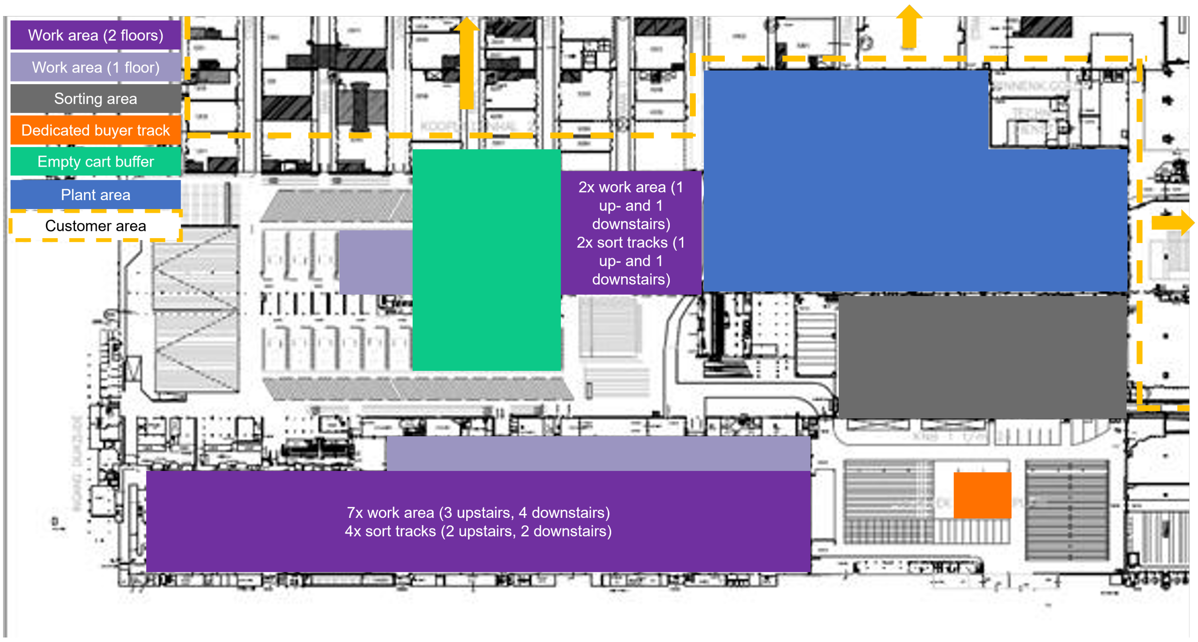


Figure 4.1: Map of RFH Naaldwijk order-picking and in-house delivery processes

To clarify the transportation moves in the area, two figures have been created. The first one, Figure 4.2, shows the transportation moves in case carts must go through the sorting process.

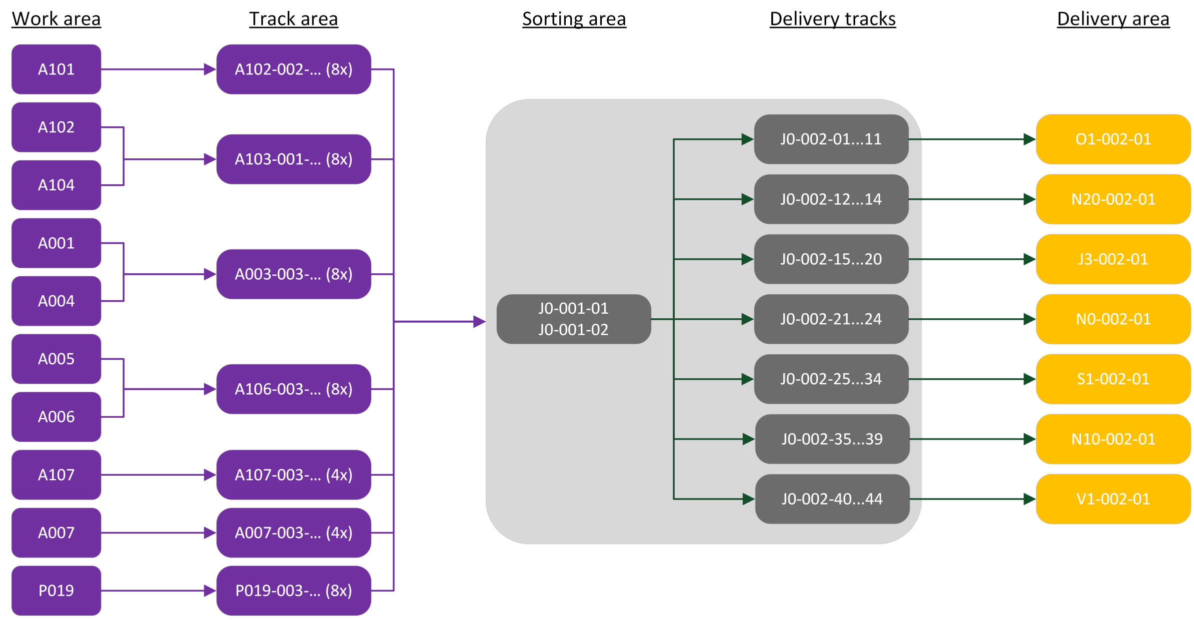


Figure 4.2: Transportation moves via the sorting area

The colours in the figures match the colours used in the map. Orders are collected in the different work areas. Each work area is assigned to a track area where order pickers can leave their gathered carts. Carts are moved from the track areas to the sorting area. This is a large space where the carts are sorted and put on the correct delivery track. The figure shows that each delivery track is assigned to a specific delivery area.

For the dedicated buyers, Figure 4.3 shows the transportation moves via the orange area. In each track area, multiple tracks are used for dedicated buyers. The carts are moved from the tracks to the dedicated buyer tracks, where they are parked until an employee picks them up again to move them to the correct delivery area. Since A007 and A107 have limited space, their track division is different than in the other areas, and they do not give out carts that go via the dedicated buyer tracks.

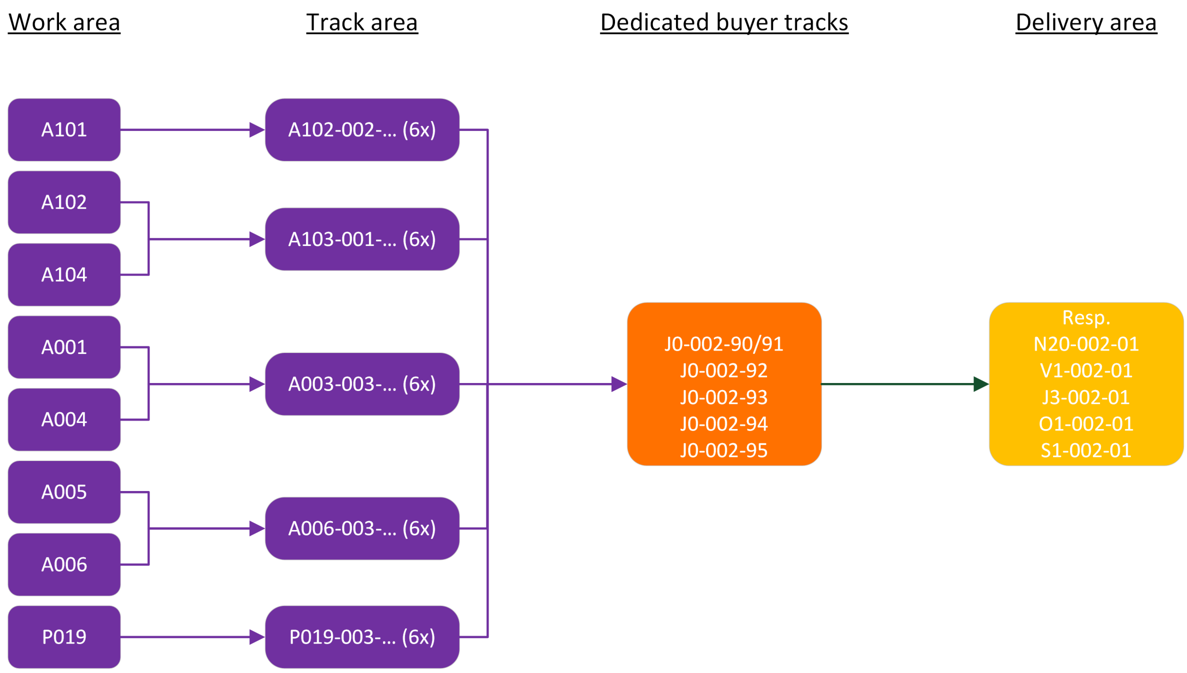


Figure 4.3: Transportation moves via the dedicated buyer tracks

4.1.2. IDEF-0 diagram

An IDEF-0 diagram has been created (Figure 4.5) where both processes are included.

Order picking

The scope of this research starts with order picking. The input needed for order picking is an order from one of the buyers. During this step, different mechanisms are required: a stand-on electric truck, a cart, the software Blue Yonder, a scanner, a printer, and an employee who knows how to pick orders. A stand-on electric truck is shown in Figure 4.4 on the left side of the picture. The stand-on electric truck has a hook at the back to which carts can be attached. In the same figure, the carts used by RFH can be seen with flowers placed on them. These carts are utilised by the order pickers and to store flowers during the order-picking process. Blue Yonder is a WMS system used by RFH since they transferred to the order-picking process. Scanners are linked to this system to gather data and provide information to employees. The printers in the work areas are also connected to the scanners. On each printer, there is a QR code present. When scanning this QR code, the printer will print the order list of what should be on the cart when scanning it. The control input of the system is the latest delivery time for the buyer. The

Figure 4.4: Carts used by RFH (Royal FloraHolland, 2021)

output of order picking is the cart with flowers and a print that mentions every product on the cart, including the latest delivery time.

Preparing for tugging
The following action is preparing for tugging. For this, only a preparer is needed who makes sure that 1) there is space on the track where an extra cart needs to be coupled to a train of other carts and 2) that the maximum train length (14 carts) is not exceeded. Unfortunately, it occurs that the maximum train length is exceeded. The result of preparing is that a train of picked carts will be waiting for the following action. In the larger work areas, there are two types of tracks. One is for the buyers who purchase a lot so that enough carts are exiting one work area to make a train specific for that buyer. It does occur that there is a mix of carts for two buyers on such a track. Both those buyers are then dedicated buyers that are located in the same delivery area. For the buyers who purchase less, their carts will be mixed in trains with other buyers' carts. Those buyers are also located in the same delivery area.

Tugging
The tugger to take a train from the order-picking area has to make sure that the train which has to be delivered the earliest will be taken first (directed by a troubleshooter) and otherwise the longest train. The tugger is also responsible for scanning the QR codes at the pick-up and drop-off locations so that the system knows which train is moved and to where. The tugger does not change anything in the train of picked carts, so the output is the same as the input of this step. As mentioned in the previous paragraphs, the location to take the train depends on whether the carts in the train are all for (a) dedicated buyer(s) or multiple smaller buyers. If all carts are for (a) dedicated buyer(s), the next step is A5. Otherwise, a sorting step is needed. The tugger leaves the train on a dedicated buyer track or in a buffer beside the sorting area.

Tugging (sorting area)
To move to the sorting track, there is a short action where another tugger moves the train from the buffer to the sorting track. Attention must be paid to which train has to be delivered the earliest (which can be seen on the prints attached to the carts) and if there is enough space on the sorting track. The tugger only looks at the first cart and does not look at the other carts. It can be that the first cart has to be delivered at 12 PM but another one attached to the train at 11 AM.

Sorting
A sorter has to detach one cart, scan the barcode of the cart and scan the QR code of the delivery track on which they place the cart but has to make sure that the maximum train length (14 carts) is not exceeded when attaching the cart to the train. On which delivery track they should place the cart is shown by the scanner (WMS) after scanning the barcode of the cart.

Delivering
The last action of the two processes is to deliver the carts to the right customer. Again, the deliverer must first deliver the train, which has to be delivered the earliest (directed by a troubleshooter) and otherwise the longest train. This deliverer must also scan every cart barcode at the track during pick-up and at the customer. The deliverers are responsible for the carts that have gone through the sorting area and those waiting on a dedicated buyer track.

The order-picking and in-house delivery processes are connected between the actions "Preparing for tugging" and "Tugging". Thus, the order-picking process is the preparation and, thus, the input for the in-house delivery process. Both processes are also connected via the WMS

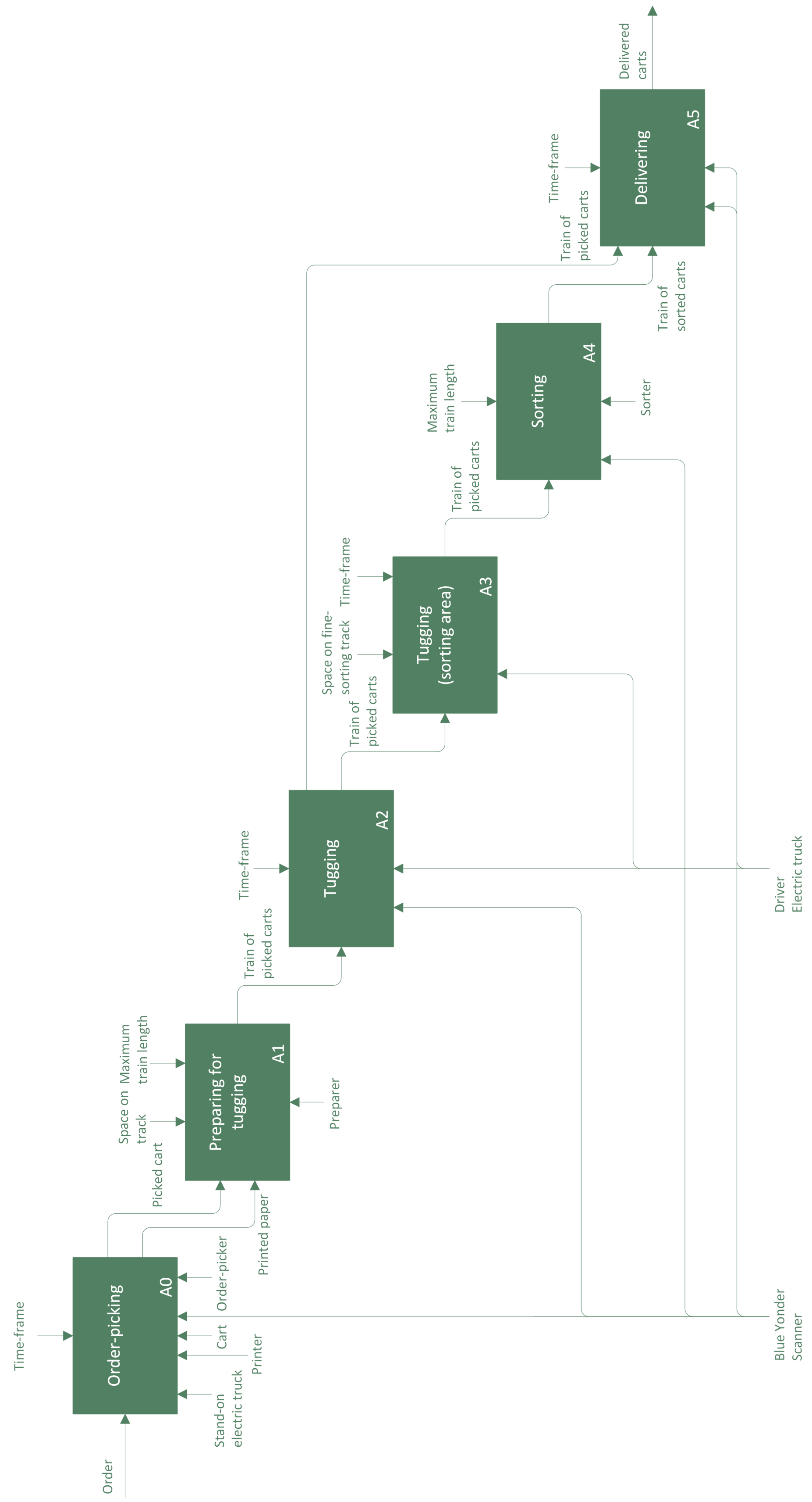


Figure 4.5: IDEF-0 diagram of current processes

since they use the same software. It can be concluded again that the order-picking and in-house delivery processes should be aligned well for an efficient overall auction process. The next step is to explain both processes separately in more detail.

4.1.3. Actors involved in the processes

Different actors are involved in the overall process. Some are very close to the process, and others are further away. Figure 4.6 shows a schematic overview of all actors involved. The further away an actor is from the process, the lighter the box around their title is. All actors involved in the day-to-day execution of the process are:

- **Order pickers** The order pickers are the main actors within the order-picking process. They must ensure that orders are collected correctly, preferably without any mistakes or damage to the flowers. Order pickers might have contact with the sorters when dropping off their cart. If issues arise, the first point of contact will be the troubleshooter located in their working area.
- **Preparers:** Preparers are responsible for attaching the carts dropped off by order pickers to the correct train. When it is busy, it sometimes happens that too many carts are dropped off by the order pickers and that the carts are not taken away soon enough. Next, the drop-off zone becomes very chaotic with many loose carts, and it can become unclear where each cart has to be attached. Prepares can ask the order picker who dropped the cart or the troubleshooter for help.
- **Tuggers:** As explained in the previous section, there are two sub-processes where tuggers are needed. Tuggers are responsible for moving carts between two locations and ensuring that each cart's current location is documented in the system by scanning the required codes at the right moment. When tuggers have a problem, they can contact one of the troubleshooters.
- **Sorters:** Sorters stay in the sorting area the whole time. They perform the final steps of sorting the carts before delivery to the customers takes place. In the sorting area, troubleshooters are also present if anything unexpected happens. The sorters and tuggers (sorting area) are in the same group of people and will switch roles during the day. The job of a sorter is physically demanding, and changing roles ensures that everyone stays healthy.
- **Troubleshooters:** When a problem occurs, the troubleshooter is the first to contact. They have more information available during the execution of the process, so it is easier for them to solve problems. Troubleshooters should also maintain an overview during the process to intervene when they see something abnormal. Troubleshooters are in close contact with the process coordinators. Troubleshooters also go around the work areas of order pickers to see if all flowers are still in the correct storage space so that order pickers will take the right flowers for their order.
- **Process coordinators:** Process coordinators are responsible for their sub-process. A coordinator has to make sure that their process runs smoothly and is in contact with other process coordinators to see how they can improve the overall process together. Process coordinators often use a solution to manage everything well: moving employees from one work area to another so that bottlenecks are there as little as possible.
- **Team managers:** Team managers are further away from the process than process coordinators. Process coordinators are always in the work area for which they are responsible, where team managers walk between different work areas to oversee the complete process or look at the currently available data on their computers. Team managers meet one or more times per day during the execution of the process to discuss the progress

up to that point and to see if they need to act on something. During the day start (the first meeting of the day), the planning of the day is discussed so that they can inform their team about what to expect. At the day start, the operational managers are also present.

- **Operational managers:** The task of an operational manager is to steer the team managers and other employees within the process. Apart from that, they are involved in the design and changes to the process.
- **Manager LO/LDK:** The managers of the order-picking and in-house delivery processes are responsible for all the actions of people closer to the process. These managers will be less in the work areas and will get updates about the process from their operational manager.

Some other actors are more present in the background. Those will not be introduced further since this research focuses on the day-to-day execution of the process.

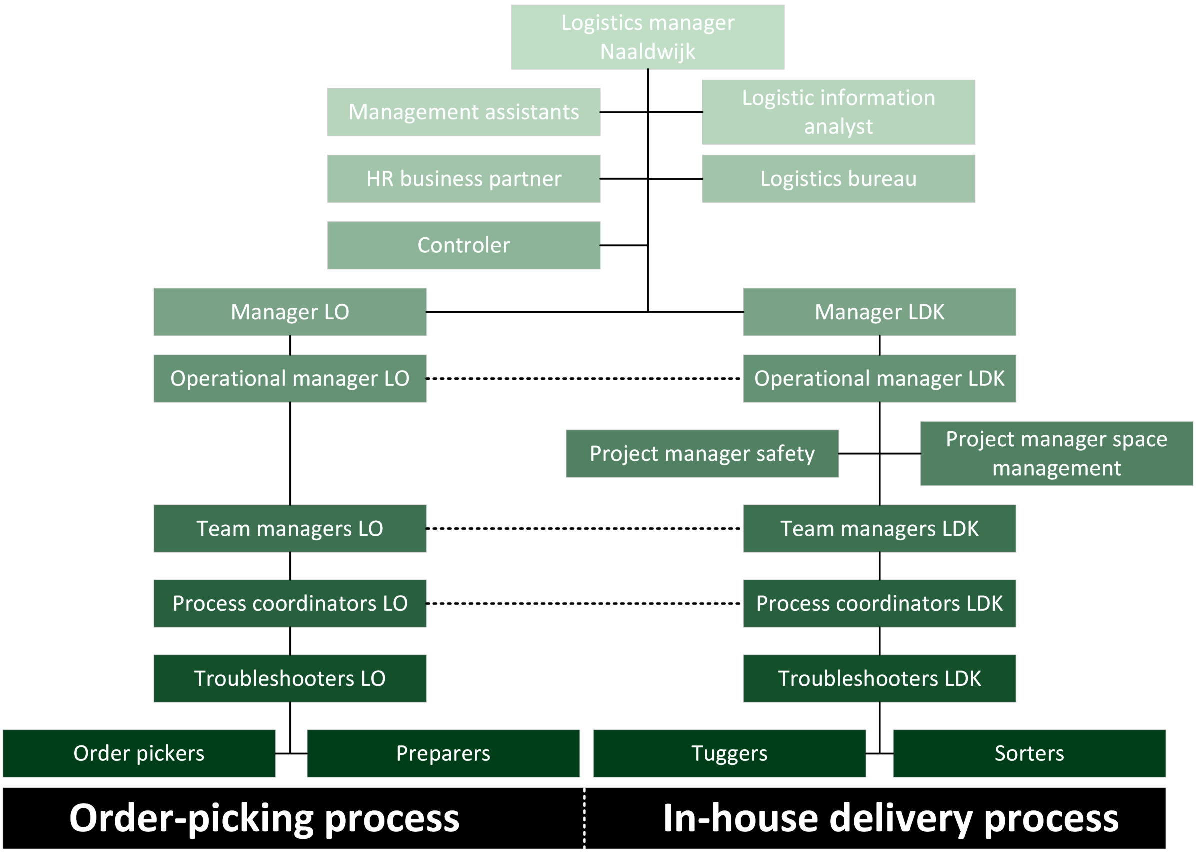


Figure 4.6: Overview of all people involved in the order-picking and in-house delivery processes

4.1.4. Order-picking process

Before the order-picking process starts, all flowers delivered by growers are placed on carts. Those carts are then put in a work area in a particular set-up so that order pickers can pass the carts with another empty cart and move the casks with flowers from storage to their buyer cart. Figure 4.7 shows an example of a work area layout. The alleys created in the storage area are in a two-way direction; thus, order pickers can work next to each other while keeping in mind that others should be able to pass them. It is only allowed to drive on the right side of an alley, and U-turns are permitted outside of an alley. A detailed visualisation of the current order-picking process is shown in Figure 4.8 (enlarged version in Appendix E).

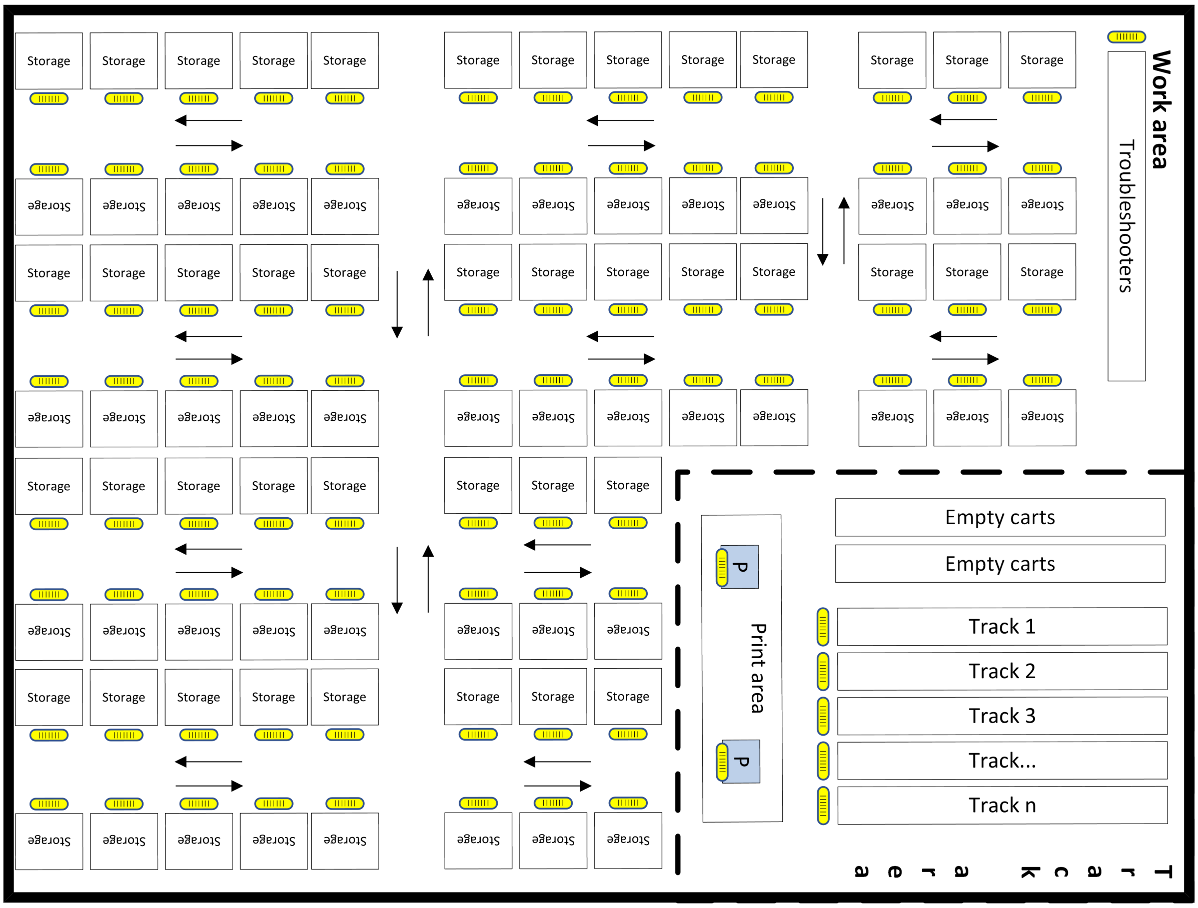


Figure 4.7: Example of a work area layout at RFH (Royal FloraHolland, 2020)

Blue Yonder (WMS)

The process starts with an order placed by a buyer. Orders are processed in the WMS (Blue Yonder) before an order picker receives one. Based on priority rules, the WMS decides which order will be sent next. This order becomes either a picklist or a pallet pick. It depends on whether the order consists of just the remaining flowers on one cart (pallet pick) or whether it is part of a cart or multiple types of flowers (picklist). The pallet pick or picklist shows up on the order picker scanner.

Order picker

An order picker always works in one work area at a time. Getting orders for a different work area is impossible if you are signed in to another. The order picker then has to accept the task. Once the task is accepted, the order picker gets an empty cart if it is a picklist or moves to the following location on the list immediately if it is a pallet pick. In the case of a picklist, when an empty cart has been taken, the barcode of the cart has to be scanned so that the WMS knows which cart belongs to the accepted task. After the cart has been taken and scanned, it is time to move to the flower storage.

In the flower storage, the order picker moves to the first location on the list. This happens both for the pallet pick and picklist situation. The picklist situation will be explained first, followed by a pallet pick situation. When arriving at the following location on the list, the order picker scans the barcode of the location. If it is the correct location, the scanner will show the order picker how many casks to place on their cart. If the location is incorrect, the scanner will notify the order picker to move to the correct location. If there are not enough casks to take at the location, the order picker goes to a troubleshooter who will help solve the problem. This does not occur often; less than 0.9% of all picks contained some mistake over the first 10 months of 2023 and will, therefore, be left out of the scope of this research. If there are enough casks, the order picker places them on their cart and agrees with the number of casks moved to their cart in the scanner. If this was the last location on the list, it is time to move to the printer. If not, the order picker returns to the step to move to the following location.

There may be another location on the list, but there is no more space on the cart to take all of the casks of the next pick. This is because the system does not know the difference between flower types. To ensure quality, some flowers must be placed on a cart with more space between casks. If this is the case, the order picker can end the list manually and then move to the printer. The system will add the remaining location(s) to another picklist or pallet pick. Another situation might be that the route to the next location is very busy, and the order picker must wait a long time. To decrease the total pick time, the order picker can move this pick to the end of the list and go to the following location. The now-skipped location will return at the end of the list. This has to be done manually; the system will not suggest it. This function is still there, but RFH is looking at the possibility of removing this function since it is error-prone.

In case of a pallet pick, the order picker moves to the location on the list without a cart. Here, the order picker disconnects the stored cart at that location from the other stored carts and scans the cart. If it is the correct location, the order picker counts the amount of casks. When correct, it is time to move to the printer and otherwise to the troubleshooter. In case it was the incorrect location, the order picker leaves the cart (connected to the other carts) at its location and moves to the correct location.

When arriving at the printer, the order picker scans the QR code on the printer to receive a print of what should be on the cart and other information, such as the latest delivery time. An extra check is in place at the printer. Here, the order picker has to count the number of casks on its cart and see if the number of casks equals the amount stated on the print. If there are not enough or too many casks, the order picker goes to the troubleshooter. If the number of casks is correct, the print is attached to the cart with the designated clamp. When done, the cart is moved to the drop-off location in front of the correct track. The scanner shows after printing which track the cart needs to go to. The WMS is programmed so that as many carts as possible of one buyer are present on the same track. The order picker scans the QR code of the correct track and leaves the cart. The system remembers this scan and now knows that this cart is waiting on a specific track to go further to the next sub-process.

Preparer
A preparer moves the cart further on the track and attaches it to the train of carts already there. This is the end of the order-picking process.

> Summary order-picking process
>
> **Input:** Orders communicated via the WMS and flowers that have been placed in storage before the auction and order-picking process starts
> **Output:** Gathered carts in a train which contain products from only one customer per cart and information in the WMS that a cart is picked and which products are on that cart
> **Actors:** Order pickers, preparers, and troubleshooters

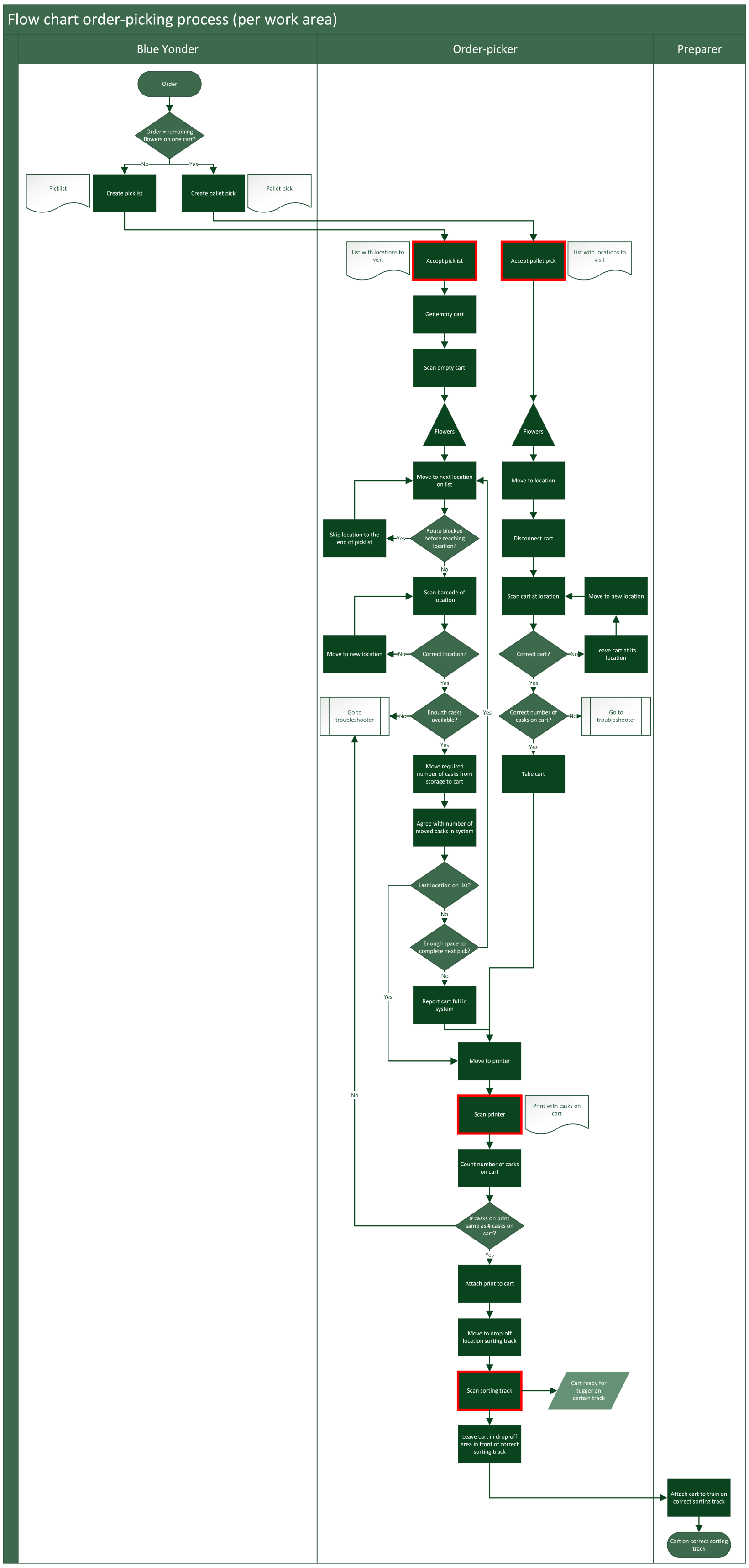


Figure 4.8: Swimlane diagram of the current order-picking process (enlarged version in Appendix E)

4.1.5. In-house delivery process

The in-house delivery process is mainly movement between areas and is shown in Figure 4.9 (enlarged version in Appendix E).

Troubleshooter

The first step in the process for a troubleshooter is to check if there is any train ready that has to be taken first to be on time for delivery. The troubleshooter puts a memo on a whiteboard if such a train exists. On another whiteboard, it is indicated if empty carts are needed in a particular work area.

Tugger (assigned to one track area)

A tugger passes the first whiteboard and checks if a memo is present. If there is, the tugger takes the memo; otherwise, it does not. When empty carts are needed, the tugger moves to the empty cart buffer and takes a train of empty carts. From here on, the tugger moves to the assigned track area with the train of empty carts. There may be no empty track to drop the empty carts on. The tugger then places them somewhere on the side. If no empty carts are needed, the tugger moves to the track area without them.

If a memo was taken, the train from the track indicated by the memo is taken by the tugger. Otherwise, the longest train has to be taken. In practice, it often occurs that not the longest train is taken because it is hard to see which is the longest or tuggers prefer to take trains from certain tracks. After coupling the train to its vehicle, the tugger scans the QR code belonging to that track so that the WMS records that the train is taken. If the train is for (a) dedicated buyer(s), it is moved to the dedicated buyer tracks and otherwise to the sorting area. In both areas, the train is dropped by the tugger. For a dedicated buyer, a specific track must be scanned, and the area is scanned for the sorting area. Again, the system registers that those carts have been moved to either the sorting area or the dedicated buyer track.

Tugger (sorting area)

In the sorting area is another tugger who moves trains from the drop-off area to the sorting track. The tugger (sorting area) checks the trains to see if one of them has an earlier time before which the carts have to be delivered. As Section 4.1.2 mentions, the tugger (sorting area) only checks the first cart, not the complete train. A random train is taken if all the trains have the same end time. In reality, this tugger often takes the train from the buffer closest to the sorting tracks. Then, a tugger coming from a track area delivers a new train on that track. The tugger (sorting area) gets the one from the closest track again. This means that trains placed in the buffer further away from the sorting tracks are left there for a long time.

Sorter

Sorters are waiting at the sorting track to disconnect one cart at a time from the train. The cart is then scanned, and the scanner of the sorter will show which delivery track the cart has to go to. The sorter moves the cart to the corresponding delivery track and scans the delivery track. On the track, the sorter connects the cart to the other carts already on that track.

Deliverer

For the last part of the in-house delivery, troubleshooters come into play again. The troubleshooter keeps track of which delivery track contains a full train and which trains must be delivered first. The troubleshooter directs a deliverer to the track with the higher priority. If there is no preference, the deliverer takes the longest train. Before leaving with a train, all carts attached to that train have to be scanned manually. This is not a QR code but the barcodes of the carts themselves. The same code as the order picker scans at the beginning of

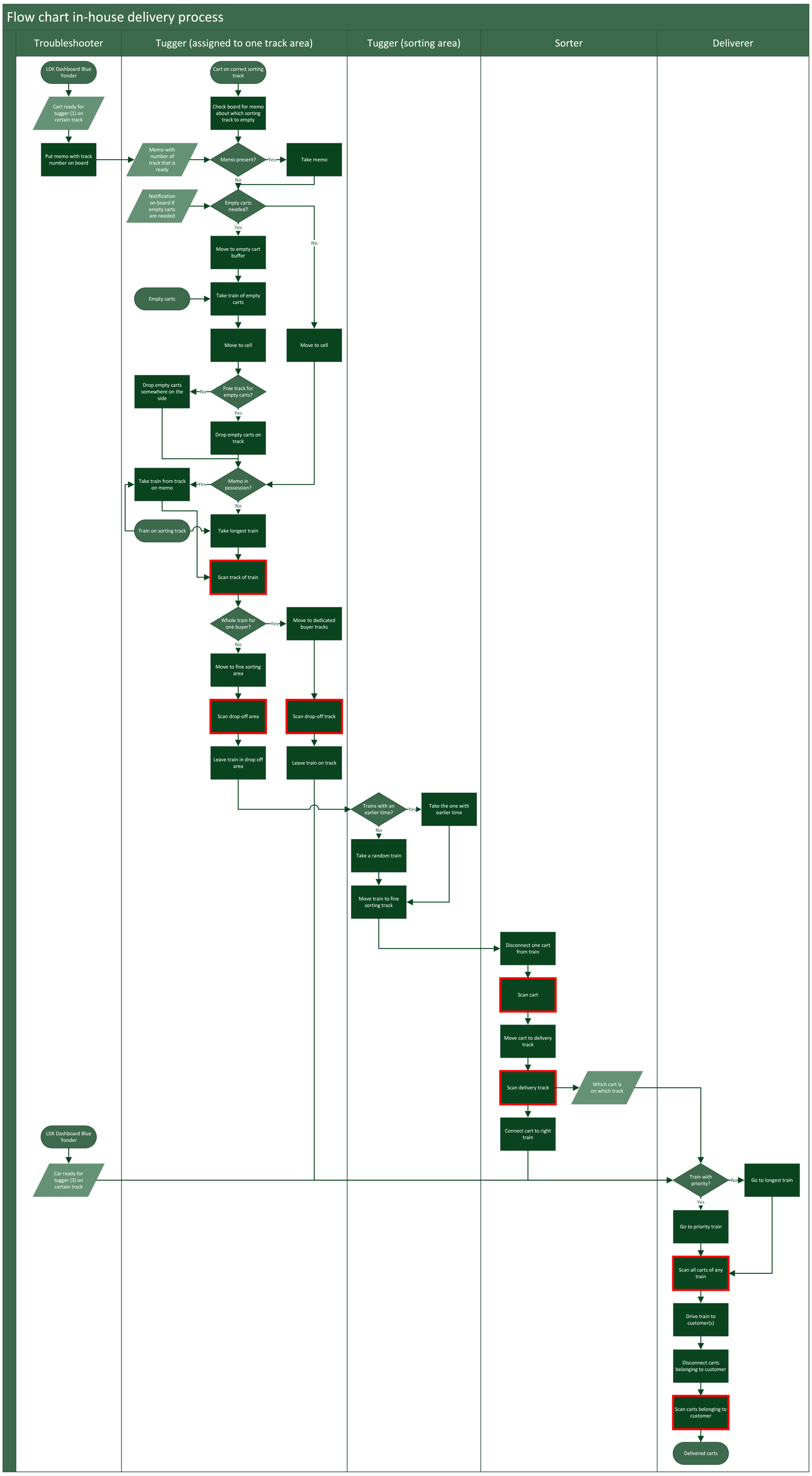


Figure 4.9: Swimlane diagram of the current in-house delivery process (enlarged version in Appendix E)

their process. After scanning, the deliverer moves the train to the customer(s). When arriving at a customer, the carts belonging to that customer are disconnected from the train and the carts delivered are scanned again. Depending on the number of customers that must be visited with one train, the deliverer moves back to the delivery tracks or goes to the next customer. For the dedicated buyer tracks, the same principle is used.

Summary in-house delivery process

Input: Information in the WMS which carts are ready for delivery and trains of carts ready to be taken from the order-picking area
Output: Delivered carts to customer areas and information on predefined positions within the process about what time a certain cart was at that position
Actors: Tuggers, deliverers, sorters, and troubleshooters

4.2. Planning and control

Planning and control are essential parts of the preparation and execution of the overall process. Understanding how the planning and control work is needed to improve the overall process.

4.2.1. Planning

RFH has a planning department at each location. Everything described in this section applies only to the planning department in Naaldwijk. The order-picking and in-house delivery process is planned per week during the week before. Based on numbers from the past, a forecast is made for the number of carts that will be delivered every day during the week. In addition to that, the number of transactions is also forecasted. The combination of the number of carts and number of transactions will give the expected number of buyer carts that have to be delivered after the order-picking process. This way, the planning department knows how many carts must be handled daily.

Employees play an essential part in the speed of the process. RFH has permanent employees but also uses temporary workers via different temporary employment agencies. In a software program, the availability of permanent employees and temporary workers is visible. Thus, the planning department knows the number of employees available daily. In Power BI, the productivity of each order-picking employee is visible. This is presented in picks per hour per employee. Since each transaction is equivalent to one pick, the number of employees can be calculated to finish the order-picking process before a specific desired time. The (average) number of employees present per process and the expected productivity are given in Table 4.1. For the in-house delivery process, approximately 80% of the people present work with an electric truck. Something that stands out is that the currently measured productivity in the sorting area is 44 carts per hour, while the planning department uses the numbers as shown.

From observations, it has been found that this is partially because the supply to the sorting area is split into two parts. It occurs that one part receives a lot of carts while the other side is waiting for carts. The photographs shown in Figure 4.10 are taken seconds apart and exemplify this situation. Such a situation would remain like this for at least an hour when observed. The actual productivity when the supply is constant is thus not known.

Table 4.1: Number of employees and productivity

	Average					Week 43				
	M	T	W	T	F	M	T	W	T	F
Number of order pickers	193	179	170	126	180	178	182	178	130	186
Number of people in-house delivery process	120	114	108	86	111	115	115	116	82	111
Number of people with electric truck	94	91	86	70	88	91	93	97	69	87
Expected productivity tugging	95 carts/hour									
Expected productivity sorting area	M: 60; T: 65; W: 65; T: 70; F: 65 carts/hour									
Expected productivity delivering	40 carts/hour									

(a) Left entry of the sorting area 7 AM on Monday, January 8th 2024

(b) Right entry of the sorting area 7 AM on Monday, January 8th 2024

Figure 4.10: Example of difference in supply two different sides sorting area

RFH has agreed with buyers that, depending on the number of transactions, the overall process should be finished before a specific time. Since the number of employees is limited daily, RFH tries to stay before that time, but it is not always feasible. However, it is thus even more critical to ensure that all different work areas are finished around the same time so that the overall process is done as soon as possible. This is why the weekly planning can be adjusted for a particular day if the expected number of carts changes significantly or if many more or fewer employees are suddenly available. In addition, the planning department receives the final number of employees and carts in the morning just after the process has started. This is to shift employees, if necessary, to another work area or from the order-picking process to the in-house delivery process and vice versa. The planning is thus a dynamic ongoing process while executing the order-picking and in-house delivery processes.

4.2.2. Control

Different communication tools are currently present in the process and have been introduced with the IDEF-0 diagram and swimlane diagrams. Since control is an essential part of the management (Section 3.3), an overview of all control types and their purpose is given in Table 4.2.

Table 4.2: Type of control per process step

Step of the process	Communication tool(s)	Type of information	Purpose
Order picking	Scanner	The next assignment decided by the WMS & on which track the gathered cart should be dropped	The next order, based on the set priority rules, which needs to be gathered will be started with & the order picker will drop the cart in front of the correct track
Preparing	Where the cart is dropped by the order picker	On which track the cart belongs	The dropped cart will be placed on the track where it belongs and will be attached to other carts that are present on that track
Tugging (1)	Memo or rule to take the longest train	Which train should be taken to the next step in the process	The train that should be taken to the waiting area or sorting area first, is taken first
Tugging (sorting area)	Paper on the first cart	Latest delivery time of the first cart in that train	The train that has the earliest latest delivery time will be sorted first
Sorting	Scanner	On which delivery track a cart needs to be placed after the sorter has chosen a random cart	The cart chosen by the sorter is put on the correct delivery track so that the cart will be taken to the buyer to which it belongs
Delivering	Paper on each cart, verbal communication from troubleshooter and rule to take the longest train	Which train should be taken to their buyer and to which buyer it belongs	The train which is ready to be moved to the buyer (based on latest delivery time or train length) will be delivered to the buyer

4.3. Data analysis

As explained in Section 2.2, much data is available at RFH. Therefore, a data analysis will be done to see what happens during both processes, where bottlenecks are, and what is going well. First, KPIs set by RFH will be introduced. Thereafter, the data analysed will be presented, and the overall process will be explained.

4.3.1. KPIs

RFH measures the performance of their processes with different KPIs. The KPIs are set to satisfy buyers and ensure a constant lead time. The KPIs that RFH uses and their threshold are the following:

- **% before end time** percentage of picks that are done before the desired end time (>98%)
- **Lead time in-house delivery process** the lead time from when a cart is ready on the track after order picking until delivery at a customer (=<55 minutes)
- **Lead time carts overall process** percentage of carts that are delivered within a certain timespan (>95%)
- **% buyer complaints** percentage of buyer complaints (<0.5%)
- **Incorrect delivery scans** the number of delivery scans with an ID ”NONE” or ”UNKNOWN”
- **Buyer carts scanned** number of buyer carts scanned divided by the number of carts picked (<expected)
- **Expansion factor** the number of buyer carts divided by the number of auctioned carts (<2.0 for week 43)
- **Productivity** productivity of order pickers in picks/hour (=>25 picks/hour)

The first KPI is explicitly set for the order-picking process. Since RFH is working with a latest delivery time per buyer, orders must be picked on time to ensure delivery is also on time. At this moment, the goal is that at least 90 minutes before the latest delivery time, the order shows up in one of the order pickers' scanners. This ensures delivery can be on time when the order-picking process is finished. There is also such a KPI for the lead time of the in-house delivery process. Here, the goal is to deliver every cart within 55 minutes from the moment the cart is ready in the track area until the buyer. The third KPI is about the lead time of the overall process. The situation is that each cart has to be delivered before a specific time, but that time can be different for each cart. This means that a cart can be order-picked at 9 AM while it has to be delivered at 12 PM. It is not necessarily bad if that cart stands on the track longer than the cart that must be delivered at 11 AM. This is also the case for the KPI of the in-house delivery process since they start measuring that time as soon as the cart is put on the tracks by an order picker.

Delivering carts on time is not the only aspect to remember during such a process. Delivery should also be done without mistakes or quality issues. Therefore, a KPI about the maximum number of buyer complaints has been set. Also, since the idea is that buyers can track their delivery via track & trace in the future, the number of carts scanned and incorrect delivery scans are monitored. This is already being monitored so that when the track & trace goes live, the quality of track & trace is high. However, there is no strict threshold yet, meaning they only monitor it but do not assess the current process based on this KPI.

RFH has to deal with a high volume of carts every day. One way to reduce the volume is to keep the expansion factor as low as possible. At this moment, the expansion factor is higher than 2.0 on average. This means that more than two carts are needed for every incoming cart to get the products from that one cart to a buyer. The threshold for the expansion factor is set based on expectations and can, therefore, differ per week. The last thing being monitored with a KPI is the productivity of order pickers. This is done via picks/hour. It might not be the best solution to monitor it this way. For example, a pick can be one cask or fifteen casks. Moving fifteen casks from one cart to another will take longer than one cask, but they both count as one pick. In addition, a pallet pick is also measured as one pick. For a pallet pick, there is a relatively high travel time for one pick compared to a picklist with multiple picks. These are a few examples of why measuring it in the current way might not be the best solution.

4.3.2. Results

The data used are the scans mentioned earlier, of which the data is stored in the WMS. Since people are responsible for making the scans, mistakes are made. For example, when an employee forgets to complete a scan. Another problem is that data is stored in the order in which it enters the system rather than based on the location of the scan. This means that it is unknown which step is not scanned if one is forgotten, but also that some information for the dedicated buyer carts is placed in the wrong column of the table. This is because those carts are scanned fewer times than the ones that go via the sorting area. A third problem is that the data stored in PowerBI sometimes contains duplicates, and it is unknown which of those is the actual case. All the filtering done for the data analysis and decisions made is explained in detail in Appendix B.

For the analysis and design, the focus will be on Mondays. Mondays are the busiest days of the week, and most problems occur. The current way of working has been present since the end of the summer of 2023. This means that analysis and design must be based on days since then. In addition, the analysis started in October 2023, giving a limited number of days to analyse. From the feasible weeks, week 43 has been selected to present in this research. Mainly because week 43 has performed average when looking at carts being too late, the number of complaints and other aspects. The analysis has also been done on other Mondays, and the same trends were visible as the ones that will be discussed in this chapter.

First of all, the flow of all carts has been investigated to see what number of carts have to go through specific process steps and to see if all the moves are appropriately documented. The flow for Monday, October 23rd and Thursday, October 26th 2023, is presented in Figure 4.11 to show the difference between busy and calm days. One of the first things that stands out is that the number of carts as an output from the order-picking process is higher than the number of delivered carts from the deliverer. This means that a certain number of carts are not correctly stored in the WMS somewhere during the process. On Monday, this was 7.2% of all the carts; on Thursday, this was 3.9%. These numbers are when impossible combinations have already been deleted from the data. According to calculations of RFH, the average of missing scans is around 5%; thus, the results found during this research align with the company's conclusions. Since there are thousands of carts daily, the decision has been made to use the correct documented carts for further analysis.

The figure also presents the expansion factor by dividing the output of buyer carts by the input of auction carts. This was 2.14 on Monday and 1.92 on Thursday. The better result on Thursday could be because of the lower number of carts for auction that day. Because there is a lower number of carts, fewer work areas are needed to store everything, and more different products are present in the same work area. This increases the chance that more transactions of one buyer are of products in one work area. Another reason the auctioning is finished earlier than on Monday is the lower number of carts for auction. When all orders are known, creating order lists that are as optimal as possible is easier.

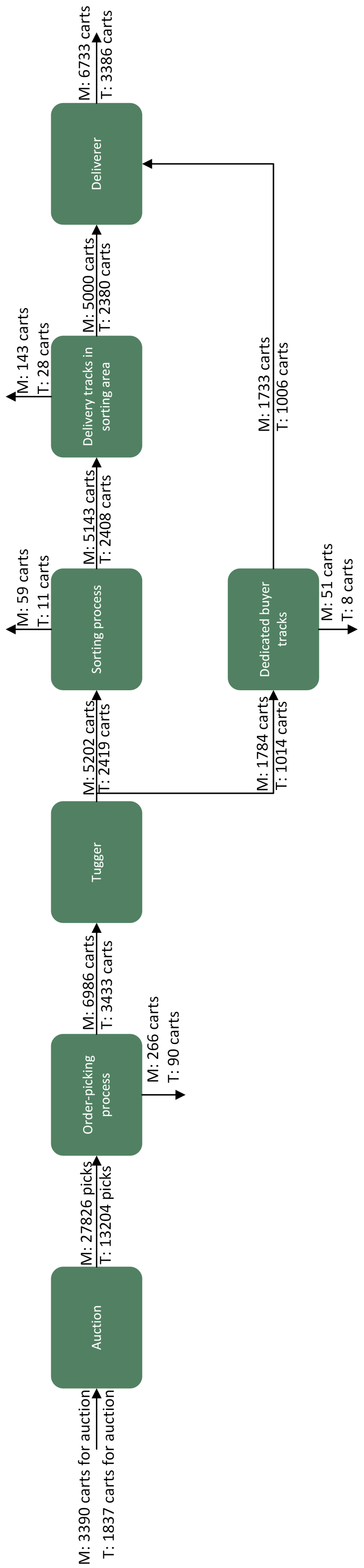


Figure 4.11: Carts flow Monday, October 23rd and Thursday, October 26th 2023

A Value Stream Map (VSM) has been created based on the data analysis. Figure 4.12 shows the complete chain from the flowers arriving at RFH until the flowers departing again. All the steps not belonging to this project's scope have been made grey. What is already visible and will be discussed in this section is the spread in the duration of specific (waiting) steps. When looking at average times, thus not the worst-case scenario, the moving time of a cart is 32.6% of the total lead time. The rest of the time, a cart is waiting somewhere. The waiting time is not always bad since waiting on certain tracks creates trains so that fewer tuggers or deliverers are needed. However, the moving time is preferably increased.

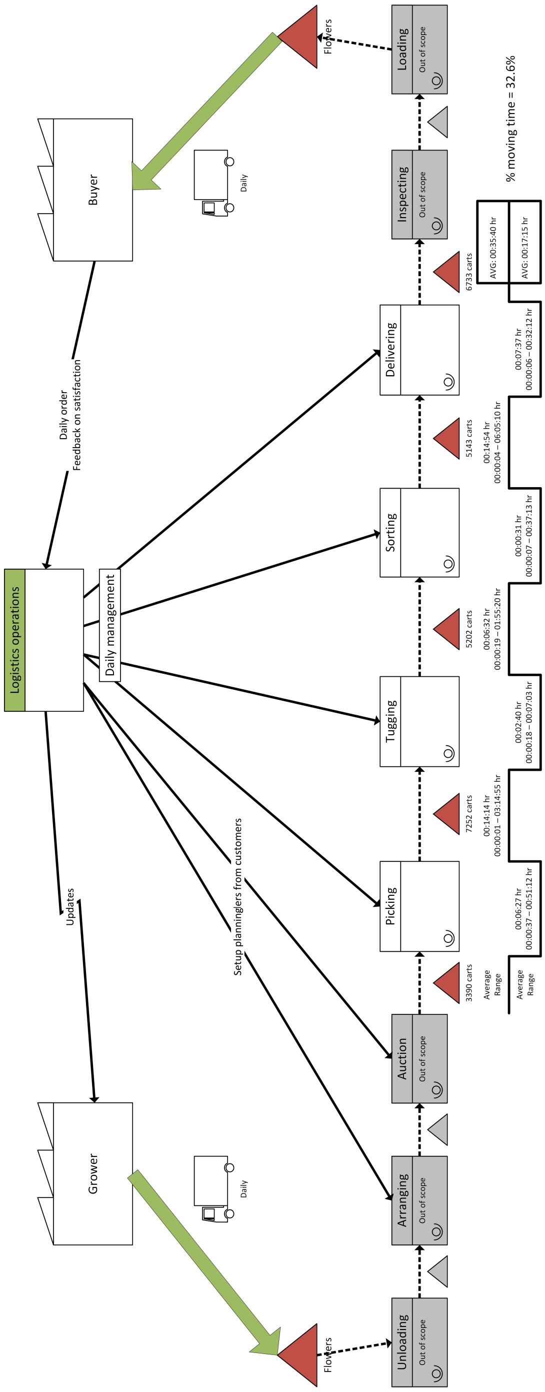


Figure 4.12: Value Stream Map (VSM) Monday, October 23rd

From different graphs created during the data analysis, it has been found that carts are often delivered too late, especially on Mondays. On Monday, October 23rd, this was the case for 25.09% of all carts, which is approximately the average in 2023 on Mondays. On Thursday of the same week, this was 0.46%. As shown in Figure 4.13, the average lead time per 15 minutes of 55 minutes for in-house delivery was exceeded on Monday. Until approximately 08:30 AM, the output of the order-picking process can be seen as the direct reason for exceeding the lead time around the same time. However, from around 08:30 AM, the average lead time per 15 minutes keeps decreasing while the output of the order-picking process increases again.

During the day, team managers shift employees from one work area to another or from the order-picking process to the in-house delivery process and vice versa. Towards the end of the day, buyer carts become more empty since a limited amount of products are still available. As a result, order picking one cart goes faster than at the beginning of the process because fewer products have to be placed on the buyer's cart. Because order picking goes faster, fewer order pickers are needed to have the same number of carts as output, so team managers shift order pickers to the in-house delivery process. This is why, towards the end of the day, the average in-house delivery lead time per 15 minutes keeps decreasing while the output of the order-picking process remains high. On Thursday, the total lead time of 55 minutes was not exceeded, but the same trend towards the end of the process was that the order-picking process output remained high while the lead time decreased, which was again visible.

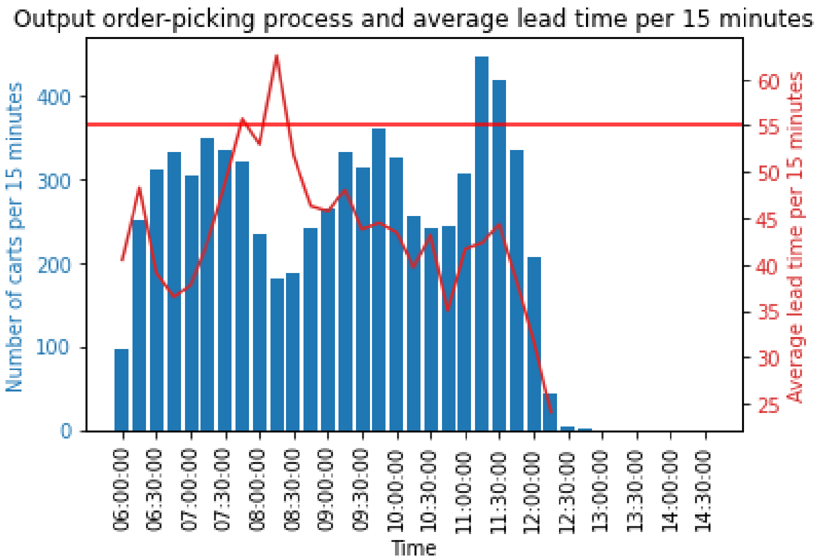


Figure 4.13: Output order-picking process vs average lead time per 15 minutes Monday, October 23rd

When looking at the output of the order-picking process and considering that the in-house delivery process may take almost an hour, nearly all carts should have been ready before 11 AM. The current division of percentage of carts per latest delivery time for 8 AM, 10 AM, 11 AM, 12 PM, and 1 PM is respectively 1.9%, 4.5%, 32.6%, 59.9%, and 1%. This means that 98.9% of all carts must be delivered before 12 PM and thus out of the order-picking process by 11 AM. Figure 4.14 shows the order-picking process's current and required cumulative output. The black crosses indicate the number of carts that need to be ready at that moment to ensure they will be delivered before their latest delivery time. The graph at 10:00 shows the output between 10:00 and 10:15. The figure demonstrates that the current output is too low to deliver every cart on time when taking the required time for the in-house delivery process in mind.

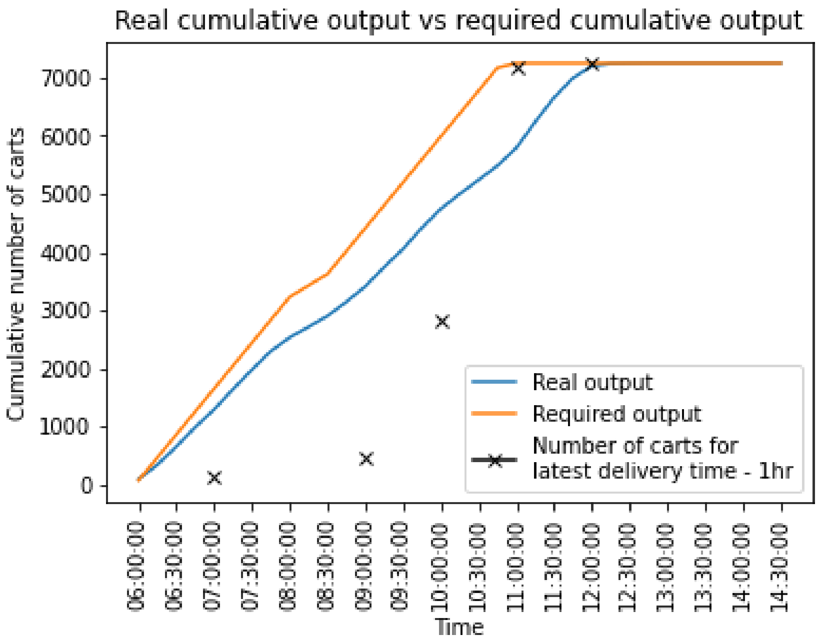


Figure 4.14: Real and required output order-picking process per 15 minutes Monday, October 23rd

Another aspect that stood out is that on this particular Monday, approximately 6.5% of the carts that were delivered too late entered the order-picking process after they should have been delivered (Figure 4.15). On Thursday, there was only one cart. Thus, this is mainly a problem on the busier days and is a reoccurring trend over the weeks. It is a known problem that the WMS sometimes leaves out an order and that it has to be moved to the top of the order list manually. The problem is that the required delivery time is not shown for those orders. Thus, troubleshooters do not know when to prioritise a certain order based on the delivery time. This means they have to guess when to give one of the orders in the list priority. Because of this, how many orders are started after the required delivery time differs per busy day. In addition, numerous other carts are started less than an hour before delivery should take place. This means that the limit of 55 minutes set for the in-house delivery process is too much to deliver those carts on time. Something that could contribute to this problem is that the auction is going on while the latest delivery time for some buyers is approaching. Then, a product is sold too late for the overall process to start on time.

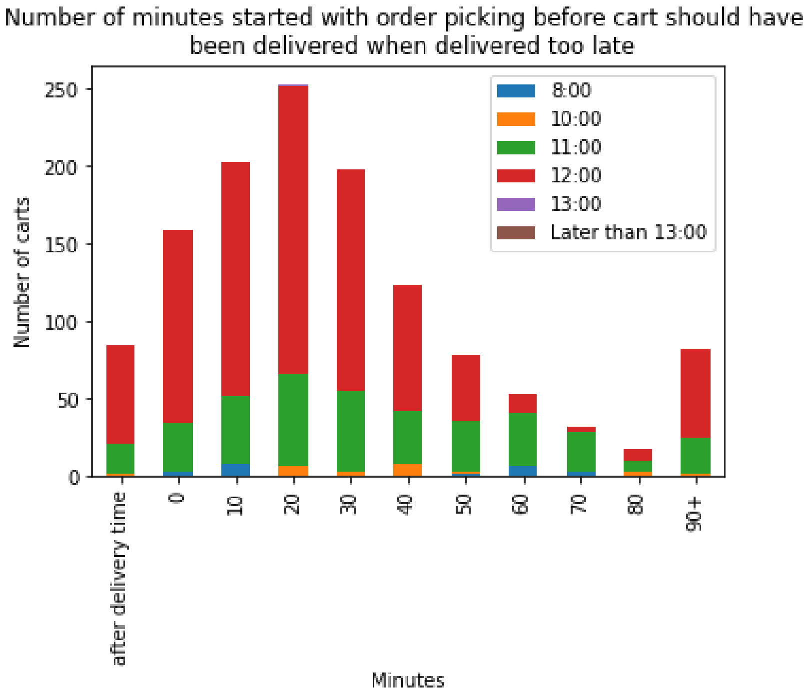


Figure 4.15: Time started with order-picking before required delivery time when a cart is delivered too late Monday, October 23rd

The waiting times at different moments during the process are very spread (Figure 4.16), making it difficult to say how long a cart is within the process in general, except for the time spent in the sorting area. However, as already mentioned, this does not have to be a problem while working with different delivery times for each cart. It is not a problem if a cart that has to be delivered later is waiting longer. Nonetheless, when a cart leaves the track area, the flowers are no longer in the storage climate. Thus, staying longer in the track area should not necessarily be a problem, but as soon as the cart leaves the track, the cart should go to the buyer quickly to ensure a high quality of flowers. At this moment, trains are created based on the buyer area. This means that in one train, there can be carts that have to be delivered at 12 PM and 10 AM. It is thus difficult to keep certain carts on the track longer because other carts from the same train need to be delivered sooner. On Thursday, the waiting times are as spread as on Monday. This means that this is an issue that occurs both during busy and slow days.

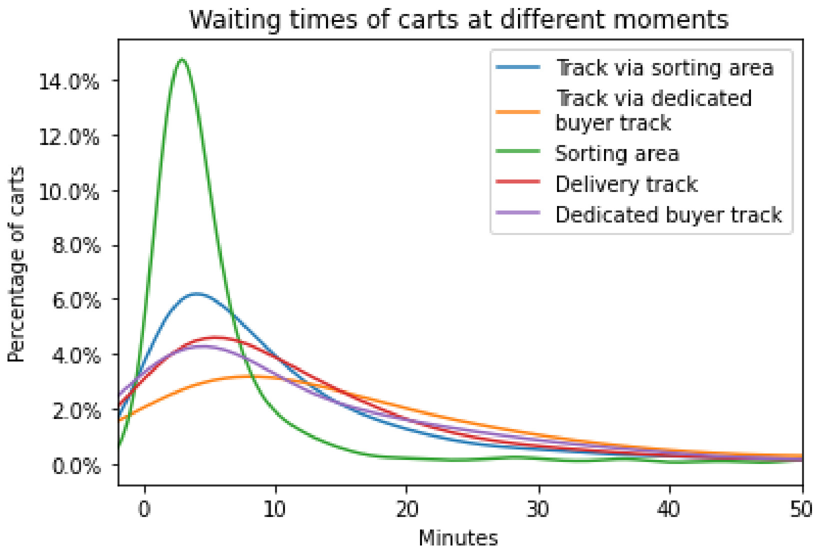


Figure 4.16: Waiting times at different steps of the process Monday, October 23rd

When plotting the share of the total average lead time per 15 minutes (Figure 4.17), it is found that at the beginning of the auction process, the waiting time in the track area is the most significant part of the total lead time and that this later switches to waiting on the delivery track or dedicated buyer track. The tugging and delivery time are constant for the carts that go via the sorting area and those that go via the dedicated buyer tracks. This means that, for a reliable lead time, the waiting times also need to become more constant. The average time spent in the sorting area remains below ten minutes except between 09:30 AM and 10:30 AM. A reason for this could be employee breaks. The waiting times in the track area and on the delivery tracks are the highest share of the total lead time for both carts that go via the sorting area and those that go via the dedicated buyer tracks. The average lead time on Thursday is lower than on Monday, but the same pattern is visible.

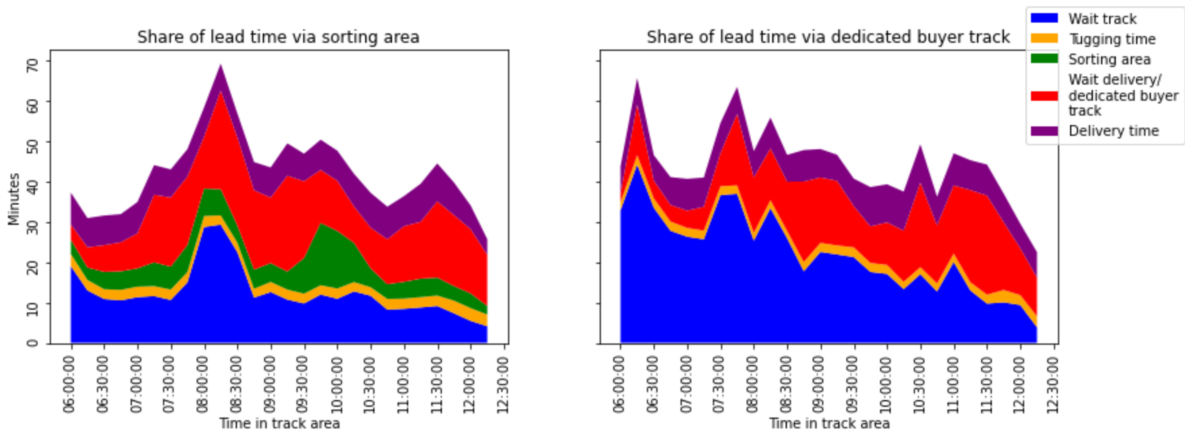


Figure 4.17: Share lead time Monday, October 23rd

In Figure 4.15, it has been shown that carts are delivered too late because the order started too late. RFH has set its KPI for the lead time of the in-house delivery process to 55 minutes. Figure 4.18 shows that the order picking should start at least 60 minutes before the required delivery time.

Figure 4.18: Order pick time Monday, October 23rd

It has been found that the 11 AM and 12 PM delivery times have the most carts delivered very early and the most delivered too late. This makes sense when looking at Figure 4.19. It can be seen that for all delivery areas, most carts have to be delivered before 12 PM. The second busiest delivery moment is 11 AM. However, according to Figure 4.13, the highest average lead time is around 8 AM. This is interesting since you would expect the peak closer to the busiest delivery moment. This indicates that RFH still tries to deliver all orders as soon as possible.

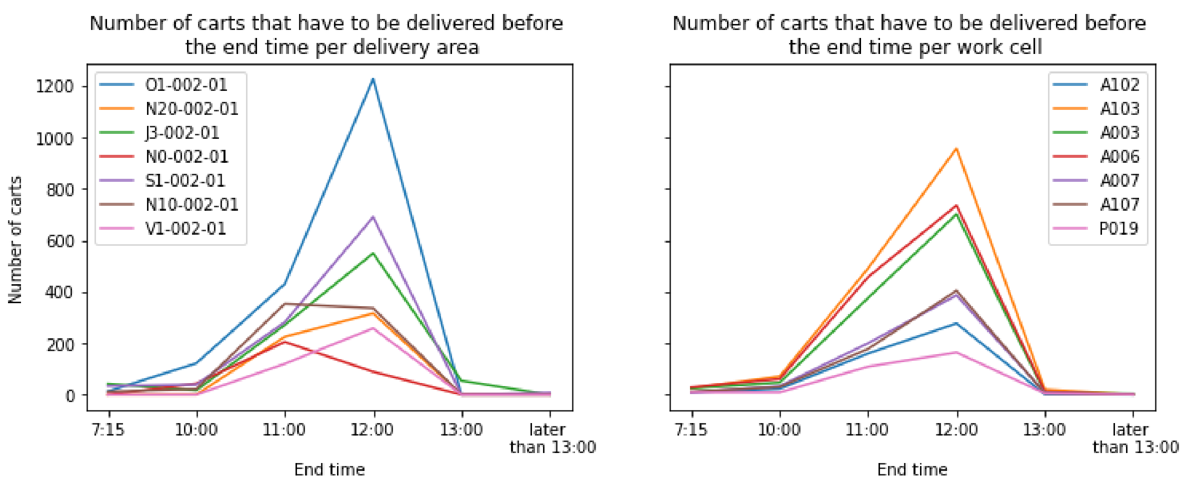


Figure 4.19: Number of carts that have to be delivered before the end time per delivery or work area Monday, October 23rd

Something else that stands out is that, relatively speaking, the number of carts that are too late per delivery area corresponds with the number of carts expected per end time (Figure 4.20). The same analysis was done for the work areas and, as a logical result from the delivery areas, the peak is again at 12 PM. What stands out is that the A003 work area does it worse than other work areas that must deliver more before 12 PM. However, this has not been a reoccurring issue over multiple (Mon)days.

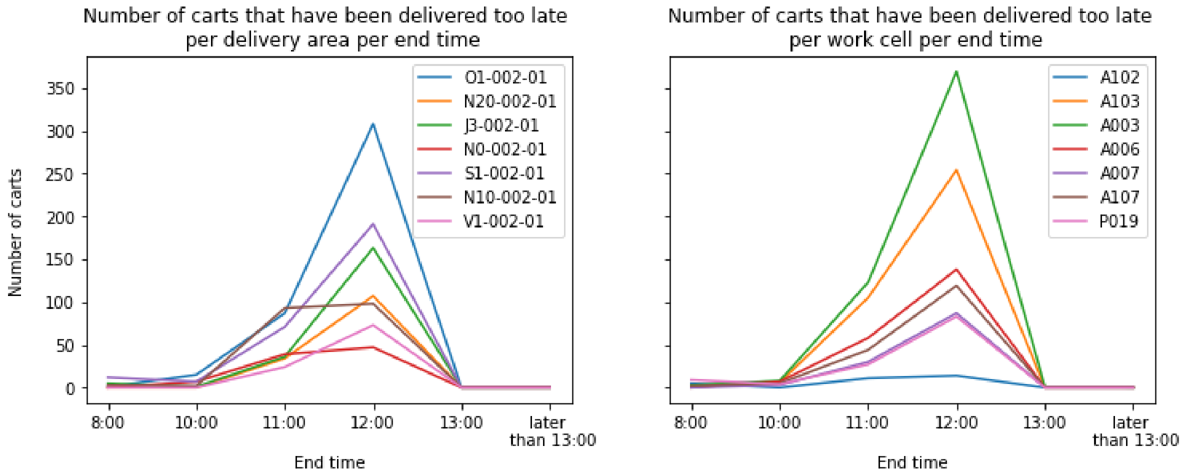


Figure 4.20: Number of carts that are delivered too late per delivery or work area Monday, October 23rd

Looking at Figure 4.21, the average lead time per delivery area per 15 minutes differs between different delivery areas. The delivery time, the time it takes to drive from the delivery or dedicated buyer track to the buyer, differs since some areas are further away than others. Another visible aspect is that the delivery time is sometimes higher and sometimes lower. This could be because of more traffic and, thus, some slight congestion, that a buyer is located at the beginning or the end of the buyer area, or that the deliverer needs to visit multiple buyers instead of one.

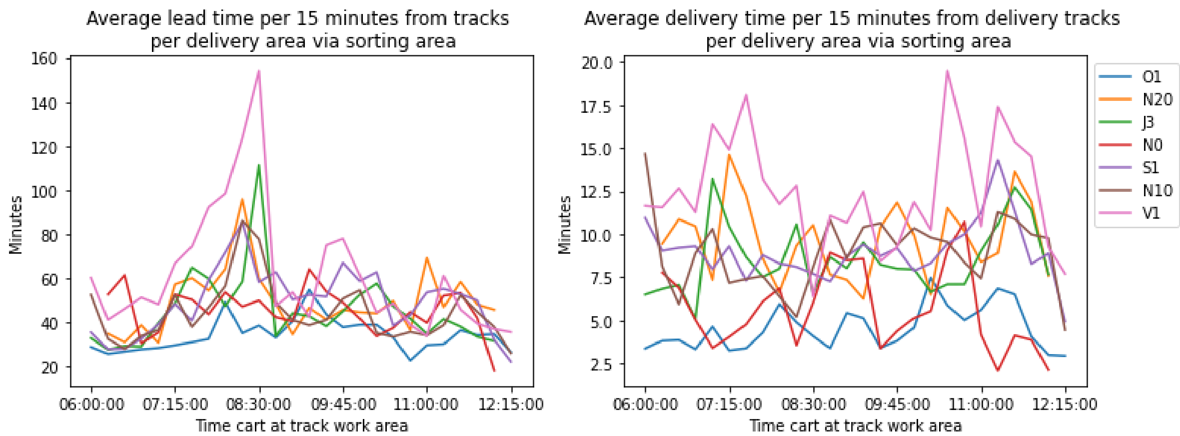


Figure 4.21: Lead time and delivery time per delivery area Monday, October 23rd

The average delivery time per fifteen minutes is relatively constant, and the spread in delivery time is negligible. Figure 4.22 shows the delivery times from the sorting area. This is the data of all areas combined. Thus, in its most extreme case, it differs from only a few minutes to thirty minutes. This was expected from Figure 4.21. It can be concluded that the delivery time is predictable.

Figure 4.22: Delivery time to all delivery areas from sorting area Monday, October 23rd

When looking at the waiting time per fifteen minutes per delivery area (Figure 4.23), the same pattern is visible as in Figure 4.21. This means the waiting times are responsible for a long or short lead time.

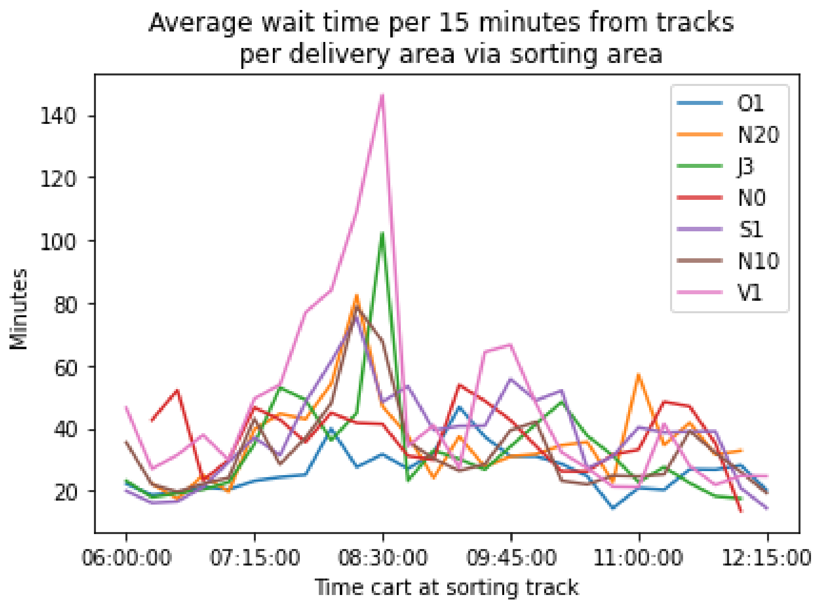
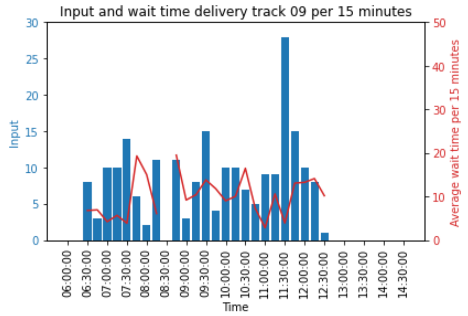
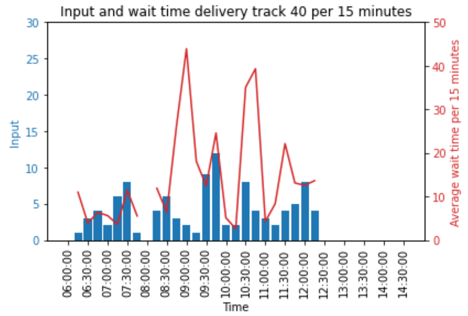


Figure 4.23: Waiting time per delivery area Monday, October 23rd

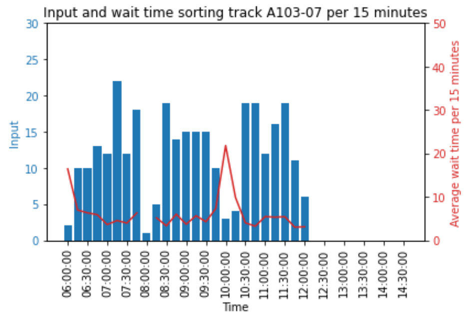
In addition, there is a distinction between delivery tracks, which process more carts during a day and delivery tracks, which process fewer carts. Figure 4.24a shows the input and average waiting time for delivery track 09, which must be delivered in area O1. Almost every fifteen minutes, a full train is on the track. On the same day for delivery track 40, which has to be delivered in delivery area V1, the input per fifteen minutes is much lower, and the average waiting time is significantly higher than for track 09. This results from the rule that each deliverer has to take the longest train from the delivery tracks. The same trend is visible at the tracks in the track areas (Figure 4.24c and 4.24d).



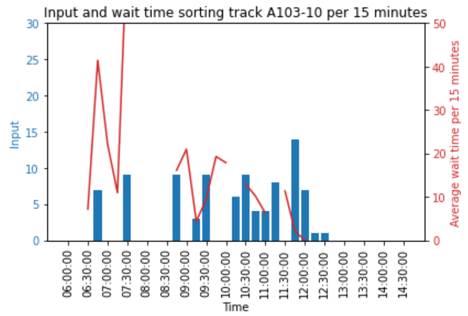
(a) Input and average waiting time per 15 minutes delivery track 09 (delivery area O1)



(b) Input and average waiting time per 15 minutes delivery track 40 (delivery area V1)



(c) Input and average waiting time per 15 minutes track A103-07 (delivery area O1)



(d) Input and average waiting time per 15 minutes track A103-10 (delivery area V1)

Figure 4.24: Input and average waiting time delivery tracks and tracks after order picking Monday, October 23rd

Conclusion data analysis

- The order-picking process performs constantly
- Often, an order is sent to an order picker too late, which makes it challenging to deliver that order on time
- The current output of the order-picking process is too low to deliver all orders on time
- The in-house delivery lead time, and thus the total lead time, is very unpredictable and is, on average, higher on busy days compared to slow days
- On average, most of the total lead time of the in-house delivery process is spent waiting on the sorting or delivery track
- The spread in lead time of the in-house delivery process has something to do with the difference in input per track and the managing of which train to take first

4.4. SWOT analysis

A SWOT analysis can be done from the results of everything investigated so far. As explained in Section 2.1, this is a method where the strengths, weaknesses, opportunities, and threats of a process are discussed. The outcome of the SWOT analysis is presented in Figure 4.25.

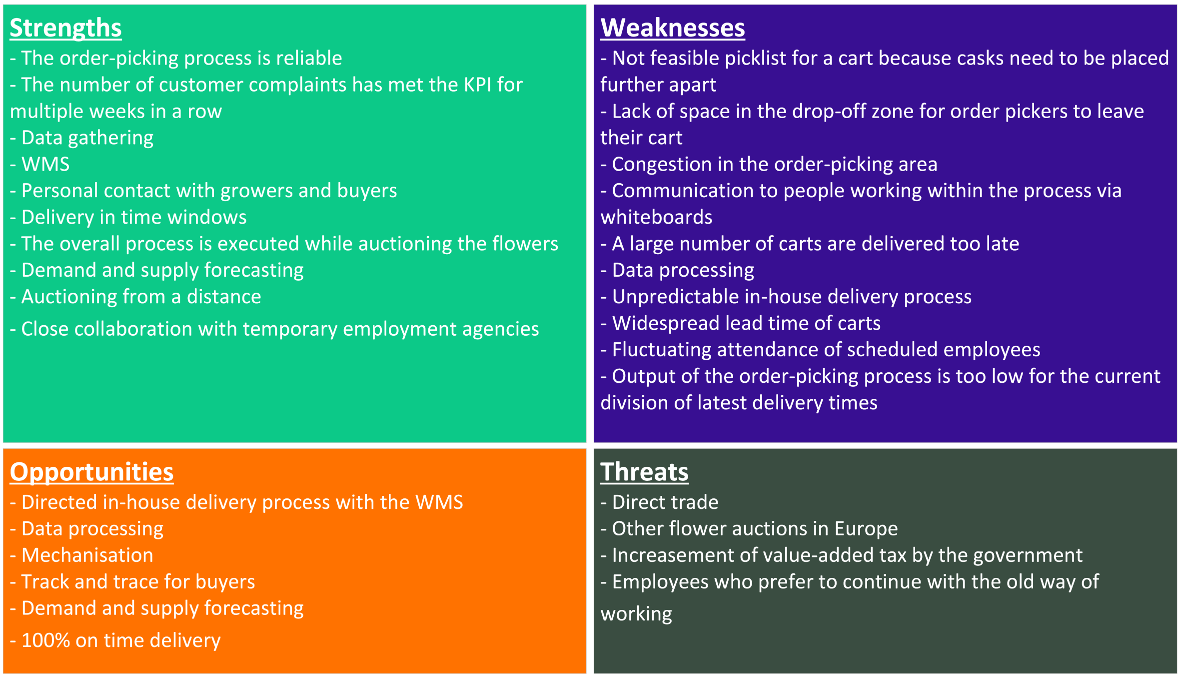


Figure 4.25: SWOT analysis of order-picking process and in-house delivery process

Strengths

- The order-picking process is reliable

During the data analysis, it was found that the time that an order picker needs for one order is very stable and does not fluctuate much between different days. This means that the order-picking process is reliable.

- The number of customer complaints has met the KPI for multiple weeks in a row

When RFH first switched to the order-picking process, there were a lot of customer complaints, and the KPI of a maximum of 0.05% complaints from all orders was easily exceeded. RFH managed to lower the number of customer complaints and keep it within KPI boundaries for location Naaldwijk.

- Data gathering

As explained in Section 4.1, a lot of data is gathered while executing both processes. This data can be used for analysis to improve the overall process further and give people a better understanding of what is happening.

- WMS

RFH uses the WMS by BlueYonder. With such a WMS, keeping track of incoming and outgoing flowers becomes easier. A WMS also allows real-time dashboarding and enough other statistical data.

- Personal contact with growers and buyers
It is essential for RFH to get along well with the growers and buyers connected to the auction. RFH keeps close contact with all their growers and buyers so that their wishes and feedback are also considered. Without the growers and buyers, RFH would not exist.

- Delivery in time windows
To allow buyers to set up their processes as preferred, RFH decided to start working with time windows. Buyers can now choose when they prefer to have their flowers delivered.

- The overall process is executed while auctioning the flowers
This is where RFH distinguishes itself from other warehouses or distribution centres. Where other companies wait for a customer to finish their order, RFH starts with order picking and delivering while the auction is ongoing. This means buyers can have their flowers delivered early, but it is also responsible for some logistical challenges.

- Demand and supply forecasting
To create a planning, RFH tries to make a forecast of the supply and the number of transactions. This allows them to predict the number of employees needed per task or work area and the time that the overall process is finished.

- Auctioning from a distance
By allowing buyers to place orders at a location of their choice, buyers no longer have to come to Naaldwijk to buy flowers from there. This saves the buyer time and RFH itself. Since fewer buyers are physically present, fewer buyers request to see products before the auction starts. This means that most products no longer have to be stored at a fixed location but can be stored in a place that is more convenient for the overall process.

- Close collaboration with temporary employment agencies
This collaboration allows RFH to expand the number of employees on a particular day in addition to their permanent employees. By increasing the number of employees, carts can be delivered earlier in the day. At the same time, RFH does not pay for the extra employees on less busy days when they are not required.

Weaknesses
- Not feasible picklist for a cart because casks need to be placed further apart
Since this happens, the number of carts produced by the order-picking process is higher than the number of carts expected by the WMS. A higher number of carts means that the order-picking and in-house delivery processes will take longer.

- Lack space in the drop-off zone for order pickers to leave their cart
As mentioned earlier in this chapter, order pickers will leave the cart in front of the corresponding track in the drop-off zone. It does occur that too many carts are dropped for the preparers to place them on the tracks, and everything becomes disordered. When the situation worsens, the order-picking process must be stopped temporarily, and valuable time is lost.

- Congestion in the order-picking area
Congestion slows down the order pickers, which has a negative influence on their productivity. A lower productivity means that the final result will differ from what has been expected based on the planning.

- Communication to people working within the process via whiteboards
Most communication with the people working within the process occurs via whiteboards placed at different positions. This means that people only get the information if they pass one of the whiteboards, and even then, they have to remember to look at the whiteboard. This means there could be a delay in providing and receiving information for employees.

- A large number of carts are delivered too late
As explained during the data analysis, many carts are delivered too late, especially on busier days. RFH finds delivering on time one of the most critical aspects of their process.

- Data processing
As discussed in the strengths, RFH's data is good. However, they are still having some issues interpreting and processing it. This means that data available to everyone within the company might not be entirely correct.

- Unpredictable in-house delivery process
The waiting time of carts at different moments during the in-house delivery process is very long and also varies a lot. This makes the in-house delivery process very unpredictable.

- Widespread lead time of carts
The widespread lead time per cart is a cause of the previous point. So again, it makes the overall process very unpredictable.

- Fluctuating attendance of scheduled employees
Almost every day, some employees do not show up for any reason, or employees are scheduled when they should not have. This means that there is a lower number of employees available than what was expected by the planning department. A lower number of employees means a slower overall process in general. Thus, another factor that makes it more difficult to say beforehand when the overall process is finished.

- Output of the order-picking process is too low for the current division of latest delivery times
As presented in Figure 4.14, the current output of the order-picking process is too low when using a required time of one hour for the in-house delivery process. This means that, regardless of other changes, not all carts will be delivered on time.

Opportunities
- Directed in-house delivery process with the WMS
The order-picking process is directed. This means that the WMS decides which order is next based on priorities entered by RFH. Order pickers receive the information about what to do on their scanner. This is different for the in-house delivery process. Here, people operate based on what they think is the best action and on experience. This makes it very hard to reach an optimal process. An opportunity thus lies in creating a directed in-house delivery process.

- Data processing
As mentioned, one of the weaknesses is the processing of gathered data. When improving this, better and more accurate analysis can be done to improve the overall process further.

- Mechanisation
At this moment, every action is done by humans. Humans are error-prone, slowing down the process and making it more unpredictable. By looking at opportunities to replace specific

actions taken by humans with actions taken by machines, the process could become more reliable.

- Track and trace for buyers
When tracking their flowers, updates of a more accurate forecast of the delivery time can be given. It becomes easier for buyers to suit their processes to the one of RFH.

- Demand and supply forecasting
As discussed earlier, RFH already uses such forecasting. However, they are still looking for the best way to do so since the forecasted numbers do not always correspond with the actual numbers. When the forecasts become more reliable, the planning is also better.

- 100% on time delivery
It should be possible to deliver all orders before the required delivery times. More time and effort are needed to reach this goal, and the other KPIs must be kept in mind while achieving this.

Threats
- Direct trade
The current overall process has been designed with the idea that most carts are auctioned. If growers and buyers are unhappy with how the overall process is executed with auction products, there is a chance that more of them will switch to direct trade.

- Other flower auctions in Europe
When other flower auctions in Europe want to grow, they need to compete with the current process at RFH. This means that other flower auctions nearby can always become a bigger competition than they are now.

- Increasement of value-added tax (VAT) by the government
If the government decides to increase the VAT for flowers, the flower sector will come under pressure to keep its costs low. It might be that, because of this, the requirements of growers and buyers change. This could result in a change in the overall process. Another possible effect is that many growers and buyers will stop their business because it has become too expensive. Then RFH needs to review everything and see where there is a future for them.

- Employees who prefer to continue with the old way of working
To make the order-picking process and in-house delivery process a success, changes are necessary. This means that all employees must be on board with all the changes. If employees are unwilling to work via the new ways, the overall process might not be as efficient as possible.

4.5. Summary

A lot of information was gathered to analyse the current state. First, the processes were mapped separately to create a clear overview of what every actor involved does and what steps are taken during the processes. From this part of the analysis, it has been concluded that the order-picking and in-house delivery processes are very dependent on each other since one output is the input of the other. Therefore, when the in-house delivery process is executed slower than the order-picking process, carts might build up in the track areas, and the order-picking process has to wait before they can restart. The other way around would also result in an undesirable situation where employees working in the in-house process would have to wait for something to do. Both situations cost RFH time and, thus, money. It was found that numerous actors are involved in the process and that communication between them can be challenging since there are so many employees. To try and manage everything well, there is a meeting with managers every morning to see what can be done to improve the overall process for that day. However, meeting once or twice for a whole day might not be enough communication between departments to execute both processes well aligned. In addition, the two sub-processes are seen as separate processes, resulting in different opinions about the best decision.

The leading actor in the order-picking process is the order picker. This employee is responsible for collecting the order from the buyer and placing the cart ready so that the in-house delivery process can pick it up. The data analysis showed that the order-picking process is a steady process where the order-pick times do not fluctuate much. The only major issue is that the current output of the process is not high enough to produce the required carts so that everything can be delivered before the latest delivery time.

More problems were found in the in-house delivery process. Multiple actors are involved, and they need to execute specific tasks. This makes it more challenging to manage the process well. Where order pickers use a scanner that tells them which order to collect, actors in the in-house delivery process must make decisions themselves. According to data analysis, this results in long waiting times on tracks. No specific work areas, delivery areas or tracks have been found where the problem originates. This implies that the problem is the general control of the in-house delivery process. Opportunities found during the SWOT analysis are a directed in-house delivery process, improvement of the data processing, and others. These are means that could improve the performance of the overall process.

As mentioned in the introduction of this chapter, an answer will be provided to the first sub-research question from Section 1.3. The sub-research question answered in this chapter is: What is the step-for-step execution of the current processes at RFH, how are they connected, and what are their main strengths and bottlenecks? This question has been answered by first describing both processes with a swimlane diagram. The processes are connected since the order-picking process has carts as output, which are the input of the in-house delivery process. Additionally, managers from both processes have contact with each other during the execution of the overall process to ensure everything runs as smoothly as possible. The strengths and bottlenecks have been described during the data analysis and SWOT analysis, where the main bottleneck is the unpredictable waiting times. The next chapter will explain what is needed for both processes to better guide the in-house delivery process and align both processes well.

5 Design

This chapter will describe the design phase, resulting in final advice for RFH about improving their overall process. Thus, sub-research questions 3 and 4 will be answered (Section 1.3). The requirements will first be discussed, followed by functions. After establishing those, different changes will be ranked based on the requirements. KPIs have been introduced from the literature and RFH themselves. This chapter will explain the KPIs that will be considered for the final design. After all this, a conceptual design will be proposed and evaluated based on the KPIs. After evaluating the conceptual design, the final design will be presented with a new swimlane diagram and VSM to compare the design easily to the current situation.

5.1. Requirements

According to the five-stage design process of Dym et al. (2014) explained in Section 2.1, part of the problem definition is identifying objectives, constraints and functions. This section will present those requirements. All objectives and constraints for the order-picking and in-house delivery processes are presented in Table 5.1. The table is split into functional constraints, non-functional constraints, functional objectives, and non-functional objectives (van Binsbergen, 2021).

Table 5.1: Constraints and objectives

Functional constraints	Non-functional constraints
1. The order-picking process must produce the correct (number of casks and type of flower) orders as output 2. The in-house delivery process must deliver orders to the right customer 3. The overall process must ensure the quality of the flowers 4. The overall process must deliver orders to buyers before the required delivery time 5. The overall process must leave room for employees to have their breaks	1. The overall process must be safe for all employees working within it 2. The overall process must be able to handle enough carts per 15 minutes to handle the peak days well 3. All steps in the overall process must be executed as designed

Functional objectives	Non-functional objectives
1. The order-picking process would preferably keep the expansion factor (Section 4.3.1) as low as possible 2. The overall process would preferably be able to deal with changes during the process 3. The overall process would preferably be able to be updated in the future	1. The lead time of the in-house delivery process would preferably be as low as possible 2. The total costs of the overall process could preferably be kept to a minimum 3. The performance of employees could preferably be tracked 4. Tasks in both the order-picking process and in-house delivery process are preferably understandable for all employees executing that task 5. Human mistakes are preferably be kept to a minimum

5.2. Functions

Based on the current state analysis from the previous chapter, numerous ideas will be presented in this section to improve the overall process. Those have been acquired during the current state analysis and by talking to experts. The ideas will be given as functions. Belonging to those functions are different means. Means should help reach the goal of the function. The functions and means discussed have been selected based on the current state analysis and during discussions with process experts. An overview of all functions and their possible means are given in Table 5.2. The functions that will be introduced are:

- **Continuous flow:** When aligning the input and output for each step in the process, there should be no bottlenecks. No bottlenecks would mean a constant and reliable flow from start to end.
- **Filling and emptying of sorting and delivery tracks:** How tracks are filled with carts greatly influences the process. If there are too many tracks, delivering those carts on time and obtaining long trains is hard. If there are too few tracks, the number of carts will probably exceed the capacity of the tracks before a train is moved to the next location.
- **Management of each step in the overall process:** Employees need to be managed to know which products to move where and at which moment. Management can be both directed and undirected. A directed way means that employees receive detailed instructions via, for example, a WMS (e.g. which exact train to take to which location). An undirected way of working is that employees follow specific rules (e.g. take the longest train).
- **Communication to employees:** Communication to employees occurs when employees are told about their next task or when they need to switch to a different role in the process. Also, breaks are communicated daily since it depends on the total time of the process, how many breaks there are and how long they are.

Table 5.2: Overview of functions with possible means

Function	Currently	Mean 1	Mean 2	Mean 3	Mean 4	Mean 5
Continuous flow	Highest output of the order-picking process as possible, switch people around to where help is needed	Capacity of each step in the overall process	Distribution of breaks	Distribution of employees		
Filling and emptying of sorting and delivery tracks	Tracks per delivery area, directed buyers go via waiting area, no limited waiting time on tracks, take the longest train	Limiting number of tracks in work area	Limited waiting time on a track	Clustering of delivery tracks	Direct delivery to the large buyers	Combining trains from not busy delivery tracks
Management of each step in the overall process	Managers physically present	Cameras present in each work area	Live dashboarding	Directed management from the WMS		
Communication to employees	Whiteboard	Traffic lights	Displays	Headphone	Scanner	

Based on the constraints from Table 5.1, all means should be possible. However, some things must be taken into account, such as that not all employees understand the Dutch language, so communication must be done in a way that everyone understands it. A short explanation of each of the means:

1. The same output per hour as input per hour for each step in the overall process

   (a) **Highest output of the order-picking process as possible, switch people around to where help is needed:** At this moment, the order-picking process tries to be finished as soon as possible without keeping in mind what kind of influence that could have on the rest of the overall process. At the same time, team leaders can request their employees to work in a different area or function to improve the flow.

   (b) **Capacity of each step in the overall process:** Limiting the capacity at certain steps so that no bottlenecks will occur elsewhere might improve the average lead time. At the same time, the capacity of each step should preferably be high enough so that all orders will be delivered on time.

   (c) **Distribution of breaks:** Making sure that all employees take their break on the time that has the least influence on the overall process could be beneficial for the overall performance.

   (d) **Distribution of employees:** For each number of carts per time unit, a different number of employees is needed for order picking, tugging, sorting, and delivering. Finding the correct distribution might improve the flow of the overall process.

2. Filling and emptying of sorting and delivery tracks

   (a) **Tracks per delivery area, directed buyers go via waiting area, no limited waiting time on tracks, take the longest train:** Currently, tracks in the track area are divided per delivery area and the trains for dedicated buyers are moved to a waiting area before delivery. No one tracks how long a cart waits at a certain place. Only the train length and latest delivery time are the determining factors.
   (b) **Limiting number of tracks in work area:** From the CSA, it follows that trains are often taken while the train is not close to the maximum train length. Because of this, more movements are needed. The train length will increase when the number of tracks in a work area is limited.
   (c) **Limited waiting time on a track:** Another thing found in the CSA is the spread waiting time on tracks. By working with a limited waiting time, the spread in those times should decrease and the overall performance should be more reliable and better predictable.
   (d) **Clustering of delivery tracks:** Something already done at the location Rijnsburg is creating clusters of the delivery tracks. In Rijnsburg, the criteria is not that one track needs to be full with the maximum train length but that several tracks must be combined. For example, if tracks 1 to 5 all go in one direction, it is waited until the tracks combined have enough carts on them. The trains from the different tracks are combined and taken to the buyers.
   (e) **Direct delivery to the large buyers:** Instead of moving trains for large buyers from the tracks after order picking to the dedicated buyer tracks, trains for large buyers are now directly delivered to the buyers. This way, the waiting time on a track for carts for large buyers can be increased.
   (f) **Combining trains from not busy delivery tracks:** When multiple trains have to be moved to the next step in the process and the combined number of carts is less than the maximum train length, one employee can take both trains. As a result, another employee who would have taken the second train can now perform another task.

3. Management of each step in the overall process

   (a) **Managers physically present:** When managers are physically present on the floor, they can see what happens in real life at that particular location in the process and interfere immediately when necessary.
   (b) **Cameras present in each work area:** By placing cameras in all the areas, managers and coordinators have a broader overview of what is happening than when they are walking around. If they see something abnormal, they can interfere.
   (c) **Live dashboarding:** With live dashboarding, it should be possible for managers and coordinators to keep track of what is happening based on real-time data. When they see that a specific output is getting too high for the next step to process, for example, they can slow down that part of the overall process or shift employees from one position to another.
   (d) **Directed management from the WMS:** One way to manage all employees is by letting the WMS decide which task is performed next based on set priority rules.

4. Communication to employees

   (a) **Whiteboard:** Via whiteboards at different locations, employees can be informed about breaks, if empty carts are needed and other issues.
   (b) **Traffic lights:** Traffic lights above tracks can indicate if the train on that track has a high, middle, or low priority. This way, employees can take the train with the highest priority.
   (c) **Displays:** Displays at different locations in the process work the same as whiteboards; only displays can be updated from one central location.
   (d) **Headphone:** Employees can be instructed about their next task via headphones. This would have to be managed from a central control room.
   (e) **Scanner:** A scanner can provide employees with information about what to do and where to go. If an employee scans a certain location, the software in the scanner knows how far along in the process the employee is and when to give that employee the next task.

5.3. Ranking of objectives and functions

The objectives from Table 5.1 are ranked on the importance of the objective, and weights have been assigned to each objective based on the ranking (Table 5.3). This ranking was done based on the information gathered during the current state analysis and was approved by employees of RFH in December 2023. The highest in the ranking is that the lead time of the in-house delivery process is kept to a minimum, and the lowest is that the performance of employees could be tracked.

Table 5.3: Weighted objectives

	Objective	Weight
FO1	The order-picking process would preferably keep the expansion factor (Section 4.3.1) as low as possible	5
FO2	The overall process would preferably be able to deal with changes during the process	3
FO3	The overall process would preferably be able to be updated in the future	2
NFO1	The lead time of the in-house delivery process would preferably be as low as possible	8
NFO2	The total costs of the overall process could preferably be kept to a minimum	7
NFO3	The performance of employees could preferably be tracked	1
NFO4	Tasks in both the order-picking process and in-house delivery process are preferably understandable for all employees executing that task	6
NFO5	Human mistakes are preferably be kept to a minimum	5

All means presented in Table 5.2 are ranked with the weighted objectives from Table 5.3. The outcome of this ranking can be found in Table C.2, C.3, C.4, and C.5. The scores given to each objective for each mean are explained in Table C.1. The sum is the weight of that objective multiplied by the score of that objective for that mean and summed over all objectives for that mean. Based on those sums for each mean, a design will be discussed in Section 5.5. The means with the highest score are the distribution of employees, limited waiting time on a track, directed management from the WMS and scanner.

5.4. KPIs

KPIs have been introduced in the literature review (Section 3.3) and in the CSA (Section 4.3.1). Some KPIs from the literature and currently in place at RFH overlap. Table C.6 has created an overview containing all mentioned KPIs. The table also explains if a KPI will be used to measure the performance of a proposed design. The KPIs that will be used for the design are displayed in the box below.

KPIs to measure design performance

- Percentage of orders that are delivered on time
- Lead time of the overall process
- Total distribution cost (measured in required work hours)

5.5. Design options

The design must consist of the means with the highest score (Appendix C), thus:

- **The same output per hour as input per hour for each step in the overall process:** Distribution of employees
- **Filling and emptying of sorting and delivery tracks:** Limited waiting time on a track
- **Management of each step in the overall process:** Directed management from the WMS
- **Communication to employees:** Scanner

A model is created in Python, which calculates the required number of employees and the end time of the process when implementing the limited waiting time. A more detailed description of the model will be given later. Since the limited waiting time is expected to negatively influence efficiency (less waiting time will probably result in shorter trains and thus more employees to move all the trains), other alternatives are created to increase the efficiency of the overall process again. An overview of the alternatives can be found in Table 5.4, and a detailed description of the final model can be found in Appendix D.

Since the current situation depends on human decisions and only a small part of the employees abide by the rules, no case is created of the current situation to validate the model. Because the main issue in the in-house delivery process is the large spread in waiting times, it has been decided that a new situation will be considered the base model with limited waiting time on tracks in the track area and delivery or dedicated buyer area.

The experimental set-up will consist of different alternatives. Those alternatives separately only change part of the original process. Therefore, it has been decided to first experiment with the various alternatives and combinations (scenarios). Thereafter, a swimlane diagram and VSM will be created for the final design to make a proper comparison to the current situation.

Table 5.4: Overview of different alternatives

Nr.	Mean	Assumptions	Input	Description
1	Limited waiting time on track **(base model)**	- Cart is ready to be picked up from track as soon as a track is scanned by order picker or sorter - Waiting time is a parameter set to 15 minutes for tracks after order picking and 15 minutes for delivery tracks - Parameters for tugging and driving back have been based on real measurements - The number of employees calculated is the number needed without breaks - Employees can switch each half an hour between different tasks - Employees work directed - All tuggers can go to all work areas - All deliverers can go to all delivery areas - There is no buffer anymore in the sorting area since enough employees will be present - The time in the sorting area is a constant based on real measurements - The delivery time and the time for a deliverer to return is based on real measurements - There is no limit on employees	Data of order-picking process output of day in the past	This alternative uses the output of the order-picking process as on a day in the past. Then, new trains are formed from the known output based on the maximum train length or the maximum waiting time. These trains are moved to the sorting area or dedicated buyer tracks based on the known driving times and then put through the sorting process. From here on, new trains are formed on the delivery tracks where a new limit for waiting time is used again. The number of tuggers and deliverers is calculated based on the time it takes to do a full round and the number of trains ready to leave the track.

2	Capacity of each step in the overall process	- The output of the order-picking process per fifteen minutes can be controlled easily - The output for the first fifteen minutes of the process is limited because of starting up the process - The output during breaks is set to half the output of a normal fifteen minutes	Data of order-picking process output of day in the past	The alternative uses the same output order from the order-picking process on a certain day. Then, the output is grouped by several orders. During the first fifteen minutes, a certain number of orders will be the output, and so on. The orders are equally distributed over the fifteen minutes to which they belong. After rearranging the orders, the base model uses the same approach.
3	Limiting number of tracks in work area	No extra assumptions have been made.	Data of order-picking process output of day in the past	This alternative uses the same input as the base model. The new aspect is that tracks, where order pickers drop their carts, are now combined. The combination is based on delivery areas. Two options have been created (Appendix C). The first option divides the sorting area into four parts, where it is now seven, and the second option divides it into three options. The combination of tracks is done by simply changing the track number in the data set, e.g. if tracks 2 and 4 need to be merged, the track number of 4 is changed to 2.
4	Direct delivery to the large buyers	- Deliverers are directed in such a way that they know beforehand if they need to go to the sorting area or one of the work areas - The waiting time for dedicated buyers in the track area is now set to 30 minutes	Data of order-picking process output of day in the past	This alternative uses the same input as the base model. However, trains for large buyers are no longer moved to the dedicated buyer tracks; instead, they are immediately delivered to the buyer. To ensure that the train is as long as possible, the waiting time on the track is set to thirty minutes instead of two times fifteen minutes, as in the base model.

5a	Combining trains from not busy delivery tracks	- If a train is taken a little earlier than the required leaving time to be combined, the assumption has been made that the train length at that moment is the same as during the required leaving time - Only trains that have to go to the same delivery area can be combined	Data of order-picking process output of day in the past	In the sorting area, trains that together still comply with the maximum train length are combined to be taken to the buyers together. The parameter for the maximum difference in required leaving time is set to 2 minutes. Trains for dedicated buyers are not combined.
5b	Clustering of delivery tracks	- The tracks within a cluster should go to the same delivery area - The tracks within a cluster should be next to each other	Data of order-picking process output of day in the past	Instead of looking per delivery track if the maximum train length or maximum waiting time is reached, this is done per cluster (a couple of tracks combined). Two different ways of clusters are tested: the first type creates 19 clusters out of the 44 delivery tracks, and the second option creates 12 clusters out of the 44 delivery tracks (Appendix C).

5.6. Experiment

This section will describe the experimental setup. After explaining the setup, the base model is validated and verified. Finally, results are presented from the model with its different alternatives.

5.6.1. Experimental set-up

The performance of the different alternatives will be tested using the new base model. Each alternative will be separately added to the model to find the influence on the new base model. The input for the model will be the sequence of the output of the order-picking process in the past. An example of a few lines of this output is given in Figure 5.1. The figure shows per cart when an order picker started with it, when the last pick was done, when the cart was dropped in the drop zone, when a cart was picked up from the track area, when it was dropped in the sorting area or at a dedicated buyer cart, when a sorter scanned it, when it was put on a delivery track, when a cart was taken from a dedicated buyer track or delivery track, and finally when it was delivered at the customer. The locations are visible in the last three columns. The data is sorted in the column 'Grof sorteer scan'. This way, the list is in the same sequence as carts were ready on the track after order picking on that day.

Datum	PicklijstID	Ladingdra	Acceptati	Einde Pick	Grof sorte	Pick up gro	Drop Fijn s	Pick up Fijn	Drop aflever	Pick up 3	Drop 3	Aflevertijd	DLT Grof s	DLT Fijn s	Loc. Grof s	Loc. Fijn s	Loc. Aflev	Loc. 3
23-10-2023	2023102	80030871	06:03:03	06:03:37	06:04:28	06:35:05	06:35:36	06:38:06	07:07:32			07:10:42	30,6167	2,5	A107-003	J0-002-27	S1-002-01	
23-10-2023	LST00000	80030871	06:03:49	06:06:34	06:07:37	06:35:07	06:39:32	06:42:02	06:42:22	06:43:30	06:49:38	06:50:39	27,5	2,5	A107-003	J0-001-01	J0-002-20	J3-002-01
23-10-2023	LST00000	80030871	06:03:08	06:06:10	06:07:49	06:34:21	06:34:41	06:35:57	06:48:21			06:48:56	26,5333	1,26667	A107-003	J0-002-25	S1-002-01	
23-10-2023	LST00000	80030871	06:05:24	06:06:48	06:08:19	06:29:34	06:31:07	06:31:48	06:38:42			06:39:29	21,25	0,68333	A103-001	J0-002-93	J3-002-01	
23-10-2023	LST00000	80030871	06:04:46	06:07:21	06:08:27	06:25:33	06:28:14	06:29:28	06:29:40	06:32:09	06:35:15	06:36:05	17,1	1,23333	A103-001	J0-001-01	J0-002-08	O1-002-0
23-10-2023	LST00000	80030871	06:04:59	06:07:40	06:08:30	06:28:22	06:31:54	06:43:10	06:43:21	06:49:16	07:04:08	07:04:57	19,8667	11,2667	A107-003	J0-001-02	J0-002-35	N10-002-
23-10-2023	LST00000	80030871	06:06:25	06:07:39	06:08:31	06:26:13	06:27:41	11:32:20	11:32:41	11:41:24	11:45:55	06:39:57	17,7	304,65	A006-003	J0-001-01	J0-002-39	N10-002-
23-10-2023	LST00000	80030871	06:06:25	06:07:39	06:08:31	06:26:13	06:27:41	06:30:57	06:31:33	06:33:39	06:39:38	06:39:57	17,7	3,26667	A006-003	J0-001-01	J0-002-95	S1-002-01
23-10-2023	LST00000	80030871	06:05:09	06:07:43	06:08:51	06:35:07	06:39:32	06:42:16	06:42:38	06:46:54	06:52:57	06:53:49	26,2667	2,73333	A107-003	J0-001-01	J0-002-19	J3-002-01
23-10-2023	LST00000	80030871	06:04:45	06:07:59	06:09:05	06:34:59	06:38:51	06:40:11	06:40:43	06:41:49	06:44:28	06:45:04	25,9	1,33333	A107-003	J0-001-01	J0-002-08	O1-002-0

Figure 5.1: Example of input data Monday, October 23rd (output order-picking process)

The data just described is linked to another dataset. This dataset contains information about the latest delivery time per cart and when the last item on the cart was auctioned.
After the data is put in the model, the model will overwrite the current timestamps with the timestamps that will occur when using the new alternatives. The description per alternative has been provided in Table 5.4. In some cases, the location was not correctly stored. A location is then assigned based on the track scanned by the order picker. Since it is a model, configuration parameters must be set (Table 5.5). The working of the final scenario will be discussed in Section 5.7.

Table 5.5: Configuration parameters

Parameter	Value	Explanation
Maximum waiting time without direct delivery (max_wait_time_sort and max_wait_time_delivery	15 minutes	Assuming that the in-house delivery process must be finished within an hour and taking into account the time tugging, sorting and delivering take. There is half an hour left to wait. This half an hour must be spread over two locations.
Maximum waiting time with direct delivery for the dedicated buyers in the track area (max_wait_time_sort _dbt)	30 minutes	The waiting time of a maximum of half an hour can now be used in one location since the waiting area has been removed for the dedicated buyer carts.
Maximum train length (max_train_length)	14 carts	Because of safety and space limitations, the maximum train length has been set to 14 carts by RFH.
Tugging time (tugging_time_to_fine)	3 minutes	The tugging time has been measured with the data, and 75% of all trains are tugged within 3 minutes.
Return time for a tugger (return_time_tugging)	3 minutes	An employee of RFH has done measurements during the process of how long it takes to return from the sorting area to a track area.
Time in the sorting area (sorting_time)	5 minutes	Based on the measurements taken by the RFH employee during the process, moving a cart within 5 minutes from the sorting buffer to the delivery tracks should be possible.
Delivery and return time to a delivery area	50th or 75th percentile of the current delivery and return times	The current delivery and return times are measured, since it cannot be certain without extra research what a reliable driving time is, two situations have been run, the 50th and 75th percentile of the current driving times per delivery area.
Productivity of the sorting employees per 30 minutes (productivity_fine_per_30_min)	22 carts per 30 minutes	The measured productivity of the sorters over multiple Mondays is 22 carts per 30 minutes.
Capacity per 15 minutes (limit_per_15_min)	390	From the calculations in Section 4.3.2, an order-picking output of 390 carts per 15 minutes is required.
Capacity between 6:00 and 6:15 hr (limit_6_00)	80	When looking at multiple days, the first 15 minutes, about 80 carts are produced by the order-picking process due to starting the auction at 6 AM.

5.6.2. Verification and validation

Verification of the model will be done by testing the following:

- The lead time of the in-house delivery process may not exceed 60 minutes
- The train length may not exceed 14 carts

Verification has been done by running the base model for eight Mondays. This outcome is shown in Table 5.6. It can be seen that all tests are completed successfully.

Table 5.6: Verification base model

Date	Maximum lead time in-house delivery (50th percentile driving times)	Maximum lead time in-house delivery (75th percentile driving times)	Maximum train length (tugging and delivering together, and 50th and 75th percentile driving times)
02-10-'23	52 minutes	60 minutes	14 carts
09-10-'23	56 minutes	60 minutes	14 carts
16-10-'23	55 minutes	58 minutes	14 carts
23-10-'23	53 minutes	59 minutes	14 carts
30-10-'23	54 minutes	57 minutes	14 carts
06-11-'23	55 minutes	60 minutes	14 carts
13-11-'23	52 minutes	58 minutes	14 carts
20-11-'23	52 minutes	59 minutes	14 carts

As already explained, the current situation could not be simulated since too many human factors are involved. Therefore, the model cannot be validated by comparing the current situation in the model to the data gathered in the past. In addition, testing the limited waiting time is not possible in the time frame of this research. Thus, validation has taken place by discussing the model with process experts. They have agreed that the model should be feasible. However, it has been decided that some uncertainties will have to be tested before full implementation, such as the delivery times.

5.6.3. Results

It has been proven during the verification that the KPI for a lead time of a maximum of sixty minutes for the in-house delivery process is met. However, the influence on the percentage of orders delivered on time and the total distribution cost has not been discussed yet. First, the total distribution cost is investigated. This is done by calculating the required number of employees. Multiplying the highest required number of employees with the time it takes to deliver all products results in the required work hours and thus the costs for employees. This is an approximation since not every employee is present from start to end, but it is a sufficient way to compare different situations. Other necessities, such as the trucks and scanners, are already present at RFH and are therefore not included in the costs.

In the current situation, 82 employees are present in the in-house delivery process for 6 hours, 53 minutes, and 26 seconds (565 work hours). When running the model with a limited waiting time, 136 employees are required, on average, for 6 hours and 30 seconds (817 work hours). The model decreases the process time by almost one hour. However, the costs have increased. Therefore, different alternatives are added to the limited waiting time to see what influence it would have on the required number of employees. The various alternatives added are the ones introduced in Table 5.4. The outcome for the required number of employees of the new situation with limited waiting time (Nr. 1) and the different alternatives added to the new situation separately are shown in Tables 5.7 and 5.8.

The required number of employees is indicated per step in the process and in total. The script calculates the required number of employees per half an hour. The numbers presented are the maximum values found in the total duration of the process. It can occur that earlier or later, fewer employees are needed. This is also why the sum of the number of tuggers, sorters, and deliverers will not always be the same as the total number of employees required. This approach was chosen because employees have switched functions during the day.

Table 5.7: Results different alternatives added to the base model separately (50th percentile of the driving times and process time of 5 hours, 58 minutes and 30 seconds)

Nr.	# Tuggers	# Sorters	# Deliverers	# Employees total	# Work hours[1]
1	33 ($\pm$ 2)	29 ($\pm$ 4)	61 ($\pm$ 5)	119 ($\pm$ 8)	711
2	35 ($\pm$ 3)	32 ($\pm$ 1)	61 ($\pm$ 3)	122 ($\pm$ 4)	728
3.1	30 ($\pm$ 2)	30 ($\pm$ 4)	63 ($\pm$ 3)	118 ($\pm$ 7)	705
3.2	27 ($\pm$ 2)	29 ($\pm$ 4)	62 ($\pm$ 4)	115 ($\pm$ 7)	687
4	24 ($\pm$ 2)	29 ($\pm$ 4)	65 ($\pm$ 3)	116 ($\pm$ 7)	693
5a	33 ($\pm$ 2)	29 ($\pm$ 4)	52 ($\pm$ 5)	110 ($\pm$ 9)	657
5b.1	33 ($\pm$ 2)	29 ($\pm$ 4)	46 ($\pm$ 4)	106 ($\pm$ 9)	633
5b.2	33 ($\pm$ 2)	29 ($\pm$ 4)	45 ($\pm$ 4)	104 ($\pm$ 9)	621

Table 5.8: Results different alternatives added to the base model separately (75th percentile of the driving times and process time of 6 hours and 30 seconds)

Nr.	# Tuggers	# Sorters	# Deliverers	# Employees total	# Work hours[1]
1	33 ($\pm$ 2)	29 ($\pm$ 4)	78 ($\pm$ 4)	136 ($\pm$ 7)	817
2	35 ($\pm$ 3)	32 ($\pm$ 2)	78 ($\pm$ 5)	138 ($\pm$ 6)	829
3.1	30 ($\pm$ 2)	30 ($\pm$ 4)	81 ($\pm$ 4)	135 ($\pm$ 9)	811
3.2	27 ($\pm$ 2)	29 ($\pm$ 4)	79 ($\pm$ 5)	132 ($\pm$ 5)	793
4	24 ($\pm$ 2)	30 ($\pm$ 4)	81 ($\pm$ 4)	132 ($\pm$ 5)	793
5a	33 ($\pm$ 2)	29 ($\pm$ 4)	66 ($\pm$ 5)	126 ($\pm$ 9)	757
5b.1	33 ($\pm$ 2)	29 ($\pm$ 4)	59 ($\pm$ 4)	117 ($\pm$ 7)	702
5b.2	33 ($\pm$ 2)	29 ($\pm$ 4)	56 ($\pm$ 5)	115 ($\pm$ 9)	690

The results show that all of the alternatives have a positive effect based on the required work hours compared to the base scenario (Nr. 1) except for alternative 2, the capacity of the process. This is because the required output is higher than the current output. However, when changing the share of every latest delivery time to 24.5% except for the 8 AM time, the minimum output is only 330 carts per 15 minutes (Appendix C), approximately the same as the current output. The percentage of the 8 AM delivery time is not changed because it is considered unrealistic that many more buyers would like to buy flowers before the auction starts against higher rates. However, the decision has been made to focus only on what would be needed to align the in-house delivery process to the order-picking process so that everything is delivered on time without altering the order-picking process or anything before that. Thus, the required output of 390 carts per 15 minutes will be used since this output can be reached by adding order pickers without altering the process itself.

Alternatives 3 and 5b were tested with two different options as explained in Section 5.5 where the second option appears to be the better solution for both. Therefore, the second option is used for both when referring to alternative 3 or 5b. Since all the other alternatives are improvements compared to the base scenario, combinations will be tested. While creating these scenarios, the required number of work hours will be presented on Monday, October 23rd, because other days processed different volumes and are thus not comparable in this aspect because different outputs are required then (Tables 5.9 and 5.10).

[1] Only for Monday October 23rd because other days have more or less carts

Table 5.9: Results combined alternatives (50th percentile of the driving times, order picking output of 390 carts/15 minutes and process time of 5 hours, 58 minutes and 30 seconds)

Nr.	Alternative						# Tuggers	# Sorters	# Deliverers	# Employees total	# Work hours[1]	% too late[1]
	1	2	3	4	5a	5b						
1.	✓	✓					35 (± 3)	32 (± 1)	61 (± 3)	122 (± 4)	728	7.9%
2.	✓	✓	✓				30 (± 2)	31 (± 1)	62 (± 2)	119 (± 3)	711	7.9%
3.	✓	✓	✓	✓			20 (± 1)	31 (± 1)	67 (± 2)	114 (± 2)	681	7.9%
4.	✓	✓	✓	✓	✓		20 (± 1)	31 (± 1)	59 (± 1)	106 (± 2)	633	7.9%
5.	✓	✓	✓	✓		✓	**20 (± 1)**	**31 (± 1)**	**49 (± 2)**	**98 (± 2)**	**585**	**7.9%**
6.	✓	✓		✓		✓	25 (± 3)	32 (± 1)	49 (± 1)	100 (± 4)	597	7.9%

Table 5.10: Results combined alternatives (75th percentile of the driving times, order picking output of 390 carts/15 minutes and process time of 6 hours and 30 seconds)

Nr.	Alternative						# Tuggers	# Sorters	# Deliverers	# Employees total	# Work hours[1]	% too late[1]
	1	2	3	4	5a	5b						
1.	✓	✓					35 (± 3)	32 (± 1)	78 (± 5)	138 (± 6)	829	8.2%
2.	✓	✓	✓				30 (± 2)	31 (± 1)	77 (± 6)	134 (± 7)	805	8.2%
3.	✓	✓	✓	✓			20 (± 1)	31 (± 1)	84 (± 7)	132 (± 8)	793	8.2%
4.	✓	✓	✓	✓	✓		20 (± 1)	31 (± 1)	74 (± 5)	121 (± 6)	727	8.2%
5.	✓	✓	✓	✓		✓	**20 (± 1)**	**31 (± 1)**	**62 (± 5)**	**109 (± 5)**	**654**	**8.2%**
6.	✓	✓		✓		✓	25 (± 3)	32 (± 1)	61 (± 4)	113 (± 5)	678	8.2%

From the different combined alternatives, scenario 5 is the most suitable solution. This is the option where all orders are delivered before 13:00 (the latest possible delivery time), requiring the least work hours compared to the other situations. Unfortunately, there are still carts delivered too late. Currently, trains that contain a cart that has to be delivered soon are given manual priority by troubleshooters. The design does not consider that since the approach ensures every cart is in the system on time, prioritising one cart over the other after order picking is no longer necessary. A solution that could solve the problem of the remaining carts being delivered too late is revising the priority rules. Now that the process is better predictable, it should be easier to know when to push which order into the system so that it is delivered on time.

Another aspect that could influence the percentage of carts delivered too late is the auction time. The latest auction time differs per day, but on a Monday, the auction commonly goes on until around 10 AM. This means that the auction is still going, and the latest delivery time of 10 AM should not receive any new orders because it is not feasible to deliver them on time. When on a busy Monday, the auction goes on until after 10 AM, the same principle holds for the latest delivery time of 11 AM. The influence of different outputs on the required number of employees and work hours has been tested, and the results are displayed in Table 5.11.

It can be seen that the total required number of employees increases while the output per 15 minutes increases, but it will simultaneously cost the company less (work hours). Thus, a trade-off needs to be made about what is reasonable, considering the number of available employees, trucks, and scanners. The required output of 390 carts per 15 minutes will be used for now.

[1] Only for Monday October 23rd because other days have more or less carts

Table 5.11: Results different order picking output Monday, October 23rd (75th percentile driving times)

Output (carts / 15 min)	# Tuggers	# Sorters	# Deliverers	# Employees total	Done before 13:00?	End time if yes	Total duration	# Work hours	% Too late
285	19	24	50	90	N				
300	17	25	50	89	N				
315	19	25	53	95	N				
330	19	27	54	97	Y	12:43:19	06:43:19	652	18.4%
345	18	28	54	95	Y	12:32:11	06:32:11	620	15.6%
360	19	29	59	100	Y	12:24:04	06:24:04	640	12.2%
375	19	30	60	104	Y	12:12:07	06:12:07	645	9.7%
390	19	31	60	109	Y	12:00:30	06:00:30	654	8.1%
405	22	31	61	108	Y	11:53:37	05:53:37	637	6.7%

5.7. Final design

The final design, the best design according to the experimental results, will be presented with a swimlane diagram and a VSM. This way, the design can be easily compared to the current state. In addition, some graphs will be presented that show how the design will perform compared to the current situation. First, the final model will be shortly explained.

5.7.1. Model

An extensive explanation of the model is given in Appendix D. The different steps taken by the model are:

- **Input:** The model uses the output of the order-picking process from a day in the past, and different parameters have been set.
- **Step 1. New division tracks:** The current tracks are overwritten by the track according to the new division.
- **Step 2. Capacity:** The required order-picking output uses the same output sequence as the current situation. Per 15 minutes, the required number of lines is taken for that time interval and evenly distributed over that time interval. Then, the output time of the order-picking process is changed to the new time according to the distribution over the time intervals.
- **Step 3. Preparing for tugging:** With the new track division and order-picking output, waiting on the track for a train is limited by either a maximum waiting time of 15 minutes for the first cart of that train or by reaching the maximum train length. As soon as one of these constraints is met, the train is taken away by a tugger.
- **Step 4. Direct delivery to dedicated buyers:** Direct delivery takes place by assigning a deliverer to the dedicated buyer track in the track area. Instead of waiting 15 minutes, the maximum waiting time is set to 30 minutes.
- **Step 5. Creating clusters:** In the sorting area, clusters are created by grouping the tracks in one cluster.
- **Step 6. Delivering from the sorting area:** Each cluster is checked if the first cart entered is not waiting longer than 15 minutes and if the tracks combined do not exceed the train length of 14 carts. When one of these limits is reached, a deliverer takes the cluster away to the buyers.

- **Output:** The model calculates the required number of employees per half an hour, the lead time, and the number of carts delivered too late.

5.7.2. Swimlane diagram final design

The swimlane diagram is presented in Figure 5.2 with an enlarged version in Appendix E. It has been decided only to create a new swimlane diagram of the in-house delivery process since the order-picking process will not be adjusted. Compared to the current situation, one of the significant changes is that the WMS will make most of the decisions and that employees execute the tasks provided by the WMS via the scanner.

The in-house delivery process starts with information retrieved during the order-picking process. The WMS knows which carts are ready on tracks to be taken to the sorting area or directly to the dedicated buyers, but also with which amount of empty carts each work area has started and how many are already used by the order pickers. The WMS then looks at two possible tasks simultaneously for the tuggers. The WMS calculates if a track is clear where a new train of empty carts can be stored. This can be done by counting the number of carts already used because the empty carts are distributed per track. When a track is clear, a task is created for the first available tugger to get a train of empty carts and bring it to the required work area. At the same time, the WMS keeps track of the carts that are ready to be taken to the sorting area. When the maximum train length or waiting time is reached, a task is created for the next available tugger to move to that track and take the train.

The first tugger to accept the task sees if the task is to pick up empty carts or to move to the work cell immediately. If empty carts are required, the tugger moves to the empty cart buffer, takes a train of empty carts and drops them on the empty track in the work area. If empty carts are not required, the tugger moves immediately to the work area in which the train is located that needs to be moved. The tugger scans the correct track and takes the train to the sorting area. The drop-off area needs to be scanned again, and the train is left in the drop-off area.

The tugger in the sorting area is responsible for bringing the dropped trains FIFO (first in, first out) to the sorting tracks. Since there are enough sorters to handle the output of the order-picking process, no trains should be waiting for a long time before they are sorted. The only moment a train needs to wait is if multiple tuggers arrive simultaneously from a track area. For the sorters, nothing changes. They still disconnect one cart from a train, scan the cart, move the cart to the correct delivery track and scan the track when dropping the cart on it.

The scans of the delivery track made by the sorters are registered in the WMS. With those scans, the WMS tracks when a particular cluster has reached the maximum train length or waiting time. At the same time, the WMS keeps track of what is happening on the dedicated buyer tracks. Thus, if the maximum train length or maximum waiting time is reached. When a cluster or dedicated buyer track is ready so that the train(s) can be taken to the buyer(s), the WMS creates a task for the first available deliverer. The deliverer goes to either the work area or the sorting area, scans the track from which the train(s) need(s) to be taken and drives the train(s) to the buyer(s). The carts belonging to that buyer are then disconnected from the train and scanned.

It has been decided to use the same scan moments as during the current state. This is because the number of scan moments and the moments taken are sufficient to measure the system's performance. In addition, the scan moments are helpful for the WMS to know when an employee has finished a particular task and can be assigned a new one. The only time

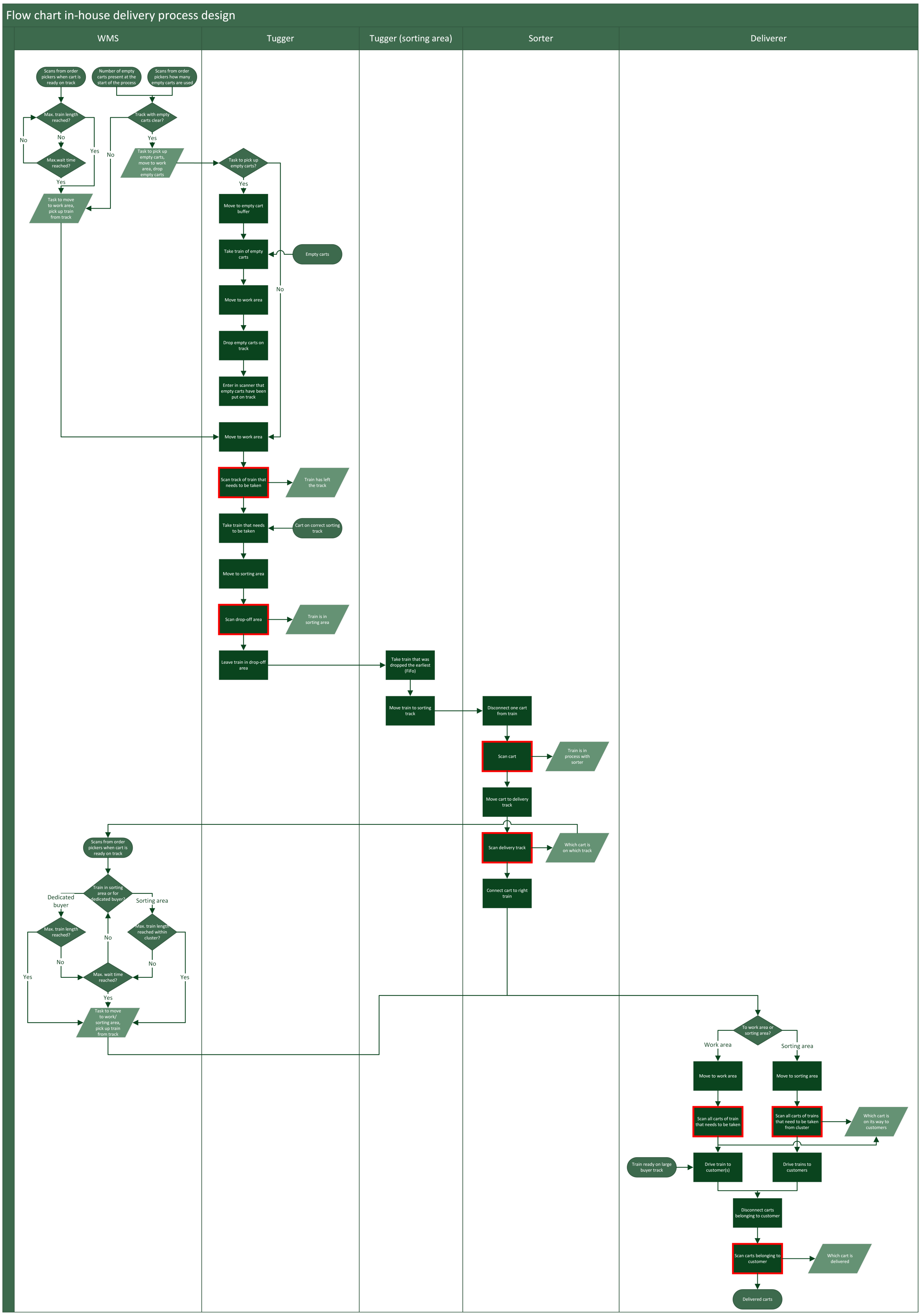


Figure 5.2: Swimlane diagram of the designed in-house delivery process (enlarged version in Appendix E)

when no scan is used is when a tugger needs to move empty carts to a work area. This problem has been solved by the tugger agreeing manually via the scanner that empty carts have been moved to the correct location. Another decision that can be made is that instead of deliverers manually saying they want a new task; deliverers have to drive to a certain point, scan a code and then receive a new task. This ensures that it is executed immediately when assigning a new task.

5.7.3. VSM final design

The VSM for the design situation is shown in Figure 5.3. In the design, the distinction has been made between carts that go via the sorting area and carts that are for dedicated buyers because the second option has half the steps compared to those that go via the sorting area. The setup of the VSM has not changed since all the steps will still be present. However, there has been a shift towards more moving time by limiting the waiting times on tracks. The moving time for the overall time is in the design around 50% while it was approximately 32% in the current state (Figure 4.12). The average lead time is slightly decreased, and the overall process has a more constant flow and is easier to predict.

5.7.4. Performance

The design performance will be scored based on the set KPIs. The KPIs to be considered for this research, as discussed in Section 5.4, are the percentage of orders delivered on time, the lead time of the overall process, and the total distribution cost. A short overview per KPI and the effect of the design on this KPI is presented in Table 5.12.

Table 5.12: Effect of design on KPIs compared to current situation

KPI	Effect	Current situation	Design
Percentage of orders that are delivered on time[1]	+	74.9%	91.8 - 92.1%
Lead time of the overall process	+	AVG: 00:46:56 hr (± 00:06:10 hr)	AVG: 00:40:58 hr (± 00:01:01 hr)
Total distribution cost[1]	-	541 work hours	585- 654 work hours

The percentage of orders that are delivered on time increases. However, the 100% desired is still not met. This is because this research focuses on aligning the in-house delivery process with the order-picking process. The sequence of orders as output is not altered. Further research can be done on the ideal priority rules for orders.

The lead time of the overall process will improve. According to the table above, the average lead time has decreased. Because of the limited waiting times, it is not possible anymore for a cart to be in the in-house delivery process for more than 60 minutes. The improvement can be seen in Figure 5.4. The weight of the graph has been slightly shifted to a higher number of minutes. However, no carts exceed the 60-minute limit anymore, and the graph is more concentrated. A more concentrated graph means a more reliable and better predictable process.

[1] Only for Monday October 23rd because other days have more or less carts

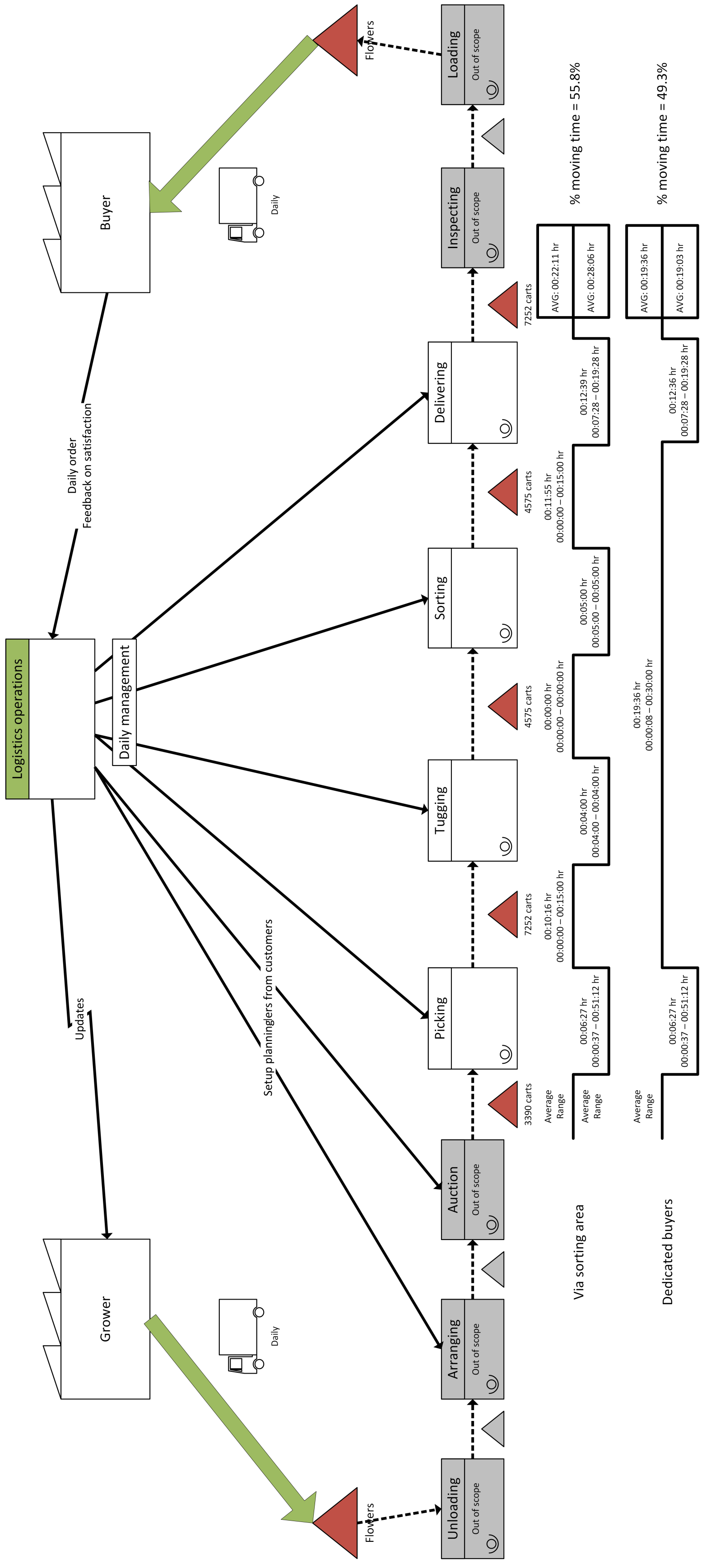


Figure 5.3: Value Stream Map (VSM) design

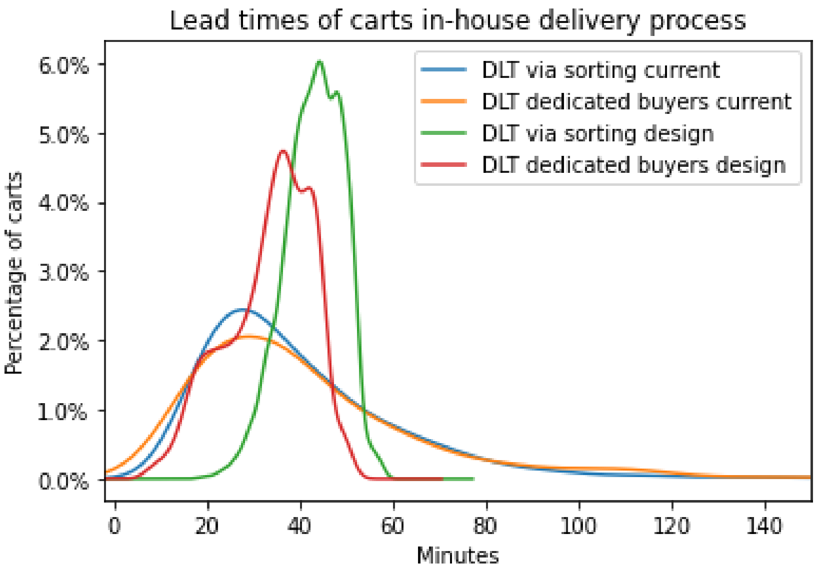


Figure 5.4: Lead times via the sorting area and for dedicated buyers Monday, October 23rd (75th percentile driving times)

The decrease in the spread of the total lead time has been discussed, but also, the share of waiting time decreases. Figures 5.5 and 5.6 show the current share of lead time and the one for the design situation on average for every 15 minutes. The red and blue areas have become smaller in proportion to the other actions. For the dedicated buyers, it is visible that direct delivery is in place and that the waiting time in the track area is twice as long as for the carts that go via the sorting area. This is allowed because the waiting time for those tracks has been set to 30 minutes because there is only one waiting point left. In addition, because of all the other measures taken added to the limited waiting time, the length of trains increase as well. This means the process is executed more efficiently than when employees move only a few carts at a time. Detailed boxplots of train length per work or delivery area and waiting times per work or delivery area can be found in Appendix C.

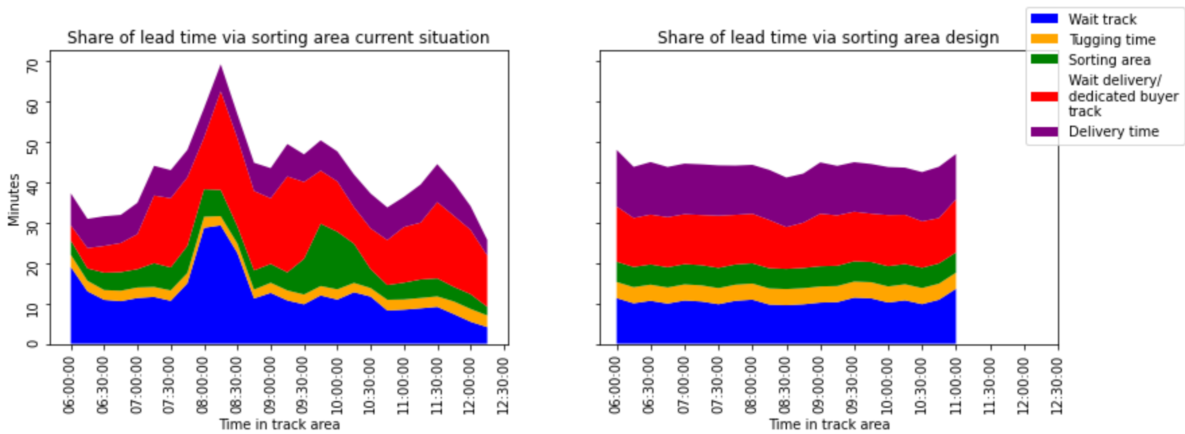


Figure 5.5: Share of lead time via sorting area current and design situation Monday, October 23rd (75th percentile driving times)

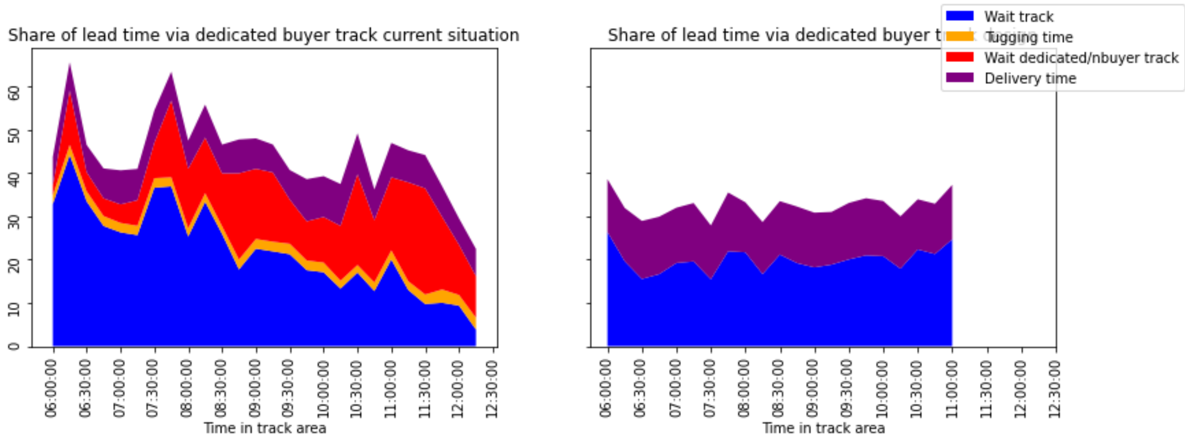


Figure 5.6: Share of lead time dedicated buyers current and design situation Monday, October 23rd (75th percentile driving times)

The last KPI taken into account is the total distribution cost. When multiplying the number of employees currently in the process by the time the overall process takes, a total of 541 hours worked is found. For the design case, 585 to 654 worked hours will be required (Figure 5.7). The assumption of the driving times is already included. In addition, the productivity in the sorting area could be higher, as shortly introduced in Section 4.2. Figure 5.7 has been created with the required number of employees per half an hour. The uncertainty that comes with the different assumptions can be seen.

It depends on the assumption of the driving times how many work hours are needed. The outcome with the 50th - 75th percentile of the current driving times is between 585 - 654 work hours. Also, the current productivity of the sorters is lower than the predicted productivity, as explained in Section 4.2. This is due to choices made in the sorting area. When applying changes to the sorting area, which will be elaborated on in Chapter 6, the productivity is expected to be brought to 60 carts per hour per employee. The increase in productivity would decrease the expected 585 - 654 work hours to 537 - 612 work hours. The actual outcome is expected to be somewhere in the middle. An overview of the required work hours in different situations can be found in Table 5.13.

Table 5.13: Required number of employees in different model situations

# Employees	Current[1]	75th percentile & productivity 44 carts/hour	50th percentile & productivity 44 carts/hour	75th percentile & productivity 60 carts/hour	50th percentile & productivity 60 carts/hour
Tuggers	30	20 (± 1)	20 (± 1)	20 (± 1)	20 (± 1)
Sorters	25	31 (± 1)	31 (± 1)	23 (± 1)	23 (± 1)
Deliverers	32	62 (± 2	49 (± 2)	62 (± 6)	49 (± 1)
Total	82	109 (± 5)	98 (± 2)	102 (± 1)	90 (± 1)
Work hours[1]	541	654	585	612	537

[1] Only for Monday October 23rd because other days have more or less carts

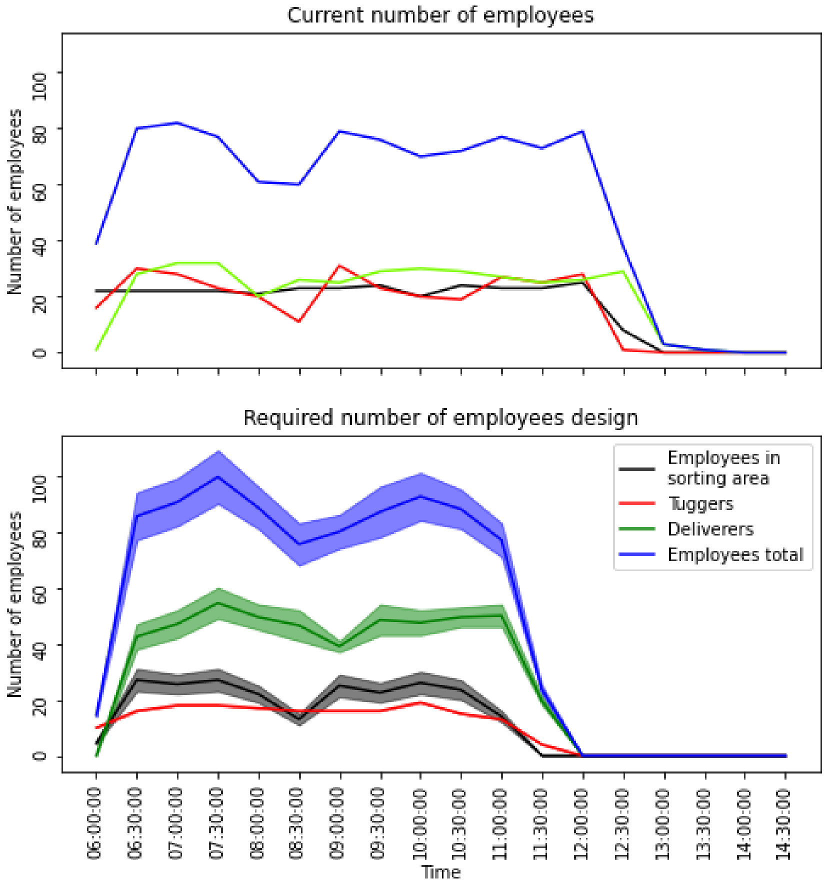


Figure 5.7: Number of employees used in the current situation and required in the design situation Monday, October 23rd

5.8. Summary

From the CSA, it followed that the main problem of the in-house delivery process was the spread in waiting times, and therefore, the overall process is very unpredictable. In addition, the output of the order-picking process needs to be higher for the current division in the latest delivery times. However, there is no point in increasing the output when the in-house delivery process cannot process the current output well. Still, a solution is found by using the required output. To find a solution to the first problem, requirements have been defined for the design. After that, functions have been created together with possible means to form possible solutions for a design. Those possible solutions have been checked for feasibility with the constraints and then ranked based on the objectives. The means that must be in the design have been found from here. In addition, the KPIs have been set to measure the design performance. The KPIs taken into account for this research are:

- Percentage of orders that are delivered on time
- Lead time of the overall process
- Total distribution cost (measured in required work hours)

From all this information, a design was created with the best possible results. Only implementing a limited waiting time on tracks satisfies the lead time KPI but decreases the efficiency significantly, which makes the process expensive. Extra measures have been taken to increase the efficiency of the process again. The answer to the third sub-research question consists of a design with the following changes:

- Limited waiting time on all tracks
- An increased output of the order-picking process
- Limiting the number of tracks in work areas
- Direct delivery to large buyers from work areas
- Clustering of delivery tracks
- All employees will work directed from scanners via the WMS

Instead of increasing the output of the order-picking process, the division of the delivery time slots can also be revised. However, for this research, it has been decided not to change the order-picking process and thus work with a higher output. To answer the fourth sub-research question, the performance was measured in the following ways:

- By predicting the influence on each of the KPIs
- By creating a new swimlane diagram for the design so that it can be compared to the current situation swimlane diagram
- By creating a new VSM for the design so that it can be compared to the current situation VSM
- By creating graphs that show the performance of the design compared to the current situation

Although the new design has been found feasible by experts, there are some discussion points regarding the results. First of all, there is a probability that more work hours are required. However, this is for a higher output of the order-picking process and with the currently lower output, the required work hours should not be an issue. In addition to the uncertainty of the required number of employees, numerous assumptions have been made that might not be fully comparable to the real-life situation, such as the delivery times. Those assumptions have been made partially because of the limited amount of available data and the quality of this data. Those discussion points are not necessarily a problem if all adjustments to the process are well-prepared and implemented in steps or if further research and extra measurements are done beforehand. Additionally, further research should show if it is more beneficial to keep an employee waiting until one of the limits is reached so that a train must be moved or that the employee is assigned to a task whether a limit is reached or not.

Another aspect mentioned multiple times is the priority rules. Those decide which order is sent to the order pickers. It has been found that orders are delivered too late even with the design improvements. This is because the order enters the system too late. With the new reliable process, the priority rules can be changed so that the orders enter the process on time.

6 Implementation

This chapter aims to highlight the changes proposed to the current process and provide a general guideline on how to make these changes. The swimlane diagrams of the current and design situation (Figures 4.9 and 5.2) will be compared to each other to find the differences. On that basis, an implementation plan will be created with what to do first and what will be done later. Figure 6.1 gives a schematic overview of implementation. The main differences are:

- Instead of troubleshooters making decisions based on information provided by the WMS, the WMS decides (based on priority rules) which task is performed next and communicates this to the employee. This means that troubleshooters will only be in the process of solving unusual situations. The decisions made by the WMS will depend on waiting time and train length.
- A tugger is no longer allowed to take any train but needs to take the one assigned to them via a scanner.
- The track area will use fewer tracks than in the current situation.
- The sorting area will only have one entry (Figure 6.2). The required number of buffer tracks should be investigated by determining how many trains arrive simultaneously and can not be processed instantly.
- The tuggers (sorting area) will work with at least two employees simultaneously and ensure that trains are brought FiFo and as soon as possible to the sorting track so that the sorters can start and no trains will be waiting unnecessarily long.
- Deliverers can be sent to a track or sorting area. The deliverer takes the train(s) that has/have been assigned to their scanner. It will occur more often than in the current situation that a deliverer needs to visit multiple buyers during one drop-off.

Figure 6.1: Schematic road to implementation

It must be kept in mind that buffers should be avoided as much as possible to reach a continuous flow. When building buffers, there is an increased risk of forgetting a cart or train and losing a clear overview of the performance of the overall process. By only implementing a limited waiting time, the overall efficiency of the process will decrease. Other steps are needed before that to ensure the efficiency stays sufficient. Different steps must be taken to adjust the current process to reach the final design. The steps proposed are:

1. All deliverers should be able to deliver to all delivery areas (currently not the case). This ensures a more optimal division of deliverers over the different tasks.
2. The sorting area should have only one entry point (Figure 6.2). The current situation is responsible for employees sometimes waiting on one side of the sorting area while the other side has too much work for them. By creating one space and making sure that there are enough tuggers (sorting area), it should become a more constant process.
3. The limited waiting time and reducing the number of tracks in the track area can be implemented simultaneously. Reducing the number of tracks automatically ensures that the maximum train length is reached sooner. Thus, the limited waiting time is reached less often than without the new track division.
4. Delivery will take place per cluster instead of per track. At the same time, the limited waiting time will also be implemented for the delivery tracks. The sorters will fill the tracks the same way as they used to. Only the deliverers now take multiple trains. This can be achieved without working directed by changing the signs of the tracks on the pick-up side for the deliverers to signs that indicate that a group of tracks is now a cluster.
5. When directed working becomes available, direct delivery to dedicated buyers can be introduced. Directed working is necessary because a deliverer can then be sent to the right area. Directed working also means that fewer tuggers will be required since they can be sent to the right area instead of only going back and forth between one area and the sorting area.
6. If the decision has been made not to change the division of the current time windows, the capacity can be increased now with close management to see if the process still performs well while increasing capacity.

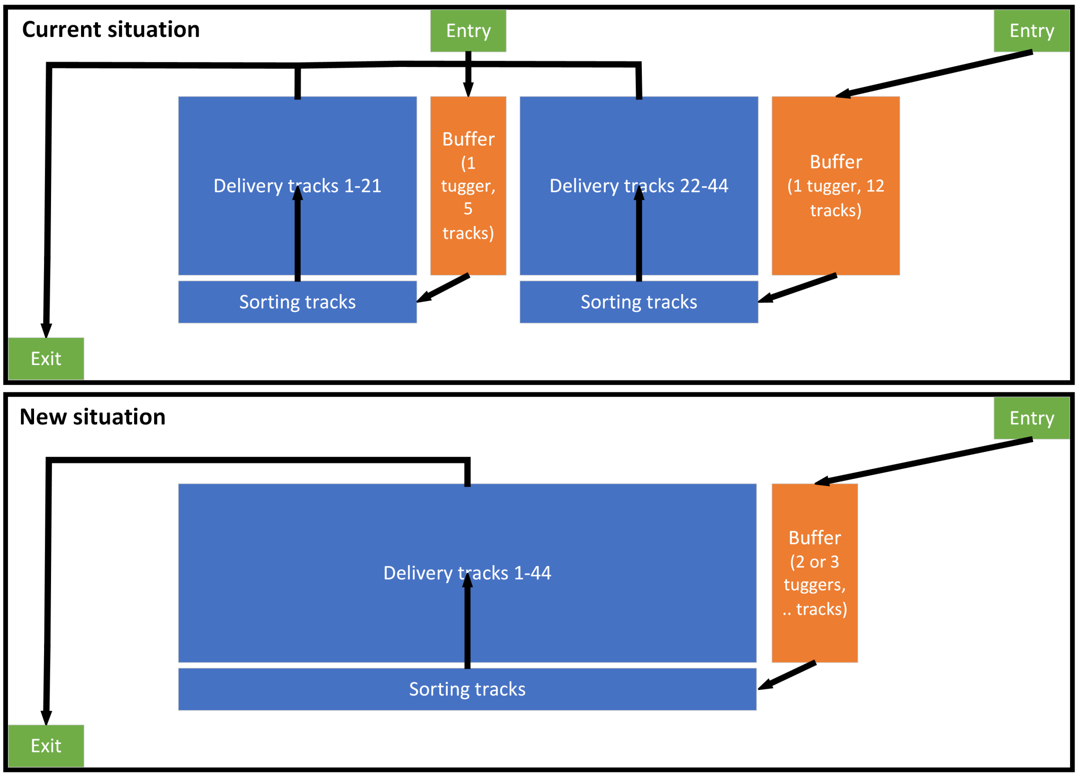


Figure 6.2: Changes to the sorting area

7 Conclusion

This work will be concluded by answering the sub-research questions introduced in Section 1.3 and the main research question. Thereafter, the contribution to literature will be discussed.

Research questions

What are the aspects, requirements, and KPIs involved in well-aligned order-picking and in-house delivery processes?

Different aspects that have been found for such a process are costs, throughput (flow), storage capacity and response time. However, it has been mentioned in the literature that there are a lot of different designs possible and that there is not one optimal solution.
Requirements that have been discussed only for the situation at RFH are, e.g. that the order-picking process must produce the correct order; the in-house delivery process must deliver orders to the right customer; the overall process must be safe for all employees working within it and others.
KPIs were found in the literature and provided by the company. The company has more process-specific requirements, whereas the literature provided general ones. The KPIs considered for this specific research are the percentage of on-time deliveries, the lead time of the overall process and the total distribution cost.

What is the step-for-step execution of the current processes at RFH, how are they connected, and what are their main strengths and bottlenecks?

The main steps in the overall process involve order picking, preparing, tugging, tugging (sorting area), and delivering. For each of those steps, different constraints and mechanisms are needed. The first input into the process is an order from one of the buyers, and the overall process ends with a cart delivered to the buyer with the correct flowers.
The connection between the order-picking and in-house delivery process can be found between the steps 'preparing' and 'tugging'. The order-picking process prepares the carts in such a way that they are waiting in trains so that the next available tugger can take a train and move it into the in-house delivery process.
Multiple strengths and bottlenecks have been found during the analysis. One of the strengths is that the order-picking process is reliable. However, the current output is insufficient to produce the minimum number of carts to deliver everything on time. This could be solved relatively easily by employing more order pickers; therefore, it is left out of scope for the rest of this research. Since the order-picking process is reliable, the focus lies on the throughput in the in-house delivery process with the output from the current order-picking process. One of the main bottlenecks is the waiting times in different buffers. As a result, the overall process

becomes unreliable, and orders are delivered too late. This is the main problem that has been focussed on.

What are different alternatives to better align the order-picking and in-house delivery processes?

Multiple options to improve different parts of the in-house delivery process have been presented in a morphological chart. Based on a multi-criteria analysis, it has been decided that a limited waiting time on tracks will be introduced together with an optimal distribution of employees, directed management from the WMS and communication via a scanner. When introducing the limited waiting time, it is found that the efficiency of the overall process decreases. To increase this again, other possible improvements are proposed. Other potential improvements are changing the capacity of the system, distribution of breaks, limiting the number of tracks in a work area, clustering of delivery tracks, direct delivery to dedicated buyers, combining trains from not busy delivery tracks, and others. Different combinations of these possible improvements have been tested with a calculation model.

How will the proposed improvement(s) perform compared to the current situation at RFH?

Based on the calculations, it is found that the two processes can be aligned better, improving the overall process's performance. The number of deliveries that are on time will increase, and the lead time of the overall process will decrease on average and become better predictable. However, there is a chance more work hours are needed to execute the process according to the proposed design. This will cost the company more money than in the current situation. However, this is based on a higher output than in the current situation since this is required based on the current division of the latest delivery times. With the current output, the costs will be approximately the same.

How can the order-picking and in-house delivery processes at a flower auction be aligned well to execute the overall auction process efficiently?

The main goal is to make sure that there are a minimum number of waiting areas and that there is a constant lead time over the complete process period every day. The minimum number of waiting areas can be achieved by ensuring enough employees are available at every step. The constant lead time is managed by ensuring that no carts exceed a set limited waiting time on each track. When only implementing the limited waiting time, the overall efficiency of the process decreases. However, by modifying the track areas and delivery tracks, the maximum train length should be reached sooner so that, in combination with the limited waiting time, fewer tuggers or deliverers are needed. This way, the efficiency of the overall process is increased again. In addition, decisions should no longer be made by the employees working in the process but by the WMS based on priority rules. Thus, managing the process plays a significant role in the success of the new process.

Contribution to the literature

In Chapter 3, it has been stated that there is a gap in the research regarding the alignment of two consecutive sub-processes in warehouses. A case study on the order-picking and in-house delivery process has been done at Royal FloraHolland to fill this gap. A flower auction is a special warehouse case where order picking starts while orders are still being placed.

Since the decision was made during the data analysis to focus on aligning the in-house delivery process to the order-picking process, this research has not contributed to the available literature on an order-picking process. However, it has been found that a minimum output is required in this industry to satisfy the agreements made with buyers, which could also apply to other industries. This could result in extra costs or logistical difficulties for a company.

For the in-house delivery process, a limit on waiting times can provide a more reliable and predictable process than when focussing on the train length. Research done before this one has not gone into those details yet. Since a waiting moment is also the link between two consecutive processes, this finding also contributes to the research gap in that there is minimal information available about how two consecutive processes can be aligned well.

Another aspect is that the later sub-process should be able to handle the same number of products or carts as the earlier sub-process. When this is not the case, a build-up will appear, and the overall process performance will decline. To prevent this, the steps previous in the overall process could be temporarily stopped so that no buffer will occur and the situation becomes disordered. Thus, strict monitoring and management are necessary where sub-processes are not managed separately but the overall process.

The aspects found during the case study described in this part of the conclusion should apply to any industry where a stream of products is present.

8 Discussion and recommendations

This chapter provides a discussion and recommendations for RFH specific and further research.

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One of the most significant assumptions made in the calculation model is the driving time of deliverers. In Figure 5.7, it can be seen that the number of deliverers is significantly higher than the other positions in the design. This is partially because the current situation does not have enough deliverers (based on the current build-up on the delivery tracks), and the driving times used in the model are quite conservative. The deliverers are also the largest expanse since the number of deliverers needed is so high. Doing further research into the driving times can be beneficial to get a clearer picture of the number of required deliverers.

Another assumption the model uses is that the process can wait by calling a tugger or deliverer until the maximum waiting time or train length is reached. Nevertheless, it cannot be expected that an employee will always be available and at the correct place within a second. Thus, the WMS must send out the task earlier. This could be after, for example, 13 minutes of waiting or when 12 carts are ready. The optimal triggers should be investigated with data and tested in practice. On the other hand, an employee may be ready while no maximum waiting time or train length is reached yet. Further research can be done to find if it is preferred to let the employee wait or assign a task before one of the limits is reached.

To further improve the outbound process at RFH, other aspects can be investigated. First of all, the division of the delivery times can be revised. With the current division, a very high output is required (higher than the current situation). A lower output is needed when a different division is in place, making delivering all orders on time more feasible. Thus, the promised delivery times by RFH should align with the overall process's capacity. The priority times have also been mentioned multiple times in the report. These are not optimal now since carts often start too late to deliver them on time. Further research on how to set them so that the WMS processes all orders correctly is advised.

Something different that could influence the required output but has not been included in this research is the setup of the flowers before order picking starts. When a more optimal setup can be found, the expansion factor could be decreased, resulting in fewer buyer carts. It could be that a pattern can be seen in which buyers purchase which products. Fewer carts mean that the same number of employees would result in a shorter process time or that the number of employees could be decreased to keep the same output as now. This would also reduce the total cost of the outbound process.

Another aspect that could be investigated to improve the current design is the optimal division of the clusters. The order of the delivery tracks is especially important. If the order is in such a way that the carts of the first buyer are in the back of the train and so on, this would increase the efficiency of the delivery. In addition to improving the current design, the priority rules should be revised. It has been shown in the current state analysis that carts are delivered too late because the order picking starts too late. Since the order-picking process is a directed process by the WMS, the issue lies within the priority rules.

In the future, it can be beneficial to increase the quality of the data and use it to monitor the process while executing it. This way, managers can adjust the process when they see something abnormal. This will become even more important when plants are added to the order-picking process. This will significantly increase the volume passing through the process. In addition, the company is moving to a central auction, which will make the auction longer than it is currently. Thus, orders will be known later in the day. The effect of this can be investigated so that proper adjustments can be made to the process.

Further general research

The current research only focused on one particular flower auction, while the research gap applies to consecutive sub-processes in all industries. Thus, the same study can be done in a different industry to verify if the manners proposed will also positively influence that industry. In addition, two other sub-processes could be investigated to see if the same principles hold. Another possibility could be removing parts of the overall process so that sub-processes are no longer necessary and one outbound process is created.

To make the overall process more efficient, research can be done about the mechanisation of (sub-)processes. Nowadays, mechanisation is more applied in standard warehouses. With perishable goods and especially vulnerable goods such as flowers, it is more difficult to use machines to handle products. However, finding employees for a relatively short shift which starts very early is difficult. This problem could be (partially) solved by using machines instead of people.

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A
Scientific paper

The paper is uploaded as a PDF and starts on the next page.

Creating a continuous outbound flow at the flower auction
A case study at Royal FloraHolland Naaldwijk

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Abstract— **This paper investigates how two sequential sub-processes at a flower auction can be well aligned to efficiently execute the overall auction process. Existing literature mainly focuses on warehouses without perishable goods and warehouses where all orders are known before the outbound process is started. However, at a flower auction, the gathering of goods and distribution takes place while the auction is still ongoing. In addition, flowers are vulnerable goods that must be handled with care.**

During a case study at Royal FloraHolland Naaldwijk, the current process of order picking and in-house delivery is investigated to find the main strengths and bottlenecks. This is done physically and with data. From this analysis, it has been found that the main issues are the spread and share of waiting times in the in-house delivery process and the output of the order-picking process that is too low. To improve the overall process based on the found issues, a calculation model has been built in Python to test possible improvements. It has been found that implementing limited waiting times and other alterations to increase efficiency results in a more reliable and better predictable process that can be executed with approximately the same number of work hours or slightly more than in the current situation.

I. Introduction

The Dutch flower auction has been growing in revenue and number of products [1], [2], [3]. This, combined with the change in buyers' needs, for example, delivery within a specific time frame during the day [4], leads to new challenges. Nowadays, at the largest Dutch flower auction, Royal FloraHolland (RFH), preparing the orders for only flowers is done by an order-picking process. For order picking, the products are gathered on carts, which must be delivered to the correct customer. What distinguishes a flower auction from a regular warehouse is that order picking occurs while the auction is still taking place, thus while customers are still placing orders. In addition, the demand and supply change dynamically [5].

Based on warehouses of distributors such as Amazon, order picking is responsible for about 55% of the warehouse operating costs [6]. Again, 55% of the order-picking time is spent travelling by a person [7]. Because of the large number of orders daily at a flower auction, it is desired to execute the outbound process as efficiently as possible. A way to improve the order-picking process is by reducing the travel time [8]. Something else to try is different types of order-picking methods [9]. A Warehouse Management System (WMS) can assist by producing pick lines and pick lists [6].

Next is to deliver the flowers to the buyers. Some performances to keep track of are the total cost, on-time shipping ratio and distribution flexibility [10]. Some research has been done about auction order fulfilment [11], [12], [13], [14]. However, that research is about order estimations and mechanisation. Minimal research has been found on how consecutive processes can be aligned well to execute the overall process efficiently. Thus, this will be the objective of this research. The research will be conducted at Royal FloraHolland at the location Naaldwijk. The two consecutive processes investigated are the order-picking process and the in-house delivery process for the flower distribution. The research question that will be answered is:

How can the order-picking and in-house delivery processes at a flower auction be aligned well to execute the overall auction process efficiently?

An answer will be found by providing answers to the following sub-research questions:

1) What are the aspects, requirements, and KPIs involved in well-aligned order-picking and in-house delivery processes?
2) What is the step-for-step execution of the current processes at RFH, how are they connected, and what are their main strengths and bottlenecks?
3) What are different alternatives to better align the order-picking and in-house delivery processes?
4) How will the proposed improvement(s) perform compared to the current situation at RFH?

This paper will first introduce the methods used during this research. After that, the topic will be introduced further in a literature section. The current state will be discussed together with its performance. A new design is proposed based on the current state, and the new performance is also calculated. Finally, a conclusion and recommendation are given.

II. Methodology

The proposed design method is presented in Figure 1 and is based on the methodology proposed by [15]. The rectangular boxes are the stages, and the ovals represent the input/output of those stages. The different steps taken during the design are:

- **Preparations** Literature research is done, and the researcher will get acquainted with the current processes.
- **Problem definition** Requirements, objectives, constraints, and functions frame the problem.
- **Conceptual design** Different concepts are created with all objectives, constraints and functions in mind. The concepts are evaluated based on specific objectives.
- **Preliminary design** The evaluated concepts are combined into a preliminary design, and more details are added.
- **Detailed design** The preliminary design is developed in greater detail, and choices made in the previous step are refined.
- **Design communication** The design process and final design are presented in a document.

The design process will be done through different methods. For each of the sub-research questions, suitable methods will be used. The methods used per sub-research question are:

1) Literature study and interviewing process experts
2) Joining the process, interviewing process experts, existing documentation, analysis (e.g. flow chart, value stream map), statistical data analysis and SWOT analysis
3) Morphological chart and multi-criteria analysis
4) Discussions with process experts, calculations of possible future states about what the expected performance will be, and analysis comparison between new and current situations (e.g. flow chart, value stream map)

III. Literature

Before going into depth with the case study, existing knowledge on different subjects connected to the objective of this research will be introduced. The subjects are warehouse design, order picking, distribution management and auction order fulfilment.

A. Warehouse design

Designing a warehouse is a very complex task where different stages are executed for a final design. Different criteria, such as costs, throughput, storage capacity, and response time, have to be met at every stage. Often, there is a large number of feasible designs. It can be complicated to find the best one for a particular application [16], [17]. A flow in a warehouse consists of the following processes [16]:

1) **Receiving** Products arrive by a certain type of transport (depending on the warehouse). Products are checked, and they must wait for transportation to the next step.
2) **Storing** Items are placed in storage. The paper makes a distinction between two types. First is the reserve area, where products are stored very close to each other (in an economical way). Second is the forward area from where the orders are picked. Thus, in this area, the products must be accessed easily.
3) **Order picking** This is the retrieval of items from storage. This can be done manually or automated.
4) **Shipping** Orders are checked, packed and then loaded into trucks or another type of transport.

Different researchers have tried to create a framework for warehouse design. One of the most elaborate frameworks is an eleven-step framework [18]. This framework has been verified with companies, but there is still no optimal solution for warehouse design.

B. Order picking

Designing an order-picking system is very complex and depends on multiple elements such as the products, customer orders, types of functional areas, combination of equipment types, and operating policies for each functional area [19]. Different elements have been experimented with to see if the order-picking process could be executed more efficiently. One of those elements has been the storage assignment policy [20]. Again, not one concrete answer has been found because it depends on the type of storage.

Other elements that have been researched are the routing algorithm [8] and congestion during order picking [21]. The main issue with routing is the trade-off that has to be made when it is beneficial to add an extra pick to the list or when it is better to do it with a new picklist because of extra travel distance. Another trade-off has to be made because of congestion. Increasing the number of order pickers will improve the overall process efficiency. Still, a higher number of order pickers results

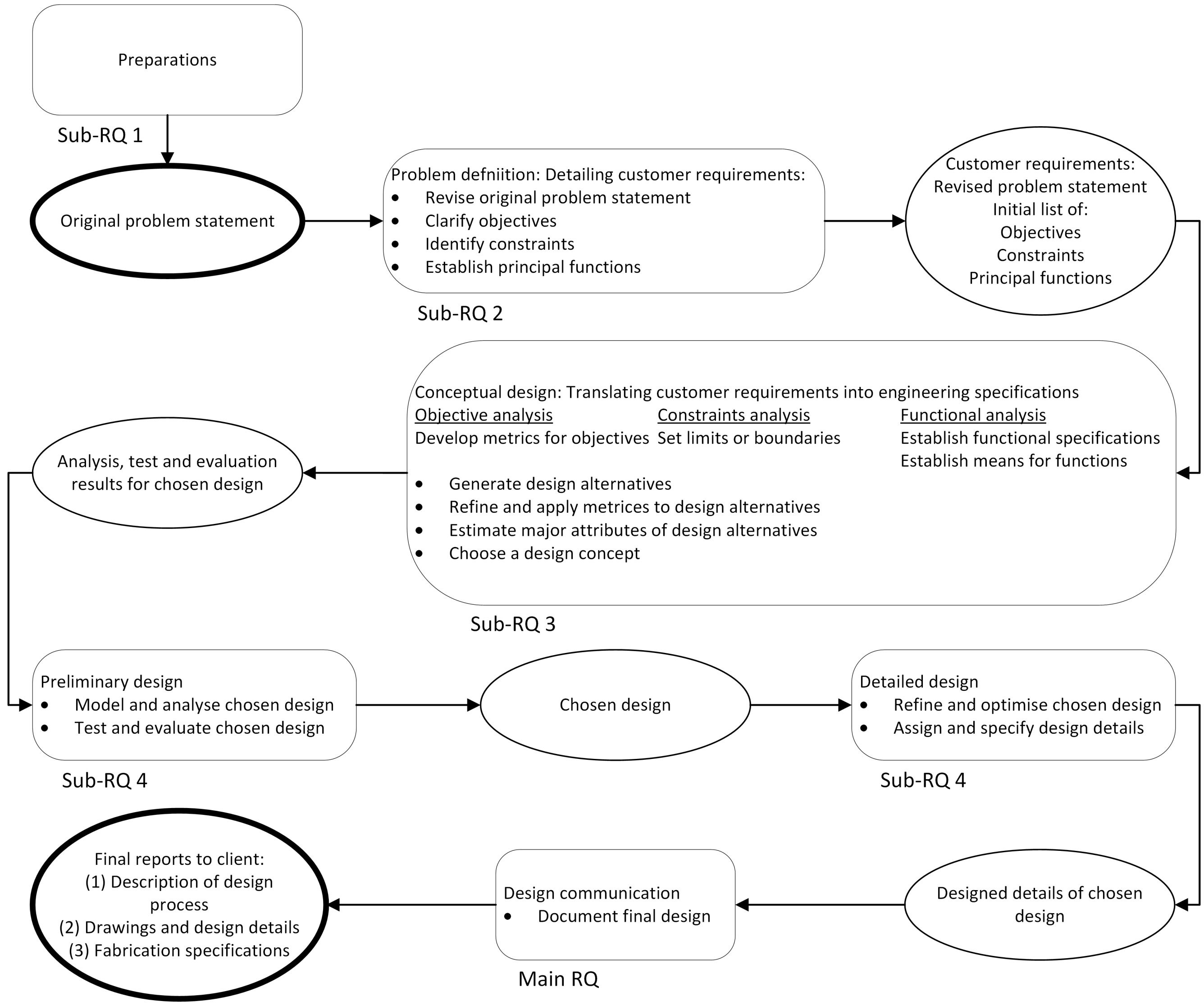

Fig. 1. Proposed design process based on [15]

in more congestion and thus lowers the overall process efficiency at the same time.

C. Distribution management

The distribution process is one of the fundamental processes in logistics [10]. The process starts with a customer's order and ends with the delivery. A company can use KPIs as a measurement tool to monitor its performance and achieve cost savings and efficiency. Two methods have been used to find the five most important KPIs in the distribution process [10]. The five most important KPIs that followed from the study are:

1) Total distribution cost (cost to deliver the product from origin to end user)
2) On-time shipping ratio (# order lines shipped on-time / total # order lines)
3) Flexibility of distribution (ability to change distribution processes efficiently to adjust to requirements of customers [22])
4) Timeliness of goods delivery (# of units delivered within the set time period defined by the customer)
5) Profitability by item (amount of profit that a certain product makes within a set time period)

In addition to those KPIs, continuously tracking the product flow is important [23]. Not only gathering information is of great importance, but also providing information to the employees working within the process is necessary during their shift. Reliable and accurate information is needed so that operational managers can use this information to solve day-to-day problems [24].

D. Auction order fulfilment

More detailed research on auction order fulfilment has been rarely done. Some of the research that has been done states that a cloud-enabled platform is important [11]. This is necessary to deal with adaptive planning. Auction logistic centres rely heavily on planners to minimise costs and lead times [11]. The possibilities of a robot-enabled execution system for perishables auction have been investigated [12]. However, it was concluded that this is uncommon and difficult in the application of perishable goods. Two other experiments that have been done are demand forecasting [13] and order postponement so that orders of certain buyers can be held until a full cart is created [14]. Both cases were successful and could be further investigated.

IV. Case Study

A case study was conducted at RFH concerning the order-picking and in-house delivery process. First, a physical analysis was done, followed by a data analysis. After this analysis, several possible improvements have been tested with a calculation model. Based on the outcome of this model, a final advice has been created, which will be discussed in the next section.

Three KPIs have been selected based on the literature study and KPIs provided by RFH to compare the later design to the current situation. The KPIs selected are:

- Percentage of orders that are delivered on time
- Lead time of the overall process
- Total distribution cost (measured in required work hours)

A. Physical analysis

During the physical analysis, multiple interesting aspects have been found. First, products are stored in different areas where orders are also gathered. This means that for one buyer, products can be in various areas. This makes it more challenging to fill carts for one buyer as efficiently as possible. In addition, buyers who purchase a lot have a dedicated track here on which trains are created especially for them. The rest of the carts go through a sorting area. The trains for the dedicated buyers are brought to a waiting area and then to the buyers without modifying the trains between those steps. Which train to take to the sorting or waiting area is up to the employee (tugger). A rule is to take the longest train, or a troubleshooter must have instructed the tugger to take a specific train. However, there is no monitoring if these rules and instructions are executed correctly. The WMS directs the order pickers via a scanner, eliminating the previous problem.

When moving the trains to the sorting area, the train is placed in a buffer again without modifying the train. Another tugger moves the train from this buffer to the sorters. They put the carts separately on a track linked to a specific buyer. From here, the trains are delivered, where again the problem arises that a deliverer needs to take the longest train or is instructed which train to take, but there is no monitoring. Figure 2 provides a schematic overview of the current process. The triangles indicate waiting times, and the red triangle is where the overall process goes from order picking to in-house delivery. The arrow on top indicates if a cart is for a dedicated buyer.

B. Data analysis

RFH has provided data. However, the data is not always complete or correct, so filters have been applied to make it more reliable. For this research, Monday, October 23rd has been presented since this has been an average Monday in 2023 when considering the number of carts processed, the number of carts delivered too late and other indicators. However, the analysis was done for multiple days, and the same trend was visible

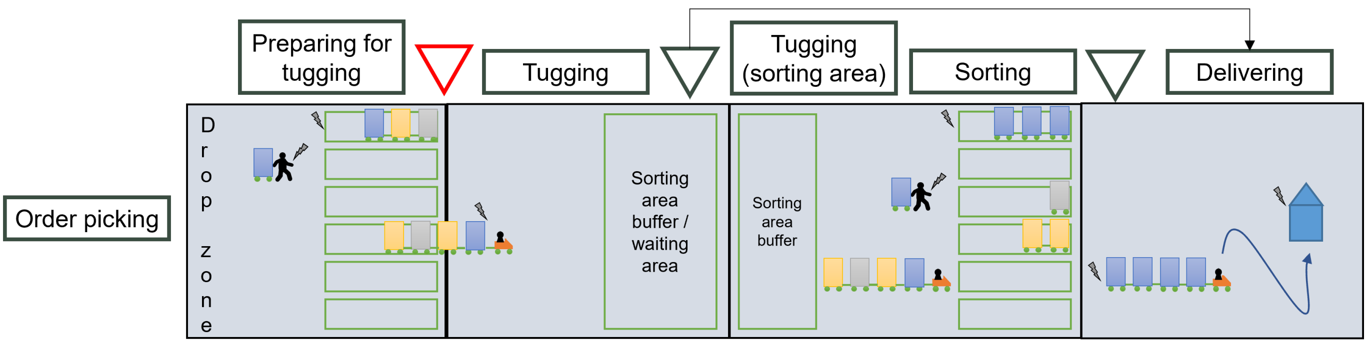

Fig. 2. Schematic overview of the current process

every day. Each step indicated in Figure 2 has been investigated. Figure 4 shows the real versus the required output of the order-picking process. The black crosses indicate the number of carts that the order-picking process should have produced based on the different latest delivery times assigned to each buyer. It can be seen that the required output is higher than the current output. However, the performance of the employees is good. Thus this problem could only be solved by adding employees or by changing the division of the latest delivery times.

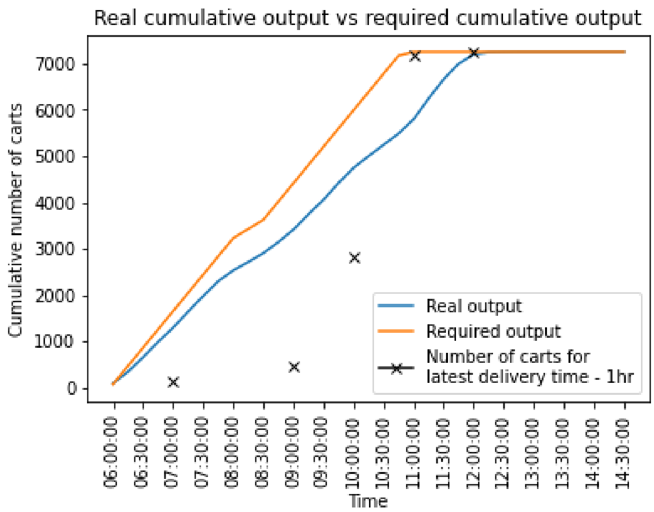

Fig. 4. Current versus required output order-picking process with latest delivery times (Monday, October 23rd)

Another interesting find in the in-house delivery process is the share of waiting times in the total lead time (Figure 3). It can be seen that the waiting times (red and blue) are the most significant part of the total lead time. The spike between 8 AM and 8:30 AM can be assigned to the breaks. The spread in waiting times is also a problem (Figure 5). The graph indicates that the sorting area performs well overall. Most carts are processed within zero to ten minutes. However, the other waiting moments are spread from zero to at least thirty minutes. The other steps in the in-house delivery process showed no issues. The main problem in the in-house delivery process is the large share of the waiting times in the total lead time and the large spread in waiting times, which makes the total lead time unpredictable.

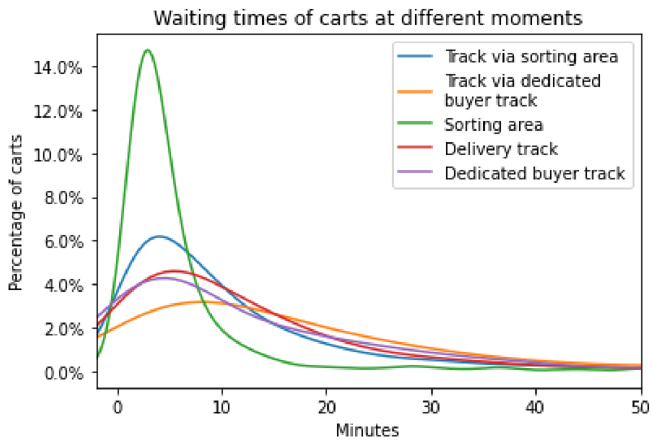

Fig. 5. Density graph of the waiting times in the in-house delivery process

On this day, approximately 25% of the carts were delivered too late. Partially because the lead time was too high. The goal is to deliver within 60 minutes after order picking, and that time has been exceeded multiple

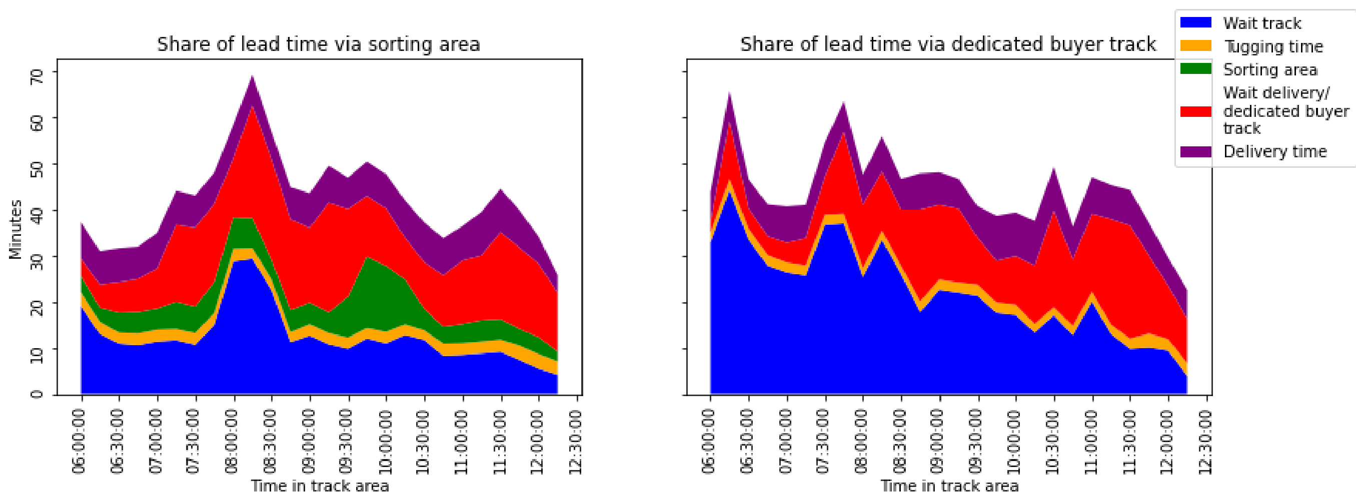

Fig. 3. Current average lead time in-house delivery process per 15 minutes

times during the day. Another reason for late delivery is that an order is sent to the order pickers too late. This means the order is started in the order-picking process less than 60 minutes before the required delivery time. This is a priority issue.

From the figures presented, it can be concluded that the in-house delivery process cannot process the current output of the order-picking process. Thus, the focus will be on changing the in-house delivery process so that it can process the current output and, preferably, the required output.

C. Design options

Multiple ideas have been tested to improve the in-house delivery process. The new base scenario will be the first alternative, limited waiting time. The KPI concerning process time is improved when implementing the limited waiting time. However, the overall efficiency decreased because of shorter trains. Thus, extra alternatives have been added to the first one to increase efficiency again. All alternatives tested are:

- **Limited waiting time on track (1)** The maximum waiting time will be 15 minutes.
- **Capacity of each step in the overall process (2)** Different capacities will be tested to see how many employees are needed and if the end time is met.
- **Limiting the number of tracks after order picking (3)** Limiting the number of tracks that go to the sorting area ensures that longer trains are formed and fewer movements are needed. In addition, carts that would have been on the track a long time because they were in a short train, are now moved sooner.
- **Direct delivery to dedicated buyers (4)** Direct delivery removes the waiting area to which the carts are moved first. With direct delivery, the carts for dedicated buyers have a limited waiting time of 30 minutes.
- **Combining trains from not busy delivery tracks (5a)** When trains together do not exceed the train length limit and should be delivered to the same area, it is allowed to take them together.
- **Clustering of delivery tracks (5b)** Instead of monitoring each delivery track separately when the waiting time or train length limit is reached, clusters (multiple tracks next to each other that go to the same delivery area) will be monitored. This means that a deliverer should always go to multiple buyers but that fewer movements are needed because the maximum train length is reached more often.

The design options explained and different combinations of those will be put in a calculation model.

D. Calculation model

This Python model uses the past output of a day's order-picking process to see what would happen when the new rules are applied. Assumptions have been made, e.g. concerning the driving times, unlimited availability of employees and that directed working with the WMS is possible. First, all ideas were tested separately to check if each was an improvement compared to the new base scenario. This was the case except when entering the required output in alternative 2. However, this was expected since the required output exceeded the current output. After this, several combinations have been tested. The results of the combined alternatives are shown in Table I. It is found that option 5 is the best. This is the design where the least number of employees are required and where everything is delivered before the latest delivery time. With the required output of 390 carts/15 minutes according to Figure 4, 109 employees are needed with an end time of 12:00:30 and 8.2% of the carts are too late. There are still carts that are too late because the order-picking process is not modified

[1]Only for Monday, October 23rd because other days have more or fewer carts

TABLE I

RESULTS COMBINED MODELS (75TH PERCENTILE OF THE DRIVING TIMES, ORDER PICKING OUTPUT 390 CARTS/15 MINUTES AND PROCESS TIME OF 6 HOURS AND 30 SECONDS)

Nr.	**Model**						**# Tuggers**	**# Sorters**	**# Deliverers**	**# Employees total**	**Work hours[1]**	**% Too late[1]**
	1	2	3	4	5a	5b						
1.	✓	✓					35 (± 3)	32 (± 1)	78 (± 5)	138 (± 6)	829	8.2%
2.	✓	✓	✓				30 (± 2)	31 (± 1)	77 (± 6)	134 (± 7)	805	8.2%
3.	✓	✓	✓	✓			20 (± 1)	31 (± 1)	84 (± 7)	132 (± 8)	793	8.2%
4.	✓	✓	✓	✓	✓		20 (± 1)	31 (± 1)	74 (± 5)	121 (± 6)	727	8.2%
5.	✓	✓	✓	✓		✓	**20 (± 1)**	**31 (± 1)**	**62 (± 5)**	**109 (± 5)**	**654**	**8.2%**
6.	✓	✓		✓		✓	25 (± 3)	32 (± 1)	61 (± 4)	113 (± 5)	678	8.2%

and thus not the sequence in which orders are processed. The final model works in the following manner:

- **Input:** The model uses the output of the order-picking process from a day in the past, and different parameters have been set.
- **Step 1. New division tracks:** The current tracks are overwritten by the track according to the new division.
- **Step 2. Capacity:** The required order-picking output uses the same output sequence as the current situation. Per 15 minutes, the required number of lines is taken for that time interval and evenly distributed over that time interval. Then, the output time of the order-picking process is changed to the new time according to the distribution over the time intervals.
- **Step 3. Preparing for tugging:** With the new track division and order-picking output, waiting on the track for a train is limited by either a maximum waiting time of 15 minutes for the first cart of that train or by reaching the maximum train length. As soon as one of these constraints is met, the train is taken away by a tugger.
- **Step 4. Direct delivery to dedicated buyers:** Direct delivery takes place by assigning a deliverer to the dedicated buyer track in the track area. Instead of waiting 15 minutes, the maximum waiting time is set to 30 minutes.
- **Step 5. Creating clusters:** In the sorting area, clusters are created by grouping the tracks in one cluster.
- **Step 6. Delivering from the sorting area:** Each cluster is checked if the first cart entered is not waiting longer than 15 minutes and if the tracks combined do not exceed the train length of 14 carts. When one of these limits is reached, a deliverer takes the cluster away to the buyers.
- **Output:** The model calculates the required number of employees per half an hour, the lead time, and the number of carts delivered too late.

V. Results

The results will be assessed based on the KPIs introduced earlier in this paper. The model has been run for multiple (8) Mondays for verification. Verification showed that the lead time limit of 60 minutes and train length of 14 carts are always within the maximum. Validation has been done by discussing the model with process experts. Table II gives an overview of the KPIs and results. First of all, the number of carts delivered on time increases. A 100% on-time delivery is not reached because of earlier mentioned reasons (e.g. priority rules).

TABLE II
RESULTS BASED ON KPIS

KPI	Effect	Current	Design
Percentage of orders that are delivered on time[1]	+	74.9%	91.8 - 92.1%
Lead time of the overall process	+	AVG: 00:46:56 hr (± 00:06:10 hr)	AVG: 00:40:58 hr (± 00:01:01 hr)
Total distribution cost[1]	-	541 work hours	585 - 654 work hours

The lead time not only decreased on average but Figure 6 demonstrates that the lead time no longer exceeds the 60-minute limit for any cart. The graphs of the design situation are more narrow than the ones from the current situation. This indicates that the in-house delivery process will become more reliable and easier to predict. It has been mentioned that only introducing the limited waiting time to increase the lead time KPI decreases the efficiency and thus increases cost. The cost is measured by calculating the required number of employees and multiplying this by the number of hours the overall process takes. In the current situation, 541 work hours are used.

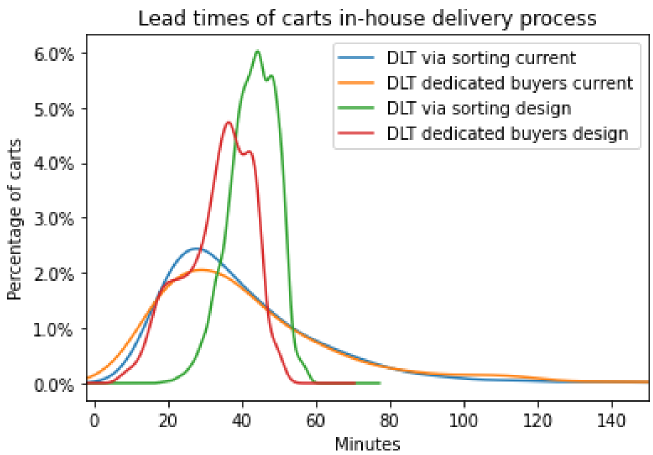

Fig. 6. Current lead time versus lead time in the design

The total number of work hours required for the design is 654 hours at most. However, the driving time to delivery areas has been set to the 75th percentile of

[1]Only for Monday, October 23rd because other days have more or fewer carts

the current driving times for this number. The required number of work hours decreases when changing this to the 50th percentile (585 work hours). In addition, the current productivity of the sorters is relatively low. This is mainly because the current sorting area is split into two parts. Because the inflow is different during the day for both parts, it occurs that sorters are waiting for carts. When the sorting area is arranged differently, productivity could be increased to 60 carts per hour per employee. This again would decrease the required number of work hours. The actual situation is somewhere between 537 and 654 work hours, comparable to the current situation, while the design requires a higher output.

TABLE III
NUMBER OF WORK HOURS IN DIFFERENT SITUATIONS (MONDAY, OCTOBER 23RD)

	Current	**Design**
# Employees	82	109
# Work hours	541	654
# Work hours (50th percentile delivery time)	-	595
# Work hours (60 carts/hour productivity sorters)	-	612
# Work hours(50th percentile delivery time and 60 carts/hour productivity sorters)	-	537

VI. CONCLUSION AND RECOMMENDATIONS

Aligning the order-picking and in-house delivery process so that the overall process is efficiently executed can be done with a combination of modifications to the process and good management. The main modification is introducing a limited waiting time on the different track locations. If only doing so, a substantial number of extra employees would be needed. Therefore, other measures have been taken, such as limiting the number of tracks after order picking, direct delivery to dedicated buyers, and clustering delivery tracks. This, together with the required output instead of the current output, results in some extra work hours, but less when only implementing the limited waiting times. The exact work hours are hard to determine since assumptions have been made. Therefore, the required number of work hours is expected to be somewhere between the current number of work hours and 100 extra work hours.

For starters, RFH could investigate their priority rules. It has been proven that, with the current ones, carts will still be too late even when the maximum delivery time is 60 minutes. When improving the priority rules, the percentage of carts on time can be increased towards 100%. In addition, RFH could do further research into the division of the delivery times. A revised division could result in a lower required output of the order-picking process, making it easier for the in-house delivery process to ensure a constant flow. Moreover, the setup of the flowers before order picking starts is left out of scope for this research but could influence how full each cart is. Fuller carts mean fewer carts are needed for the same number of products, making it easier for the overall process to handle all products within the required time. An addition to this paper's research could be looking at the optimal cluster division. Especially in which order the tracks of one cluster should be placed. When the first customer is at the end of the train, it is easier to unload at delivery, which saves the deliverer time. The last recommendation for RFH is to increase the quality of its data. When the quality is increased, management will become easier, and the process can be evaluated in more detail to improve further. This will become more important when plants are added to the same process.

Other general research can be done to see how much of the proposed alterations and means can be applied to other industries. The limited waiting times are expected to be beneficial in all warehouses where there are different steps in an overall process. Something else that could be investigated is the mechanisation of the current process at a flower auction. In standard warehouses (e.g. Amazon), mechanisation is a larger part of the execution than at a flower auction. This is mainly because, at the auction, products are perishable and vulnerable. However, it has been mentioned that finding employees for a relatively short shift which starts very early is difficult. This problem could be (partially) solved by using machines instead of people.

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B
Data analysis

Reasoning behind the chosen week and weekdays
In Figure B.1, the supply per auction day can be seen. On some days, the auction was closed because of holidays. Those days are indicated with a black rectangle and the corresponding holiday at the end of the row. The colour scale indicates whether there was a relatively large amount of carts for auction on a weekday compared with the rest of the year. Dark green means that it was a large amount and white means that it was a small amount. There are three weeks indicated with a coloured rectangle around them. The red rectangle shows week one where the supply was the lowest. The yellow rectangle around week 19 shows a week where the supply was very high (peak period). The blue rectangle indicates the week that has been used for data analysis. There are multiple reasons that this week has been used. First of all, it is an average week so standard issues will show, but not the issues that occur only 4 or 5 times per year on the busiest days. Second, not all scans described in the current state analysis have been done all year. The last scans were added at the end of the summer.

In Section **??**, it has been mentioned that Monday and Thursday of week 43 will be investigated further since Monday is the busiest day of the week and Thursday is the quietest day of the week. This can also be seen in the figure already provided but to make it clear, Figure B.2 shows a graph of the amount auctioned carts per day for every week in 2023. It can be seen that Monday is always the highest line and Thursday the lowest. There are two spikes in the Tuesday graph. In both of these weeks, there was no auction on Monday due to Easter or Whitsun. Therefore, more than average was sold on Tuesday. The Thursdays that nothing was auctioned, are because of Kings Day and Ascension Day. As a result, more was auctioned on the Fridays after.

Filter steps to obtain the flow of carts
The flow of carts individually has been found by exporting the data from the table ”Tijden per ladingsdrager” in the LDK dashboard in Power BI for the desired dates. This table can be found under ”Details Buffers NW”. During conversations with employees who are experienced with this data, it became clear that it sometimes happens that the system registers a cart wrong because one cart can be used multiple times during one auction cycle. To remove mistakes like this, first, the rows that do not have an ID number of the picklist are removed. In addition, all lines where the next step has an earlier timestamp than the previous step are removed since a cart cannot go back in time. Then, remove the lines where there are still duplicate values in ’PicklijstID’. Each order has an individual picklist ID, thus it is not possible that there are multiple duplicates. What remains is the output of the order-picking process. To find the carts that are taken from the sorting tracks, all lines are removed where there is no pick up scan.

	Monday	Tuesday	Wednesday	Thursday	Friday	
2023-01	2.113	1.608	1.516	1.085	1.911	
2023-02	2.399	1.784	1.711	1.218	2.114	
2023-03	2.554	1.821	1.713	1.278	2.083	
2023-04	2.515	1.857	2.001	1.407	2.402	
2023-05	2.927	2.119	2.157	1.633	2.686	
2023-06	3.399	2.704	2.627	2.155	3.225	
2023-07	3.154	2.202	1.999	1.592	2.689	
2023-08	3.431	2.629	2.540	2.053	3.023	
2023-09	3.519	2.497	2.491	1.871	2.814	
2023-10	3.166	2.210	2.050	1.503	2.497	
2023-11	3.188	2.400	2.254	1.662	2.727	
2023-12	3.300	2.426	2.220	1.585	2.487	
2023-13	3.186	2.205	2.092	1.706	2.786	
2023-14	3.583	2.736	2.465	1.891	2.613	
2023-15		3.518	2.549	2.039	2.785	Easter
2023-16	3.431	2.471	2.349	1.749	2.848	
2023-17	3.441	2.721	2.753		3.548	Kingsday
2023-18	4.130	3.143	3.003	2.383	3.554	
2023-19	4.549	3.528	3.309	2.504	3.133	
2023-20	3.681	2.971	2.954		3.651	Ascension day
2023-21	4.282	3.191	2.996	2.278	3.402	
2023-22		4.789	3.332	2.459	3.212	Whitsun
2023-23	3.674	2.715	2.554	1.999	2.944	
2023-24	3.682	2.775	2.593	2.007	3.043	
2023-25	3.681	2.803	2.625	2.050	2.944	
2023-26	3.731	2.999	2.699	2.002	2.874	
2023-27	3.404	2.616	2.490	1.840	2.730	
2023-28	3.363	2.588	2.627	1.963	2.814	
2023-29	3.330	2.400	2.260	1.695	2.409	
2023-30	3.093	2.240	2.120	1.629	2.373	
2023-31	2.992	2.380	2.297	1.775	2.651	
2023-32	3.428	2.372	2.260	1.669	2.638	
2023-33	3.317	2.591	2.469	1.950	2.907	
2023-34	3.765	2.788	2.656	2.027	3.080	
2023-35	3.827	2.776	2.535	1.867	2.795	
2023-36	3.428	2.678	2.676	2.013	3.053	
2023-37	3.810	2.874	2.779	1.998	2.981	
2023-38	3.624	2.838	2.691	1.881	2.915	
2023-39	3.529	2.547	2.443	1.841	3.025	
2023-40	3.603	2.767	2.550	1.917	2.916	
2023-41	3.587	2.641	2.512	1.865	2.851	
2023-42	3.390	2.489	2.336	1.728	2.650	
2023-43	3.390	2.524	2.387	1.837	2.738	

Figure B.1: Supply of carts per day in 2023

From the tugger (1) two options are possible. First is the stream of carts going to the fine sorting area. For this the location of the fine sorting area (”Loc. Fijn sorteer”) was filtered on J0-001-01 and J0-001-02, the rest was removed. There were also some carts where the tugger (1) had forgotten to scan the fine sorting area and the next scan was already the delivery track in the fine sorting area. Those carts have been removed by setting the location of the fine sorting area (”Loc. Fijn sorteer”) to J0-002-01, ..., J0-002-44. The last stream via the dedicated buyer lanes has been found by setting the location of the fine sorting area (”Loc. Fijn sorteer”) to J0-002-90, ..., J0-002-95.

For the fine sorting area to the delivery tracks in the fine sorting area, an extra filter has been added. The location of the delivery tracks (”Loc. Aflever”) has been filtered to J0-002-01, ..., J0-002-44. To find the output of the delivery tracks, the pick-up time from those tracks (”Pick up 3”) was not allowed to be blank.

To find the stream via the dedicated buyer tracks, the mentioned location of the fine sorting area was in place. The output of the dedicated buyer tracks was found by setting the pick up

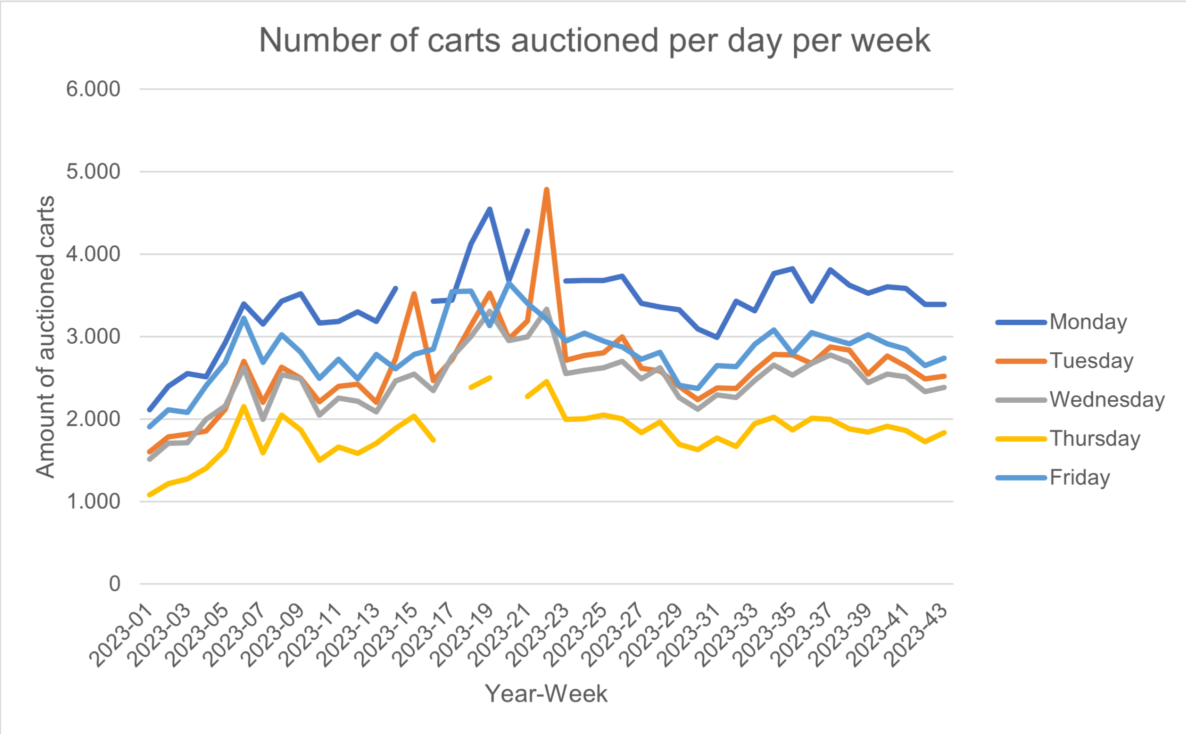


Figure B.2: Supply of carts per day in 2023

time from the fine sorting area to not blank. A short overview of the filters used is given in Table B.1.

Table B.1: Used filters for flow of carts

Stream	**Filters**
Input Tugger (1)	Remove lines where ”PicklijstID” has no value* Remove lines where next step is earlier than the previous one* Remove lines with duplicates in ”PicklijstID”* Remove lines where ”Pick up grof sorteer” has no value*
Input fine sorting process	”Loc. Fijn sorteer” = J0-001-01, J0-001-02
Input dedicated buyer tracks	”Loc. Fijn sorteer” = J0-002-90, ..., J0-002-95
Input delivery tracks in fine sorting area from fine sorting area	”Loc. Fijn sorteer” = J0-001-01, J0-001-02; ”Loc. Aflever” = J0-002-01, ..., J0-002-44
Output delivery tracks in fine sorting area via fine sorting area	”Loc. Fijn sorteer” = J0-001-01, J0-001-02; ”Loc. Aflever” = J0-002-01, ..., J0-002-44; ”Pick up 3” ≠ ’blank’
Output dedicated buyer tracks	”Loc. Fijn sorteer” = J0-002-90, ..., J0-002-95; ”Pick up Fijn sorteer” ≠ ’blank’

*This filter was present for every other stream

C
Design

Scoring of the objectives

Table C.1: Score 1-5 per objective

FO1	1. Very negative influence on the expansion factor (expansion factor increases) 2. Little negative influence on the expansion factor (expansion factor increases) 3. No influence on the expansion factor 4. Little positive influence on the expansion factor (expansion factor decreases) 5. Very positive influence on the expansion factor (expansion factor decreases)
FO2	1. Design is never able to adjust to changes during the process 2. Design is rarely able to adjust to changes during the process 3. Design is occasionally able to adjust to changes during the process 4. Design is frequently able to adjust to changes during the process 5. Design is very frequently or always able to adjust to changes during the process
FO3	1. Not updatable 2. Can be limitedly updated 3. Can be updated overall 4. Can be updated further 5. Can be updated constantly
NFO1	1. Lead time increases a lot 2. Lead time increases a little 3. Lead time does not change 4. Lead time decreases a little 5. Lead time decreases a lot
NFO2	1. Not affordable 2. Significant rise in costs 3. Moderate rise in costs 4. Slight rise in costs 5. Does not increase current costs

NFO3	1. Performance cannot be tracked 2. Performance can be tracked less than in the current situation 3. Performance can be tracked on the same level as in the current situation 4. Performance can be tracked more than in the current situation 5. Performance can be tracked every minute of the process
NFO4	1. Not understandable at all 2. Hard to understand 3. Medium to understand 4. Easy to understand 5. Everything is run automatically
NFO5	1. Many more mistakes than in the current process 2. A little more mistakes than in the current process 3. The same number of mistakes as in the current process 4. A little fewer mistakes than in the current process 5. Many fewer mistakes than in the current process

Weighted means per function

Table C.2: Weighted means of the same output per hour as input per hour for each step in the overall process

	FO1	FO2	FO3	NFO1	NFO2	NFO3	NFO4	NFO5	sum
Highest output of the order-picking process as possible, switch people around to where help is needed	3	2	2	3	5	3	3	3	120
Capacity of each step in the overall process	3	4	4	2	4	3	3	4	120
Distribution of breaks	3	3	3	4	5	3	4	3	139
Distribution of employees	3	4	4	4	5	3	4	3	144

Table C.3: Weighted means of filling and emptying of sorting and delivery tracks

	FO1	FO2	FO3	NFO1	NFO2	NFO3	NFO4	NFO5	sum
Tracks per delivery area, directed buyers go via waiting area, no limited waiting time on tracks, take the longest train	3	2	2	3	5	3	3	3	120
Limiting number of tracks in work area	3	4	4	4	4	3	4	4	142
Limited waiting time on a track	4	3	4	5	4	3	4	3	147
Clustering of delivery tracks	3	4	3	5	4	3	3	2	132
Direct delivery to the large buyers	3	4	4	4	4	3	4	2	132
Combining trains from not busy tracks	3	3	5	4	5	3	3	3	129

Table C.4: Weighted means of management of each step in the overall process

	FO1	FO2	FO3	NFO1	NFO2	NFO3	NFO4	NFO5	sum
Managers physically present	3	2	2	3	5	3	4	3	126
Cameras present in each work area	3	3	3	3	3	3	4	3	117
Live dashboarding	3	4	4	4	3	3	4	3	130
Directed management from the WMS	3	5	5	4	3	4	5	5	152

Table C.5: Weighted means of communication to employees

	FO1	FO2	FO3	NFO1	NFO2	NFO3	NFO4	NFO5	sum
Whiteboard	3	1	1	3	5	1	3	3	113
Traffic lights	3	2	2	4	3	1	4	4	123
Displays	3	3	3	4	2	1	4	4	121
Headphone	3	2	2	4	4	2	3	4	125
Scanner	3	4	5	5	3	3	4	5	150

KPI decisions

Table C.6: KPIs from RFH and the literature

KPI	Selected? Yes	Selected? No	Reason
% before end time (RFH)	✓		Main goal to deliver everything on time
Lead time carts overall process (RFH)	✓		This project focuses on the overall process
On-time shipping ratio (Literature)	✓		Same as the KPI above in this table
Total distribution cost (Literature)	✓		The cost is calculated by multiplying the required number of employees with the number of hours it takes to finish the overall process
Lead time in-house delivery process (RFH)		✓	This project focuses on the overall process and not only in-house delivery
% buyer complaints (RFH)		✓	Buyers complain not only about on-time delivery but also about quality. The design will not influence the quality and it is unsure how many buyers submit a complaint.
Incorrect delivery scans (RFH)		✓	Is the performance of an employee and not of the overall process
Buyer carts scanned (RFH)		✓	Is the performance of an employee and not of the overall process
Expansion factor (RFH)		✓	The design will not influence the order-picking process and thus not the expansion factor
Productivity (RFH)		✓	Does not necessarily change when not focussing on it (from experience) and thus does not influence the performance of the overall process
Flexibility of distribution (Literature)		✓	Flexibility of distribution is visible in the other KPIs and does not need a separate one
Timeliness of goods delivery (Literature)		✓	For an auction is this the same as the on-time shipping ratio
Profitability by item (Literature)		✓	This will decrease when the lead time increases

Calculations minimum required output
It has been found that the following percentages of carts need to be delivered before the corresponding latest delivery time. The percentages do not perfectly add up to 100% since some orders can be delivered later and do not have a fixed latest delivery time. Those numbers are the same for every day of the week.

- **8 AM** 1.9%
- **10 AM** 4.5%
- **11 AM** 32.6%
- **12 AM** 59.9%

- **13 AM** 1.0%

The goal is to find the minimum required output per 15 minutes so that all carts can be delivered on time. The calculations are done based on the expected number of buyer carts and the following calculations are used:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

per_8_00 = 1.9
per_10_00 = 4.5
per_11_00 = 32.6
per_12_00 = 59.9
per_13_00 = 1.0

limit_6_00 = 80

number_of_carts = np.arange(2000, 10200, 200)
limit_per_15 = np.arange(0, 1000, 1)
limit_per_15_final = []

for i in range(len(number_of_carts)):
    for j in range(len(limit_per_15)):
        real_8 = per_8_00/100 * number_of_carts[i]
        real_10 = per_10_00/100 * number_of_carts[i]
        real_11 = per_11_00/100 * number_of_carts[i]
        real_12 = per_12_00/100 * number_of_carts[i]
        real_13 = per_13_00/100 * number_of_carts[i]

        max_8 = limit_6_00 + 3* limit_per_15[j]
        max_10 = 10* limit_per_15[j] + limit_6_00 - real_8
        max_11 = 14* limit_per_15[j] + limit_6_00 - real_8 - real_10
        max_12 = 18* limit_per_15[j] + limit_6_00 - real_8 - real_10 - real_11
        max_13 = 22* limit_per_15[j] + limit_6_00 - real_8 - real_10 - real_11
        - real_12
        if max_8 >= real_8 and max_10 >= real_10 and max_11 >= real_11 and
        max_12 >= real_12 and max_13 >= real_13:
            limit_per_15_final.append(limit_per_15[j])
            break
```

There is some starting effect, thus the limit of the first 15 minutes is set to 80 carts. In addition, it is considered that only half of the carts are produced during the break instead of the full amount. When running this code the following figure is the result (Figure C.1). For the day analysed, this results in approximately 390 carts per 15 minutes.
When rearranging the percentages to something else, for example:

- **8 AM** 1.9%
- **10 AM** 24.5%
- **11 AM** 24.5%
- **12 AM** 24.5%
- **13 AM** 24.5%

Then, Figure C.2 is the outcome where only an output of 330 carts per 15 minutes is required for the analysed day. Numerous other solutions are available, but this is an example.

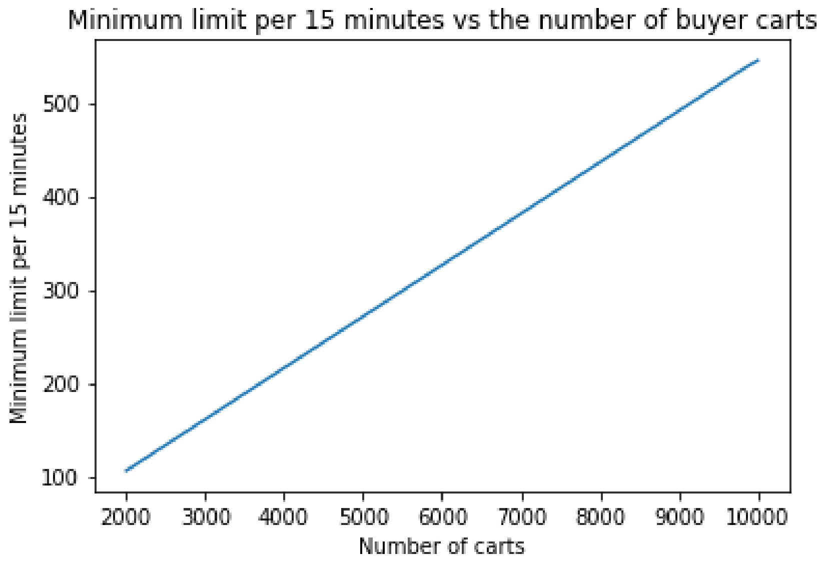


Figure C.1: Limit per 15 minutes based on number of buyer carts

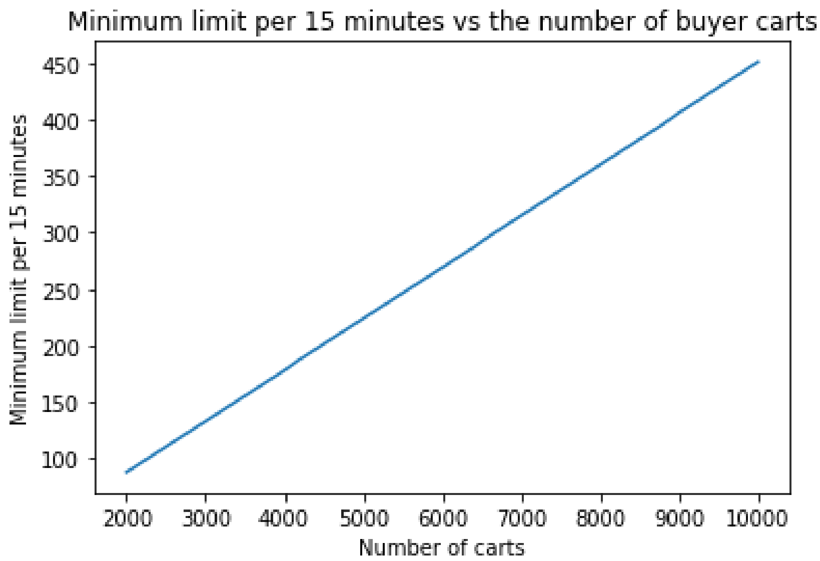


Figure C.2: Limit per 15 minutes based on number of buyer carts new situation

Alternatives for track division and clusters
The tracks placed in groups are the track numbers that are combined into one new track for the track division or one cluster for the clusters.

Track division 1: [[2,4,5], [3,10], [7.8]]
Track division 2: [[2,9], [3,4,5,10], [7,8]]

Cluster version 1: [[1,2], [3,4], [5], [6,7], [8], [9], [10,11], [12,13,14], [15,16,17,18], [19,20], [21,22,23], [24], [25,26], [27,28], [29,30,31,32,33,34], [35], [36,37], [38,39], [40,41,42,43,44]]
Cluster version 2: [[1,2,3], [4,5], [6,7,8], [9,10,11], [12,13,14], [15,16,17,18,19,20], [21,22,23,24], [25,26,27], [28,29,30,31,32,33,34], [35,36], [37,38,39], [40,41,42,43,44]]

Separate model results on different Mondays (Table 5.8)

Table C.7: Results model 1 from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-’23	35	27	79	137
09-10-’23	30	23	75	125
16-10-’23	34	27	83	139
23-10-’23	32	28	74	132
30-10-’23	31	35	84	150
06-11-’23	32	31	78	136
13-11-’23	34	31	71	131
20-11-’23	35	33	77	137

Table C.8: Results model 2 from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-’23	34	32	78	138
09-10-’23	34	32	85	142
16-10-’23	35	30	83	145
23-10-’23	33	31	74	132
30-10-’23	42	33	75	142
06-11-’23	31	33	81	142
13-11-’23	33	32	69	126
20-11-’23	34	32	79	136

Table C.9: Results model 3.1 from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-’23	33	27	81	134
09-10-’23	29	25	80	134
16-10-’23	30	27	82	132
23-10-’23	27	26	79	129
30-10-’23	29	37	88	154
06-11-’23	28	32	84	143
13-11-’23	32	31	73	128
20-11-’23	30	32	79	128

Table C.10: Results model 3.2 from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-’23	30	28	77	130
09-10-’23	26	24	74	124
16-10-’23	27	27	80	131
23-10-’23	26	26	75	124
30-10-’23	26	36	88	150
06-11-’23	26	31	85	140
13-11-’23	30	31	75	131
20-11-’23	28	32	77	126

Table C.11: Results model 4 from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	24	27	81	131
09-10-'23	22	23	85	128
16-10-'23	25	28	86	133
23-10-'23	24	28	78	127
30-10-'23	24	35	84	142
06-11-'23	22	31	82	130
13-11-'23	26	31	76	128
20-11-'23	27	33	79	138

Table C.12: Results model 5a from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	35	27	63	121
09-10-'23	30	23	60	112
16-10-'23	34	27	73	123
23-10-'23	32	28	64	122
30-10-'23	31	35	76	142
06-11-'23	32	31	67	136
13-11-'23	34	31	63	123
20-11-'23	35	33	65	126

Table C.13: Results model 5b.1 from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	35	27	54	112
09-10-'23	30	23	55	107
16-10-'23	34	27	64	114
23-10-'23	32	28	57	115
30-10-'23	31	35	65	131
06-11-'23	32	31	61	119
13-11-'23	34	31	55	115
20-11-'23	35	33	58	120

Table C.14: Results model 5b.2 from Table 5.8 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	35	27	56	111
09-10-'23	30	23	51	103
16-10-'23	34	27	59	113
23-10-'23	32	28	56	114
30-10-'23	31	35	66	132
06-11-'23	32	31	58	116
13-11-'23	34	31	49	109
20-11-'23	35	33	54	119

Combine model results on different Mondays (Table 5.10)

Table C.15: Results model 1 from Table 5.10 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	34	32	78	138
09-10-'23	34	32	85	142
16-10-'23	35	30	83	145
23-10-'23	33	31	74	132
30-10-'23	42	33	75	142
06-11-'23	31	33	81	142
13-11-'23	33	32	69	126
20-11-'23	34	32	79	136

Table C.16: Results model 2 from Table 5.10 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	30	31	78	135
09-10-'23	29	31	88	146
16-10-'23	31	29	82	142
23-10-'23	33	31	71	131
30-10-'23	33	33	74	131
06-11-'23	29	32	77	134
13-11-'23	29	31	69	123
20-11-'23	29	31	73	132

Table C.17: Results model 3 from Table 5.10 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	21	31	85	134
09-10-'23	21	31	98	147
16-10-'23	19	29	89	136
23-10-'23	19	31	82	131
30-10-'23	22	33	78	128
06-11-'23	19	32	84	133
13-11-'23	18	31	76	119
20-11-'23	19	31	77	124

Table C.18: Results model 4 from Table 5.10 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	21	31	75	122
09-10-'23	21	31	84	133
16-10-'23	19	29	77	124
23-10-'23	19	31	71	120
30-10-'23	22	33	71	119
06-11-'23	19	32	72	121
13-11-'23	18	31	69	115
20-11-'23	19	31	69	116

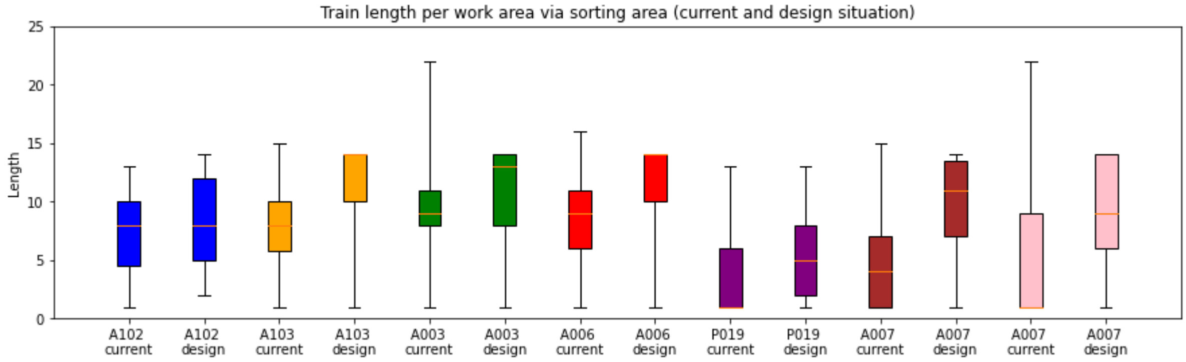
Table C.19: Results model 5 from Table 5.10 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	21	31	61	110
09-10-'23	21	31	71	110
16-10-'23	19	29	65	109
23-10-'23	19	31	60	109
30-10-'23	22	33	58	108
06-11-'23	19	32	62	111
13-11-'23	18	31	56	102
20-11-'23	19	31	59	105

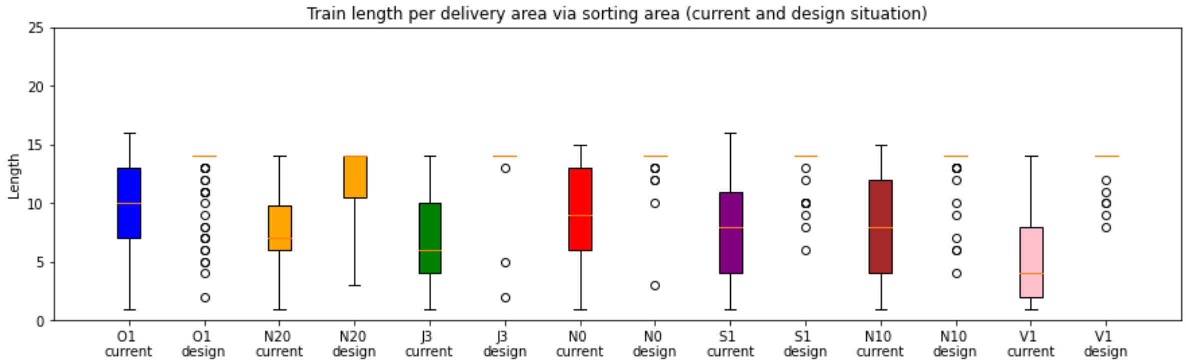
Table C.20: Results model 6 from Table 5.10 on different Mondays

Date	# Tuggers	# Sorters	# Deliverers	# Employees total
02-10-'23	25	32	62	111
09-10-'23	27	32	69	118
16-10-'23	24	30	64	114
23-10-'23	23	31	60	109
30-10-'23	31	33	57	119
06-11-'23	23	33	64	117
13-11-'23	24	32	56	103
20-11-'23	24	32	58	111

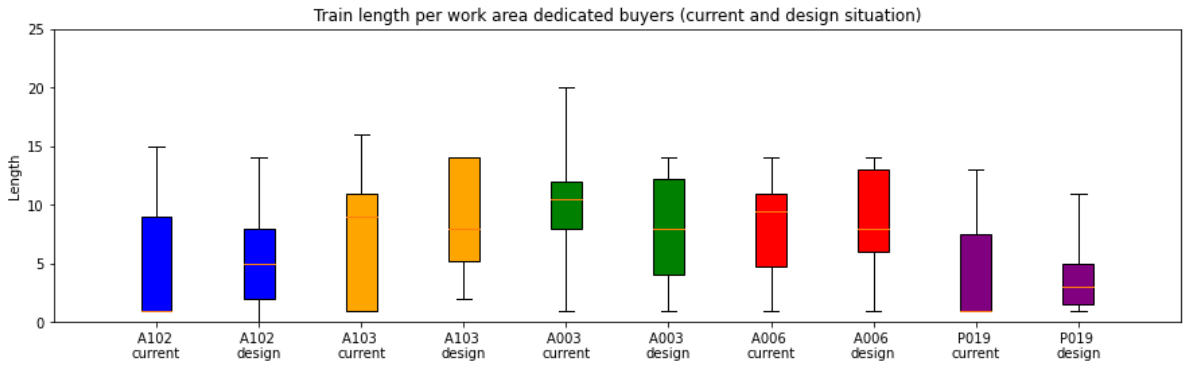
Train length and waiting times, current situation versus design



(a) Train length working area via sorting area

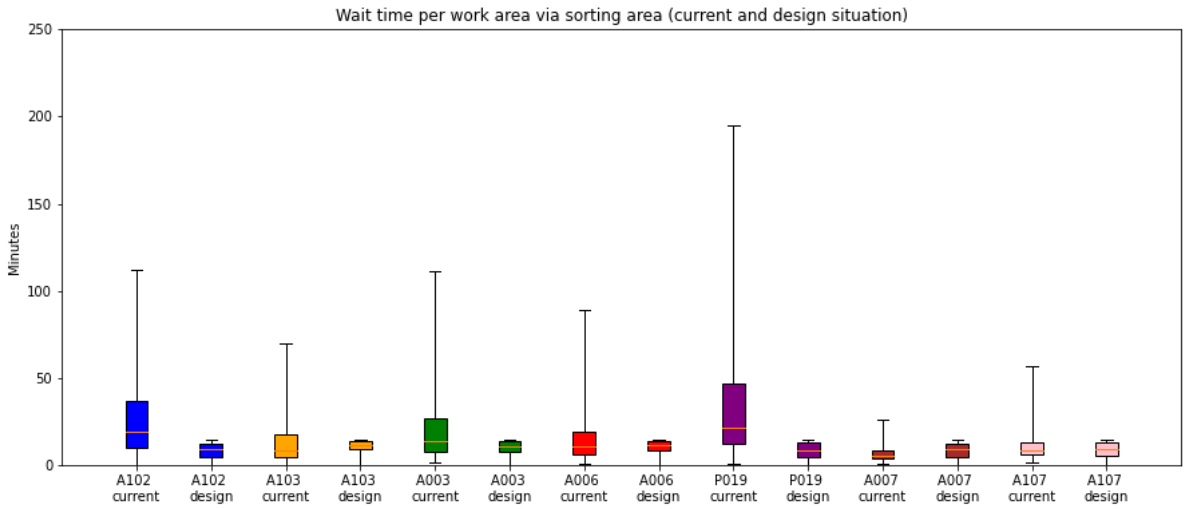


(b) Train length delivery tracks

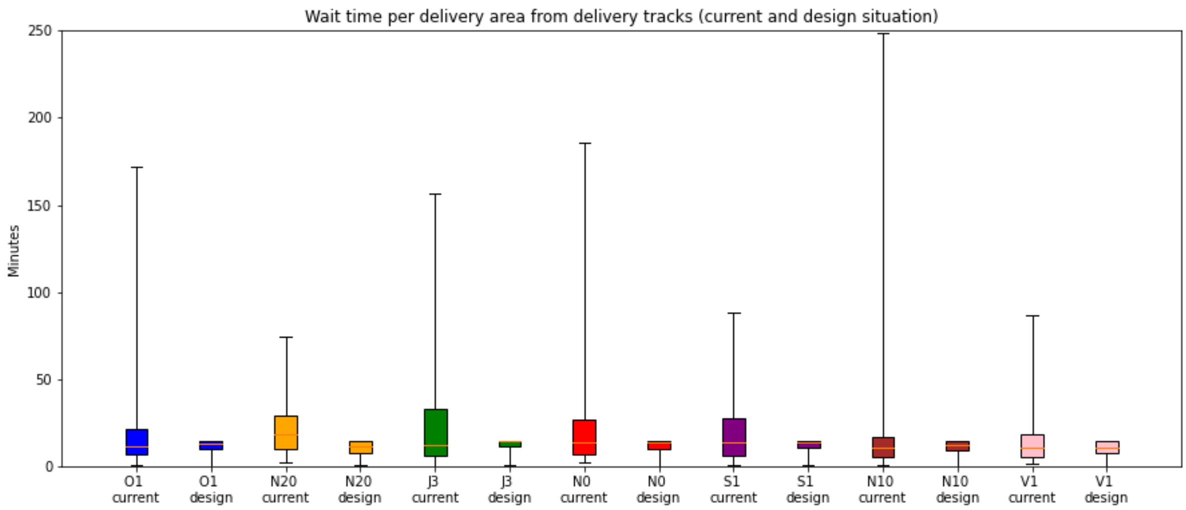


(c) Train length dedicated buyers

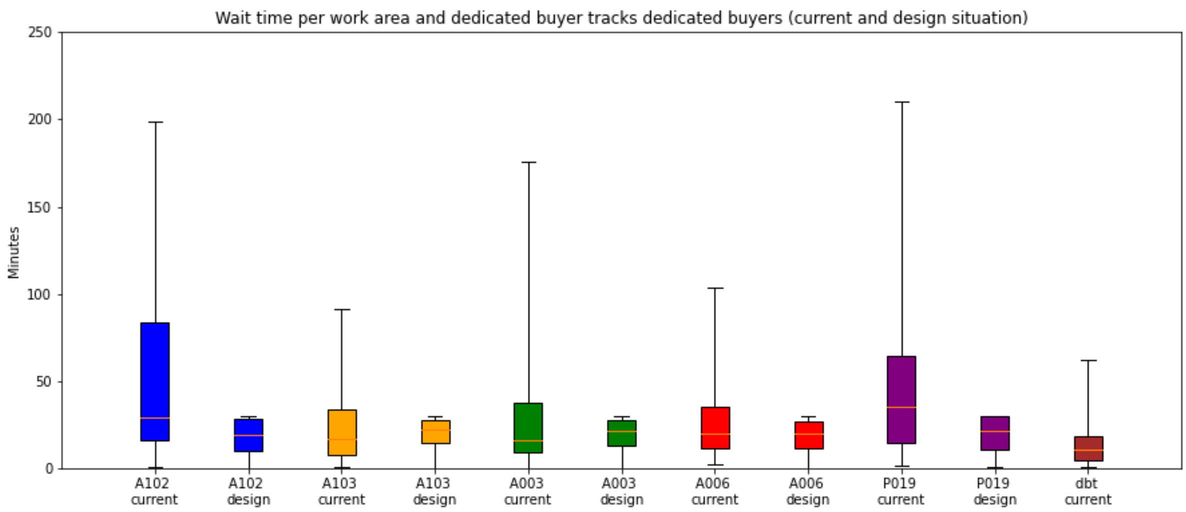
Figure C.3: Train lengths at different steps of the process



(a) Train length working area via sorting area



(b) Train length delivery tracks



(c) Train length dedicated buyers

Figure C.4: Train lengths at different steps of the process

D

Model

This appendix will provide parts of the Python script created by the researcher. First, the input is explained. Then, different steps taken by the model to simulate what should happen are described. Finally, the output of the model is discussed.

Input

The data that is used as input has been discussed in Section 5.6.1 and shown in Figures 5.1 and **??**. In addition, some parameters have been set.

```
max_wait_time_sort = 15
max_wait_time_sort_dbt = 30
max_wait_time_delivery = 15
tugging_time_to_fine = 3
return_time_tugging = 3
sorting_time = 5
max_train_length = 14
productivity_fine_per_30_min = 22
limit_6_00 = 80
limit_per_15_min = 390
option_number = 2
```

Next, filtering is done for the first data set which contains the scan information. It has been explained in Section 4.3.2 that the data contains faults which have to be removed from the data set.

```
df = df[df['PicklijstID'].notna()]  #remove lines that are not a picklist
rows_with_picklist_value = len(df)
df = df.sort_values(by=['PicklijstID']) #sort by picklist ID

#remove lines where the next step is earlier
df = df.drop(df[df['Aflevertijd'] < df['Drop␣3']].index.to_list())
df = df.drop(df[df['Drop␣3'] < df['Pick␣up␣3']].index.to_list())
df = df.drop(df[df['Pick␣up␣3'] < df['Drop␣aflever']].index.to_list())
df = df.drop(df[df['Drop␣aflever'] < df['Pick␣up␣Fijn␣sorteer']].index.to_list())
df = df.drop(df[df['Pick␣up␣Fijn␣sorteer'] < df['Drop␣Fijn␣sorteer']].index.to_list())
df = df.drop(df[df['Drop␣Fijn␣sorteer'] < df['Pick␣up␣grof␣sorteer']].index.to_list())
df = df.drop(df[df['Pick␣up␣Fijn␣sorteer'] < df['Grof␣sorteer␣scan']].index.to_list())
df = df.drop(df[df['Grof␣sorteer␣scan'] < df['Einde␣PickTijd']].index.to_list())
df = df.drop(df[df['Einde␣PickTijd'] < df['Acceptatie␣Pick␣Opdracht']].index.to_list())

rows_without_step_back_in_time = len(df)

#find all remaining duplicates and create a list of picklijstID values that are
duplicates
ids = df["PicklijstID"]
dup1 = df[ids.isin(ids[ids.duplicated()])].sort_values("PicklijstID")
ids1 = dup1['LadingdragerID']
dup2 = dup1[ids1.isin(ids1[ids1.duplicated()])].sort_values("LadingdragerID")
unique = dup2['PicklijstID'].unique()

#remove all duplicates
df = df[~df['PicklijstID'].isin(unique)]
```

The time it takes for a deliverer to drive from the delivery track to the buyer and return is calculated by using the current times and taking the 75th percentile of these values.

```
df_employees = df[df['Loc.␣3'].notna()]
df_employees = df_employees[df_employees['Medewerker␣(nr)␣Afl'].notna()]

employees = df_employees['Medewerker␣(nr)␣Afl'].unique()

direction = []
last_scan = []
next_scan = []
difference = []

for i in range(len(employees)):
    df_new = df_employees[df_employees['Medewerker␣(nr)␣Afl'] == employees[i]]
    df_new = df_new.sort_values('Pick␣up␣3')
    df_new = df_new.reset_index(drop = True)
    for j in range(len(df_new)-1):
        if (datetime.combine(date.today(), df_new['Pick␣up␣3'].iloc[j+1])-
        datetime.combine(date.today(), df_new['Pick␣up␣3'].iloc[j])).total_seconds()/60
        > 5:
            direction.append(df_new['Loc.␣3'][j])
            last_scan.append(df_new['Pick␣up␣3'][j])
            next_scan.append(df_new['Pick␣up␣3'][j+1])
            difference_minutes = (datetime.combine(date.today(),
            df_new['Pick␣up␣3'].iloc[j+1])-
            datetime.combine(date.today(),
            df_new['Pick␣up␣3'].iloc[j])).total_seconds()/60
            difference.append(round(difference_minutes, 2))

df_result = pd.DataFrame({'Direction': direction, 'Last␣scan': last_scan,
'Next␣scan': next_scan, 'Difference': difference})

df_O1 = df_result[df_result['Direction'].str.startswith('O1')]
df_V1 = df_result[df_result['Direction'].str.startswith('V1')]
df_S1 = df_result[df_result['Direction'].str.startswith('S1')]
df_J3 = df_result[df_result['Direction'].str.startswith('J3')]
df_N0 = df_result[df_result['Direction'].str.startswith('N0')]
df_N10 = df_result[df_result['Direction'].str.startswith('N10')]
df_N20 = df_result[df_result['Direction'].str.startswith('N20')]

df_O1_list = df_O1['Difference'].to_list()
df_V1_list = df_V1['Difference'].to_list()
df_S1_list = df_S1['Difference'].to_list()
df_J3_list = df_J3['Difference'].to_list()
df_N0_list = df_N0['Difference'].to_list()
df_N10_list = df_N10['Difference'].to_list()
df_N20_list = df_N20['Difference'].to_list()

delivery_time_O1 = np.percentile(df_O1_list, 75)
delivery_time_N20 = np.percentile(df_N20_list, 75)
delivery_time_J3 = np.percentile(df_J3_list, 75)
delivery_time_N0 = np.percentile(df_N0_list, 75)
delivery_time_S1 = np.percentile(df_S1_list, 75)
delivery_time_N10 = np.percentile(df_N10_list, 75)
delivery_time_V1 = np.percentile(df_V1_list, 75)
```

Step 1: New division tracks

Limiting the number of tracks in a work area has been done by overwriting the track number with the new desired track number in the data frame. Two different options were tested. Which option is used, can be changed by changing the parameter ”option_number”.

```
#Option 1: −O1, −N20 and J3, −N10 and V1, −N0 and S1
if option_number == 1:
    option = 'Option␣1'
    for i in range(len(df_design_limited_output)):
        if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('08'):
            new_value = re.sub('−08', '−07',
            df_design_limited_output['Loc.␣Grof␣sorteer'][i])
            df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
            if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('10'):
                new_value = re.sub('−10', '−03',
                df_design_limited_output['Loc.␣Grof␣sorteer'][i])
                df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
            if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('05'):
                new_value = re.sub('−05', '−02',
                df_design_limited_output['Loc.␣Grof␣sorteer'][i])
                df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
            if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('04') and not
            (df_design_limited_output['Loc.␣Grof␣sorteer'][i].startswith('A007') or
            df_design_limited_output['Loc.␣Grof␣sorteer'][i].startswith('A107')):
                new_value = re.sub('−04', '−02',
                df_design_limited_output['Loc.␣Grof␣sorteer'][i])
                df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value

#Option 2: −O1, −N20, J3 and N0, −S1, V1 and N10
if option_number == 2:
    option = 'Option␣2'
    for i in range(len(df_design_limited_output)):
        if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('08'):
            new_value = re.sub('−08', '−07',
            df_design_limited_output['Loc.␣Grof␣sorteer'][i])
            df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
        if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('09'):
            new_value = re.sub('−09', '−02',
            df_design_limited_output['Loc.␣Grof␣sorteer'][i])
            df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
        if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('10'):
            new_value = re.sub('−10', '−03',
            df_design_limited_output['Loc.␣Grof␣sorteer'][i])
            df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
        if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('05'):
            new_value = re.sub('−05', '−03',
            df_design_limited_output['Loc.␣Grof␣sorteer'][i])
            df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
        if df_design_limited_output['Loc.␣Grof␣sorteer'][i].endswith('04') and not
        (df_design_limited_output['Loc.␣Grof␣sorteer'][i].startswith('A007') or
        df_design_limited_output['Loc.␣Grof␣sorteer'][i].startswith('A107')):
            new_value = re.sub('−04', '−03',
            df_design_limited_output['Loc.␣Grof␣sorteer'][i])
            df_design_limited_output.loc[i, 'Loc.␣Grof␣sorteer'] = new_value
```

Step 2: Capacity

To obtain the required order-picking output, the same sequence of output is used as in the current situation. However, the number of lines per 15 minutes will change. Per 15 minutes, the required number of lines is taken for that time interval and evenly distributed over that time interval. Then, the output time of the order-picking process is changed to the new time according to the distribution over the time intervals.

```
for i in range(len(times)−1):
    if times[i] == '06:00:00':
        datetime_range = pd.date_range(start = datetime.combine(date.today(),
        datetime.strptime(times[i], '%H:%M:%S').time()), end =
        (datetime.combine(date.today(), datetime.strptime(times[i+1], '%H:%M:%S').time())
        − timedelta(seconds = 1)), periods = limit_6_00)
```

```
        timestamp_range = []
        for j in range(len(datetime_range)):
            timestamp = datetime_range[j].time().replace(microsecond=0)
            timestamp_range.append(timestamp)
        df_design_limited_output.loc[0:limit_6_00-1, 'Grof␣sorteer␣scan'] =
        timestamp_range
    if times[i] >= '06:15:00' and times[i] <= '08:00:00':
        datetime_range = pd.date_range(start = datetime.combine(date.today(),
        datetime.strptime(times[i], '%H:%M:%S').time()), end =
        (datetime.combine(date.today(), datetime.strptime(times[i+1], '%H:%M:%S').time())
        - timedelta(seconds = 1)), periods = limit_per_15_min)
        timestamp_range = []
        for j in range(len(datetime_range)):
            timestamp = datetime_range[j].time().replace(microsecond=0)
            timestamp_range.append(timestamp)
        start = limit_6_00 + (i-1) * limit_per_15_min
        end = start + limit_per_15_min - 1
        df_design_limited_output.loc[start:end, 'Grof␣sorteer␣scan'] =
        timestamp_range
    if times[i] == '08:15:00' or times[i] == '08:30:00':
        datetime_range = pd.date_range(start = datetime.combine(date.today(),
        datetime.strptime(times[i], '%H:%M:%S').time()), end =
        (datetime.combine(date.today(), datetime.strptime(times[i+1], '%H:%M:%S').time())
        - timedelta(seconds = 1)), periods = limit_break)
        timestamp_range = []
        for j in range(len(datetime_range)):
            timestamp = datetime_range[j].time().replace(microsecond=0)
            timestamp_range.append(timestamp)
        start = limit_6_00 + (times.index('08:15:00')-1) * limit_per_15_min +
        (i - times.index('08:15:00')) * limit_break
        end = start + limit_break - 1
        df_design_limited_output.loc[start:end, 'Grof␣sorteer␣scan'] = timestamp_range
    if times[i] >= '08:45:00':
        start = limit_6_00 + (times.index('08:15:00')-1) * limit_per_15_min +
        (times.index('08:45:00') - times.index('08:15:00')) * limit_break +
        (i - times.index('08:45:00')) * limit_per_15_min
        if start + limit_per_15_min < len(df_design_limited_output):
            end = start + limit_per_15_min - 1
            datetime_range = pd.date_range(start = datetime.combine(date.today(),
            datetime.strptime(times[i], '%H:%M:%S').time()), end =
            (datetime.combine(date.today(), datetime.strptime(times[i+1], '%H:%M:%S').time())
            - timedelta(seconds = 1)), periods = limit_per_15_min)
            timestamp_range = []
            for j in range(len(datetime_range)):
                timestamp = datetime_range[j].time().replace(microsecond=0)
                timestamp_range.append(timestamp)
            df_design_limited_output.loc[start:end, 'Grof␣sorteer␣scan'] =
            timestamp_range
        if start + limit_per_15_min >= len(df_design_limited_output):
            end = len(df_design_limited_output) - 1
            datetime_range = pd.date_range(start = datetime.combine(date.today(),
            datetime.strptime(times[i], '%H:%M:%S').time()), end =
            (datetime.combine(date.today(), datetime.strptime(times[i+1], '%H:%M:%S').time())
            - timedelta(seconds = 1)), periods = limit_per_15_min)
            timestamp_range = []
            for j in range(len(datetime_range)):
                timestamp = datetime_range[j].time().replace(microsecond=0)
                timestamp_range.append(timestamp)
            new_end = end-start + 1
            timestamp_range = timestamp_range[0:new_end]
            df_design_limited_output.loc[start:end, 'Grof␣sorteer␣scan'] = timestamp_range
```

```
            break
```

Step 3: Preparing for tugging

After creating the new order-picking output and setting the new track division, new groups are formed on the tracks based on either the waiting time of the first cart or the train length. The groups have a pick-up time that is exactly 15 minutes after the first cart has been placed on the track or when the maximum train length is reached. The current data frame is overwritten with the new pick-up time, new drop-off time at the sorting area and the time a cart is at the delivery track. This can all be calculated at once because the time it takes a tugger to move the carts and the time a cart can be in the sorting area are set to a constant.

```
def design_max_wait_time_tracks_fine(df, length_design, time, track, delivery_track,
    sort_scan_time):
    start = 0
    stop = False
    for i in range(len(df)):
        i = start
        if stop == True:
            break

        group = []
        track_at_moment = []
        new_group = []

        for j in range(len(df)):
            j = j + start
            if j >= len(df):
                stop = True
                break
            if (datetime.combine(date.today(), df['Grof␣sorteer␣scan'].iloc[j])-
            datetime.combine(date.today(),
            df['Grof␣sorteer␣scan'].iloc[i])).total_seconds()/60 > max_wait_time_sort:
                start = j
                break
            new_group.append(df['Loc.␣Aflever'].iloc[j])
            group.append(df['Grof␣sorteer␣scan'].iloc[j])
            if len(group) == max_train_length:
                start = j
                break
            track_at_moment.append(df['Loc.␣Grof␣sorteer'].iloc[i])
            if len(group) == max_train_length:
                end_time = group[-1]
            else:
                end_time = (datetime.combine(date.today(), group[0]) + timedelta(minutes
                = max_wait_time_sort)).time()
        for z in range(len(new_group)):
            new_list = [i for i in new_group if str(i).startswith('J0-002')]
            if not str(new_group[z]).startswith('J0-002'):
                if len(new_list) > 0:
                    new_group[z] = random.choice(new_list)
        delivery_track.append(new_group)
        time.append(end_time)
        track.append(track_at_moment[0])
        length_design.append(len(group))
        sort_scan_time.append(group)
    for i in range(len(sort_scan_time)):
        for j in range(len(sort_scan_time[i])):
            for k in range(len(df)):
                if df['Grof␣sorteer␣scan'][k] == sort_scan_time[i][j]:
                    df.loc[k, 'Pick␣up␣grof␣sorteer'] = time[i]
                    df.loc[k, 'Drop␣Fijn␣sorteer'] = (datetime.combine(date.today(),
                    df.loc[k, 'Pick␣up␣grof␣sorteer']) + timedelta(minutes =
                    tugging_time_to_fine)).time()
```

```
                df.loc[k, 'Drop␣aflever'] = (datetime.combine(date.today(),
                df.loc[k, 'Drop␣Fijn␣sorteer']) + timedelta(minutes =
                sorting_time)).time()
                df.loc[k, 'Loc.␣Aflever'] = delivery_track[i][j]
```

Step 4: Direct delivery to dedicated buyers

After order picking, orders for dedicated buyers are delivered directly without placing the carts in a waiting area first. Here, the waiting time is 30 minutes instead of 15 minutes. In addition, the delivery time can be put in the data frame since the driving times have been calculated for the input and there are no steps in between.

```
def design_max_wait_time_tracks_dbt(df, length_design, time, track, delivery_track,
sort_scan_time):
    start = 0
    stop = False
    for k in range(len(df)):
        if str(df['Loc.␣Aflever'][k]).startswith('J0-002-9') and
        str(df['Loc.␣Fijn␣sorteer'][k]).startswith('J0-001'):
            df.loc[k, 'Loc.␣Fijn␣sorteer'] = df['Loc.␣Aflever'][k]
            df.loc[k, 'Loc.␣Aflever'] = df['Loc.␣3'][k]
            df.loc[k, 'Loc.␣3␣'] = ''
    for i in range(len(df)):
        i = start
        if stop == True:
            break

        group = []
        track_at_moment = []
        new_group = []

        for j in range(len(df)):
            j = j + start
            if j >= len(df):
                stop = True
                break
            if (datetime.combine(date.today(), df['Grof␣sorteer␣scan'].iloc[j])-
            datetime.combine(date.today(),
            df['Grof␣sorteer␣scan'].iloc[i])).total_seconds()/60 > max_wait_time_sort_dbt:
                start = j
                break
            new_group.append(df['Loc.␣Fijn␣sorteer'].iloc[j])
            group.append(df['Grof␣sorteer␣scan'].iloc[j])
            if len(group) == max_train_length:
                start = j + 1
                break
            track_at_moment.append(df['Loc.␣Grof␣sorteer'].iloc[i])
            if len(group) == max_train_length:
                end_time = group[-1]
            else:
                end_time = (datetime.combine(date.today(), group[0]) +
                timedelta(minutes = max_wait_time_sort_dbt)).time()
        for z in range(len(new_group)):
            new_list = [i for i in new_group if str(i).startswith('J0-002-9')]
            if not str(new_group[z]).startswith('J0-002-9'):
                if len(new_list) > 0:
                    new_group[z] = random.choice(new_list)
        delivery_track.append(new_group)
        time.append(end_time)
        if track_at_moment:
            track.append(track_at_moment[0])
        length_design.append(len(group))
        sort_scan_time.append(group)
    for i in range(len(sort_scan_time)):
```

```
        for j in range(len(sort_scan_time[i])):
            for k in range(len(df)):
                if df['Grof␣sorteer␣scan'][k] == sort_scan_time[i][j]:
                    df.loc[k, 'Pick␣up␣grof␣sorteer'] = time[i]
                    if df['Loc.␣Grof␣sorteer'][k].endswith('01') or
                    df['Loc.␣Grof␣sorteer'][k].endswith('14'):
                        df.loc[k, 'Drop␣Fijn␣sorteer'] = (datetime.combine(date.today(),
                        df.loc[k, 'Pick␣up␣grof␣sorteer']) + timedelta(minutes =
                        np.nanmax(minutes_delivery_N20_fine))).time().replace(microsecond=0)
                        df.loc[k, 'Loc.␣Fijn␣sorteer'] = delivery_track[i][j]
                    if df['Loc.␣Grof␣sorteer'][k].endswith('06'):
                        df.loc[k, 'Drop␣Fijn␣sorteer'] = (datetime.combine(date.today(),
                        df.loc[k, 'Pick␣up␣grof␣sorteer']) + timedelta(minutes =
                        np.nanmax(minutes_delivery_J3_fine))).time().replace(microsecond=0)
                        df.loc[k, 'Loc.␣Fijn␣sorteer'] = delivery_track[i][j]
                    if df['Loc.␣Grof␣sorteer'][k].endswith('11'):
                        df.loc[k, 'Drop␣Fijn␣sorteer'] = (datetime.combine(date.today(),
                        df.loc[k, 'Pick␣up␣grof␣sorteer']) + timedelta(minutes =
                        np.nanmax(minutes_delivery_S1_fine))).time().replace(microsecond=0)
                        df.loc[k, 'Loc.␣Fijn␣sorteer'] = delivery_track[i][j]
                    if df['Loc.␣Grof␣sorteer'][k].endswith('12'):
                        df.loc[k, 'Drop␣Fijn␣sorteer'] = (datetime.combine(date.today(),
                        df.loc[k, 'Pick␣up␣grof␣sorteer']) + timedelta(minutes =
                        np.nanmax(minutes_delivery_O1_fine))).time().replace(microsecond=0)
                        df.loc[k, 'Loc.␣Fijn␣sorteer'] = delivery_track[i][j]
                    if df['Loc.␣Grof␣sorteer'][k].endswith('13'):
                        df.loc[k, 'Drop␣Fijn␣sorteer'] = (datetime.combine(date.today(),
                        df.loc[k, 'Pick␣up␣grof␣sorteer']) + timedelta(minutes =
                        np.nanmax(minutes_delivery_V1_fine))).time().replace(microsecond=0)
                        df.loc[k, 'Loc.␣Fijn␣sorteer'] = delivery_track[i][j]
                df.loc[k, 'Aflevertijd'] = df['Drop␣Fijn␣sorteer'][k]
```

Step 5: Creating clusters

Clustering has been done similarly as limiting the number of tracks in a track area. Multiple tracks are put under one name. As soon as the cluster meets the criteria of either the limited waiting time or maximum train length, a cluster is emptied.

```
df_cluster_1 = pd.concat([df_input_design_01_limited_output,
df_input_design_02_limited_output, df_input_design_03_limited_output], ignore_index=True)
df_cluster_1 = df_cluster_1.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_2 = pd.concat([df_input_design_04_limited_output,
df_input_design_05_limited_output], ignore_index=True)
df_cluster_2 = df_cluster_2.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_3 = pd.concat([df_input_design_06_limited_output,
df_input_design_07_limited_output, df_input_design_08_limited_output], ignore_index=True)
df_cluster_3 = df_cluster_3.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_4 = pd.concat([df_input_design_09_limited_output,
df_input_design_10_limited_output, df_input_design_11_limited_output], ignore_index=True)
df_cluster_4 = df_cluster_4.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_5 = pd.concat([df_input_design_12_limited_output,
df_input_design_13_limited_output, df_input_design_14_limited_output], ignore_index=True)
df_cluster_5 = df_cluster_5.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_6 = pd.concat([df_input_design_15_limited_output,
df_input_design_16_limited_output, df_input_design_17_limited_output,
df_input_design_18_limited_output, df_input_design_19_limited_output,
df_input_design_20_limited_output], ignore_index=True)
df_cluster_6 = df_cluster_6.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_7 = pd.concat([df_input_design_21_limited_output,
df_input_design_22_limited_output, df_input_design_23_limited_output,
df_input_design_24_limited_output], ignore_index=True)
df_cluster_7 = df_cluster_7.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_8 = pd.concat([df_input_design_25_limited_output,
```

```
df_input_design_26_limited_output , df_input_design_27_limited_output] , ignore_index=True)
df_cluster_8 = df_cluster_8.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_9 = pd.concat([df_input_design_28_limited_output ,
df_input_design_29_limited_output , df_input_design_30_limited_output ,
df_input_design_31_limited_output , df_input_design_32_limited_output ,
df_input_design_33_limited_output , df_input_design_34_limited_output] , ignore_index=True)
df_cluster_9 = df_cluster_9.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_10 = pd.concat([df_input_design_35_limited_output ,
df_input_design_36_limited_output] , ignore_index=True)
df_cluster_10 = df_cluster_10.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_11 = pd.concat([df_input_design_37_limited_output ,
df_input_design_38_limited_output , df_input_design_39_limited_output] , ignore_index=True)
df_cluster_11 = df_cluster_11.sort_values('Drop␣aflever').reset_index(drop=True)
df_cluster_12 = pd.concat([df_input_design_40_limited_output ,
df_input_design_41_limited_output , df_input_design_42_limited_output ,
df_input_design_43_limited_output , df_input_design_44_limited_output] , ignore_index=True)
df_cluster_12 = df_cluster_12.sort_values('Drop␣aflever').reset_index(drop=True)
```

Step 6: Delivering from the sorting area

This step uses the same principle as used in steps 3 and 4. Thus, groups are created based on waiting time and train length. Then, the new arrival time at a buyer is defined by adding the driving time to the time a cart leaves the delivery track.

```
def design_max_wait_time_delivery(df, length_design, time, track, input_time):
    start = 0
    stop = False
    for i in range(len(df)):
        i = start
        if stop == True:
            break

        group = []
        track_at_moment = []

        for j in range(len(df)):
            j = j + start
            if j >= len(df):
                stop = True
                break
            if (datetime.combine(date.today(), df['Drop␣aflever'].iloc[j])-
            datetime.combine(date.today(), df['Drop␣aflever'].iloc[i])).total_seconds()
            /60 > max_wait_time_delivery:
                start = j
                break
            group.append(df['Drop␣aflever'].iloc[j])
            if len(group) == max_train_length:
                start = j
                break
            track_at_moment.append(df['Loc.␣Aflever'].iloc[i])
            if len(group) == max_train_length:
                end_time = group[-1]
            else:
                end_time = (datetime.combine(date.today(), group[0]) +
                timedelta(minutes = max_wait_time_delivery)).time()
        time.append(end_time)
        track.append(track_at_moment[0])
        length_design.append(len(group))
        input_time.append(group)
    for i in range(len(input_time)):
        for j in range(len(input_time[i])):
            for k in range(len(df)):
                if df['Drop␣aflever'][k] == input_time[i][j]:
```

```
                df.loc[k, 'Pick␣up␣3'] = time[i]
    for k in range(len(df)):
        if df['Loc.␣Aflever'][k] == 'J0-002-12' or df['Loc.␣Aflever'][k] == 'J0-002-13'
        or df['Loc.␣Aflever'][k] == 'J0-002-14':
            df.loc[k, 'Drop␣3'] = (datetime.combine(date.today(),
            datetime.strptime(str(df.loc[k, 'Pick␣up␣3']), '%H:%M:%S').time()) +
            timedelta(minutes =
            np.nanmax(minutes_delivery_N20_fine))).time().replace(microsecond=0)
        if df['Loc.␣Aflever'][k] == 'J0-002-35' or df['Loc.␣Aflever'][k] == 'J0-002-36'
        or df['Loc.␣Aflever'][k] == 'J0-002-37' or df['Loc.␣Aflever'][k] == 'J0-002-38'
        or df['Loc.␣Aflever'][k] == 'J0-002-39':
            df.loc[k, 'Drop␣3'] = (datetime.combine(date.today(),
            datetime.strptime(str(df.loc[k, 'Pick␣up␣3']), '%H:%M:%S').time()) +
            timedelta(minutes =
            np.nanmax(minutes_delivery_N10_fine))).time().replace(microsecond=0)
        if df['Loc.␣Aflever'][k] == 'J0-002-21' or df['Loc.␣Aflever'][k] == 'J0-002-22'
        or df['Loc.␣Aflever'][k] == 'J0-002-23' or df['Loc.␣Aflever'][k] == 'J0-002-24':
            df.loc[k, 'Drop␣3'] = (datetime.combine(date.today(),
            datetime.strptime(str(df.loc[k, 'Pick␣up␣3']), '%H:%M:%S').time()) +
            timedelta(minutes =
            np.nanmax(minutes_delivery_N0_fine))).time().replace(microsecond=0)
        if df['Loc.␣Aflever'][k] == 'J0-002-25' or df['Loc.␣Aflever'][k] == 'J0-002-26'
        or df['Loc.␣Aflever'][k] == 'J0-002-27' or df['Loc.␣Aflever'][k] == 'J0-002-28'
        or df['Loc.␣Aflever'][k] == 'J0-002-29' or df['Loc.␣Aflever'][k] == 'J0-002-30'
        or df['Loc.␣Aflever'][k] == 'J0-002-31' or df['Loc.␣Aflever'][k] == 'J0-002-32'
        or df['Loc.␣Aflever'][k] == 'J0-002-33' or df['Loc.␣Aflever'][k] == 'J0-002-34':
            df.loc[k, 'Drop␣3'] = (datetime.combine(date.today(),
            datetime.strptime(str(df.loc[k, 'Pick␣up␣3']), '%H:%M:%S').time()) +
            timedelta(minutes =
            np.nanmax(minutes_delivery_S1_fine))).time().replace(microsecond=0)
        if df['Loc.␣Aflever'][k] == 'J0-002-40' or df['Loc.␣Aflever'][k] == 'J0-002-41'
        or df['Loc.␣Aflever'][k] == 'J0-002-42' or df['Loc.␣Aflever'][k] == 'J0-002-43'
        or df['Loc.␣Aflever'][k] == 'J0-002-44':
            df.loc[k, 'Drop␣3'] = (datetime.combine(date.today(),
            datetime.strptime(str(df.loc[k, 'Pick␣up␣3']), '%H:%M:%S').time()) +
            timedelta(minutes =
            np.nanmax(minutes_delivery_V1_fine))).time().replace(microsecond=0)
        if df['Loc.␣Aflever'][k] == 'J0-002-01' or df['Loc.␣Aflever'][k] == 'J0-002-02'
        or df['Loc.␣Aflever'][k] == 'J0-002-03' or df['Loc.␣Aflever'][k] == 'J0-002-04'
        or df['Loc.␣Aflever'][k] == 'J0-002-05' or df['Loc.␣Aflever'][k] == 'J0-002-06'
        or df['Loc.␣Aflever'][k] == 'J0-002-07' or df['Loc.␣Aflever'][k] == 'J0-002-08'
        or df['Loc.␣Aflever'][k] == 'J0-002-09' or df['Loc.␣Aflever'][k] == 'J0-002-10'
        or df['Loc.␣Aflever'][k] == 'J0-002-11':
            df.loc[k, 'Drop␣3'] = (datetime.combine(date.today(),
            datetime.strptime(str(df.loc[k, 'Pick␣up␣3']), '%H:%M:%S').time()) +
            timedelta(minutes =
            np.nanmax(minutes_delivery_O1_fine))).time().replace(microsecond=0)
        if df['Loc.␣Aflever'][k] == 'J0-002-15' or df['Loc.␣Aflever'][k] == 'J0-002-16'
        or df['Loc.␣Aflever'][k] == 'J0-002-17' or df['Loc.␣Aflever'][k] == 'J0-002-18'
        or df['Loc.␣Aflever'][k] == 'J0-002-19' or df['Loc.␣Aflever'][k] == 'J0-002-20':
            df.loc[k, 'Drop␣3'] = (datetime.combine(date.today(),
            datetime.strptime(str(df.loc[k, 'Pick␣up␣3']), '%H:%M:%S').time()) +
            timedelta(minutes =
            np.nanmax(minutes_delivery_J3_fine))).time().replace(microsecond=0)
    for k in range(len(df)):
        df.loc[k, 'Aflevertijd'] = df['Drop␣3'][k]
```

Output

During the steps, the timestamps are changed to the new times that a scan takes place. The new times can be used to calculate the lead time by simply subtracting the starting time from the delivery time. In addition, the number of carts that are too late is calculated by first combining the two datasets and then by comparing the actual delivery time with the required delivery time.

```
ids10 = delivery_moment["Karnummer"]
dup1 = delivery_moment[ids10.isin(ids10[ids10.duplicated()])].sort_values("Karnummer")
unique1 = dup1['Karnummer'].unique()
delivery_moment = delivery_moment[~delivery_moment['Karnummer'].isin(unique1)]
ind = df_limited_output_final[df_limited_output_final['LadingdragerID'].isin(
delivery_moment['Karnummer'])].index
ind2 = delivery_moment[delivery_moment['Karnummer'].isin(df_limited_output_final[
'LadingdragerID'])].index

a = df_limited_output_final.loc[ind, 'LadingdragerID']
delivery_moment = delivery_moment[delivery_moment['Karnummer'].isin(
delivery_moment.loc[ind2, 'Karnummer'])]
delivery_moment = delivery_moment.sort_values('Karnummer')
delivery_moment = delivery_moment.reset_index(drop=True)

duplicated = a.duplicated()
a = a.drop_duplicates()
df_delivery_times_limited_output = df_limited_output_final
df_delivery_times_limited_output =
df_delivery_times_limited_output.loc[df_delivery_times_limited_output[
'LadingdragerID'].isin(a)]
df_delivery_times_limited_output = df_delivery_times_limited_output.drop_duplicates(
subset=['LadingdragerID'])
df_delivery_times_limited_output =
df_delivery_times_limited_output.sort_values('LadingdragerID')
df_delivery_times_limited_output = df_delivery_times_limited_output.reset_index(drop=True)

df_delivery_times_limited_output =
df_delivery_times_limited_output.join(delivery_moment['Karnummer'])
df_delivery_times_limited_output =
df_delivery_times_limited_output.join(delivery_moment['Eindtijd␣Norm'])
df_delivery_times_limited_output = df_delivery_times_limited_output.join(
delivery_moment['Veil␣Tijd'])
df_delivery_times_limited_output = df_delivery_times_limited_output.join(
delivery_moment['Te␣laat?'])
df_delivery_times_limited_output =
df_delivery_times_limited_output.join(delivery_moment['Kopernummer'])

df_delivery_times_limited_output['Eindtijd␣Norm'] = df_delivery_times_limited_output[
'Eindtijd␣Norm'].replace([datetime.strptime('07:15:00', '%H:%M:%S').time()],
datetime.strptime('08:00:00', '%H:%M:%S').time())
df_delivery_times_limited_output = df_delivery_times_limited_output[~
(df_delivery_times_limited_output['Eindtijd␣Norm'].isna())]
df_delivery_times_limited_output['Too␣late'] = ""

for i in range(len(df_delivery_times_limited_output)):
    if df_delivery_times_limited_output['Aflevertijd'][i] >
    df_delivery_times_limited_output['Eindtijd␣Norm'][i]:
        df_delivery_times_limited_output.loc[i, 'Too␣late'] = 'yes'
    else:
        df_delivery_times_limited_output.loc[i, 'Too␣late'] = 'no'
```

The number of employees per step in the process per half an hour has been calculated based on the time an employee needs to perform the task and return. Based on this, trains have been assigned to a tugger or deliverer and this has been repeated until there are no more tasks left. The number of employees are calculated to determine the number of work hours needed. The number of work hours are the costs of the process.

Tuggers

```
def design_required_number_tuggers(time_design, number_tuggers,
number_of_times_per_tugger, groups):
```

```
    min_spacing = tugging_time_to_fine + return_time_tugging
    time_design.sort()
    time_list = time_design

    while len(time_list) > 0:
        new_group = [time_list[0]]

        idx_to_remove = [0]

        # Create group with 7 min spacing
        for idx, time in enumerate(time_list[1:]):
            if timedelta(hours=time.hour - new_group[-1].hour,
                              minutes = time.minute - new_group[-1].minute,
                              seconds=time.second -
                              new_group[-1].second).seconds > min_spacing * 60:
                new_group.append(time)
                idx_to_remove.append(idx + 1)  # Start the enumerate at 1
        number_of_times_per_tugger.append(len(new_group))
        # Remove used indices backwards
        for idx in idx_to_remove[-1::-1]:
            time_list.pop(idx)

        groups.append(new_group)
    number_tuggers.append(len(groups))
```

Sorters

```
input_fine_sorting_design_times_limited_output = []
input_fine_sorting_design_values_limited_output = []
for i in range(len(half_an_hour)-1):
    start_date = datetime.strptime(half_an_hour[i], '%H:%M:%S').time()
    end_date = datetime.strptime(half_an_hour[i+1], '%H:%M:%S').time()
    df_new =
    df_input_fine_sorting_design_limited_output.loc[
    (df_input_fine_sorting_design_limited_output['times'] > start_date) &
    (df_input_fine_sorting_design_limited_output['times'] < end_date)]
    sum_per_30 = df_new['length'].sum()
    input_fine_sorting_design_times_limited_output.append(half_an_hour[i])
    input_fine_sorting_design_values_limited_output.append(sum_per_30)

number_of_people_fine_design_limited_output = []
for i in range(len(input_fine_sorting_design_values_limited_output)):
    number_of_people = math.ceil(input_fine_sorting_design_values_limited_output[i] /
    productivity_fine_per_30_min)
    number_of_people_fine_design_limited_output.append(number_of_people)
```

Deliverers

```
def design_required_number_deliverers(time_design, number_deliverers,
number_of_times_per_deliverer, min_spacing, groups):
    time_design.sort()
    time_list = time_design

    while len(time_list) > 0:
        new_group = [time_list[0]]

        idx_to_remove = [0]

        # Create group with 7 min spacing
        for idx, time in enumerate(time_list[1:]):
            if timedelta(hours=time.hour - new_group[-1].hour,
                              minutes = time.minute - new_group[-1].minute,
                              seconds=time.second - new_group[-1].second).seconds
```

```
                        > min_spacing * 60:
                new_group.append(time)
                idx_to_remove.append(idx + 1)  # Start the enumerate at 1
        number_of_times_per_deliverer.append(len(new_group))
        # Remove used indices backwards
        for idx in idx_to_remove[-1::-1]:
            time_list.pop(idx)

        groups.append(new_group)
    number_deliverers.append(len(groups))
```

E
Enlarged figures

Enlarged versions of the following figures will be displayed in this appendix:

- Figure 4.8
- Figure 4.9
- Figure 5.2

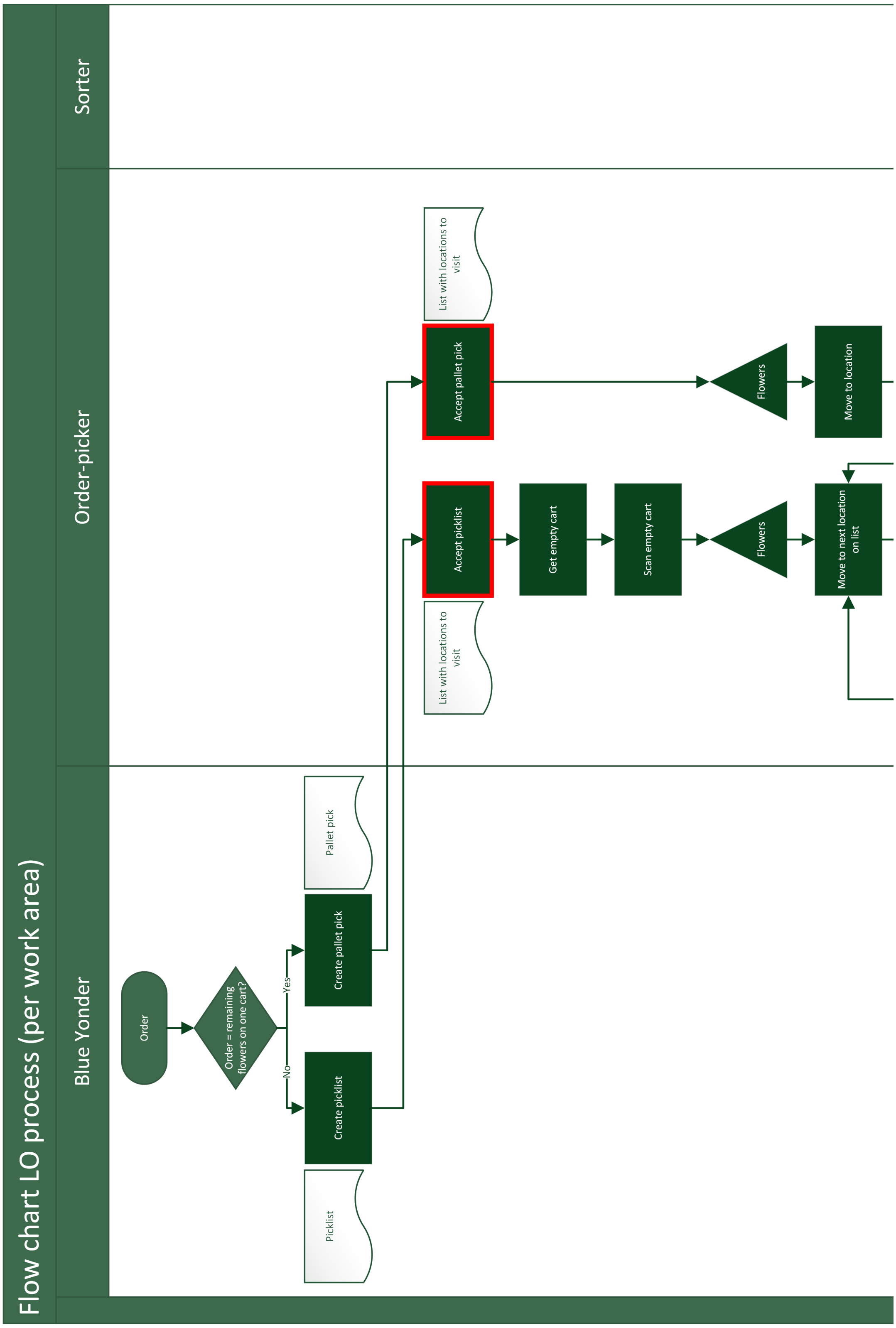


Figure E.1: Enlarged version of Figure 4.8 part 1/3

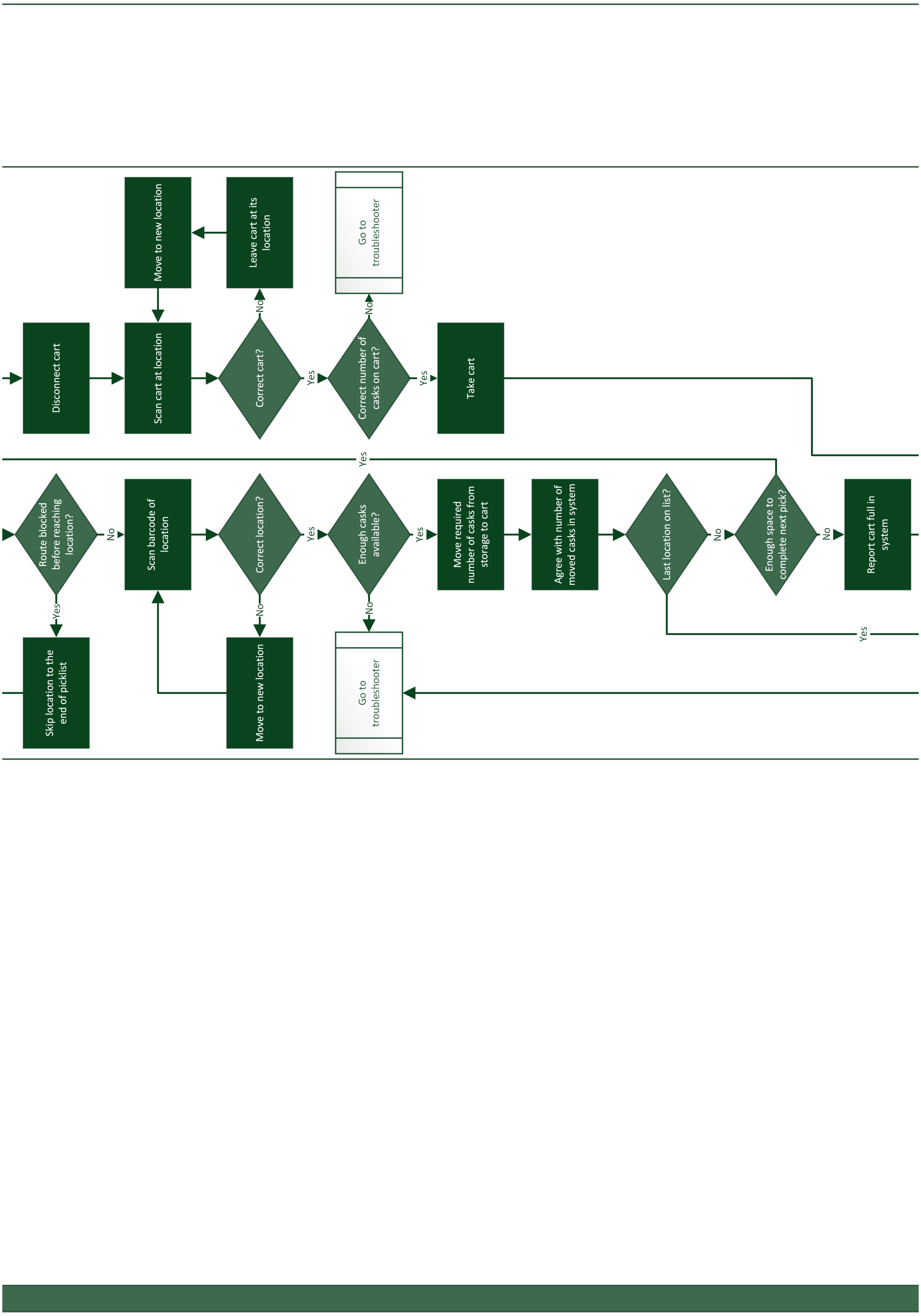


Figure E.2: Enlarged version of Figure 4.8 part 2/3

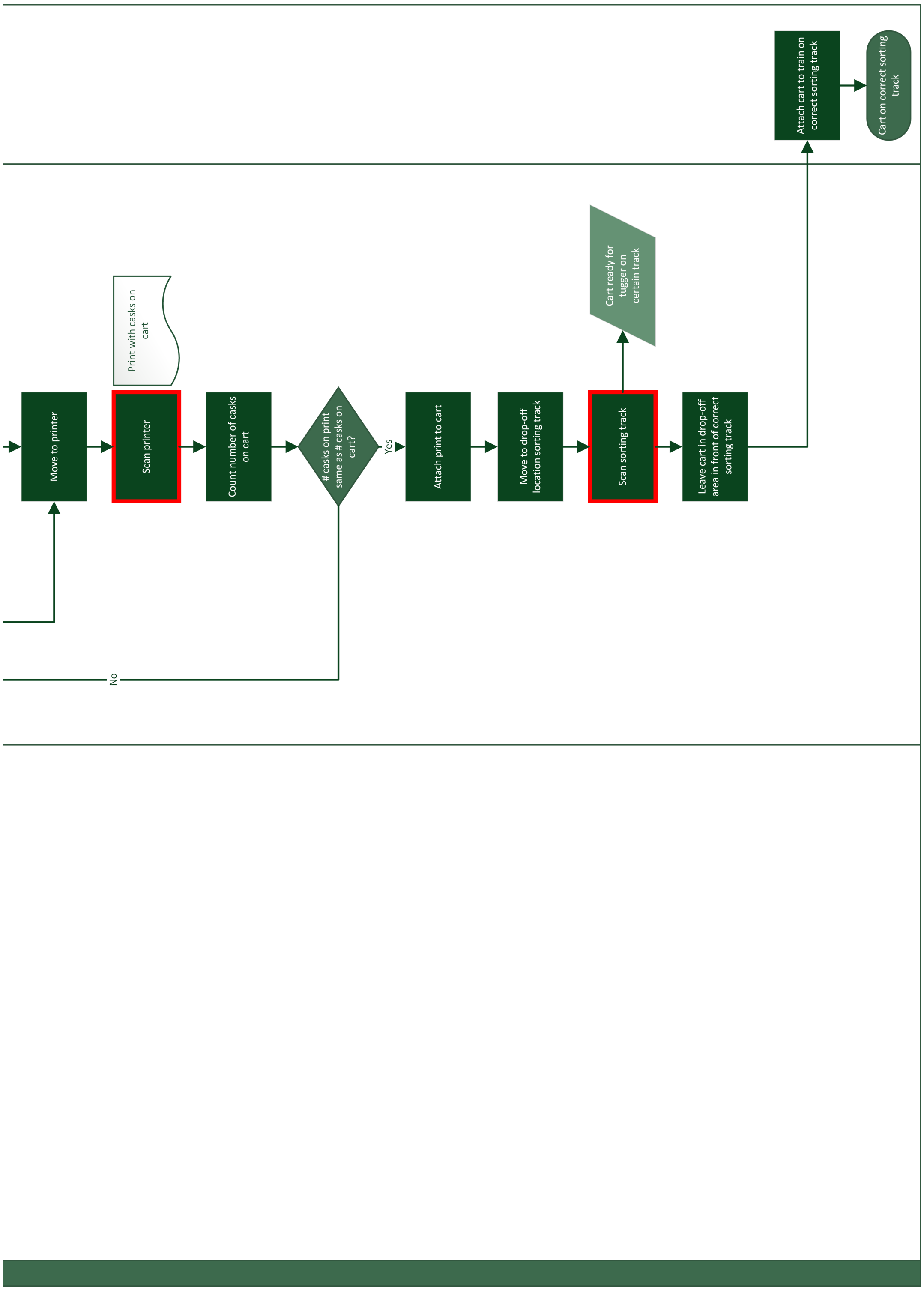


Figure E.3: Enlarged version of Figure 4.8 part 3/3

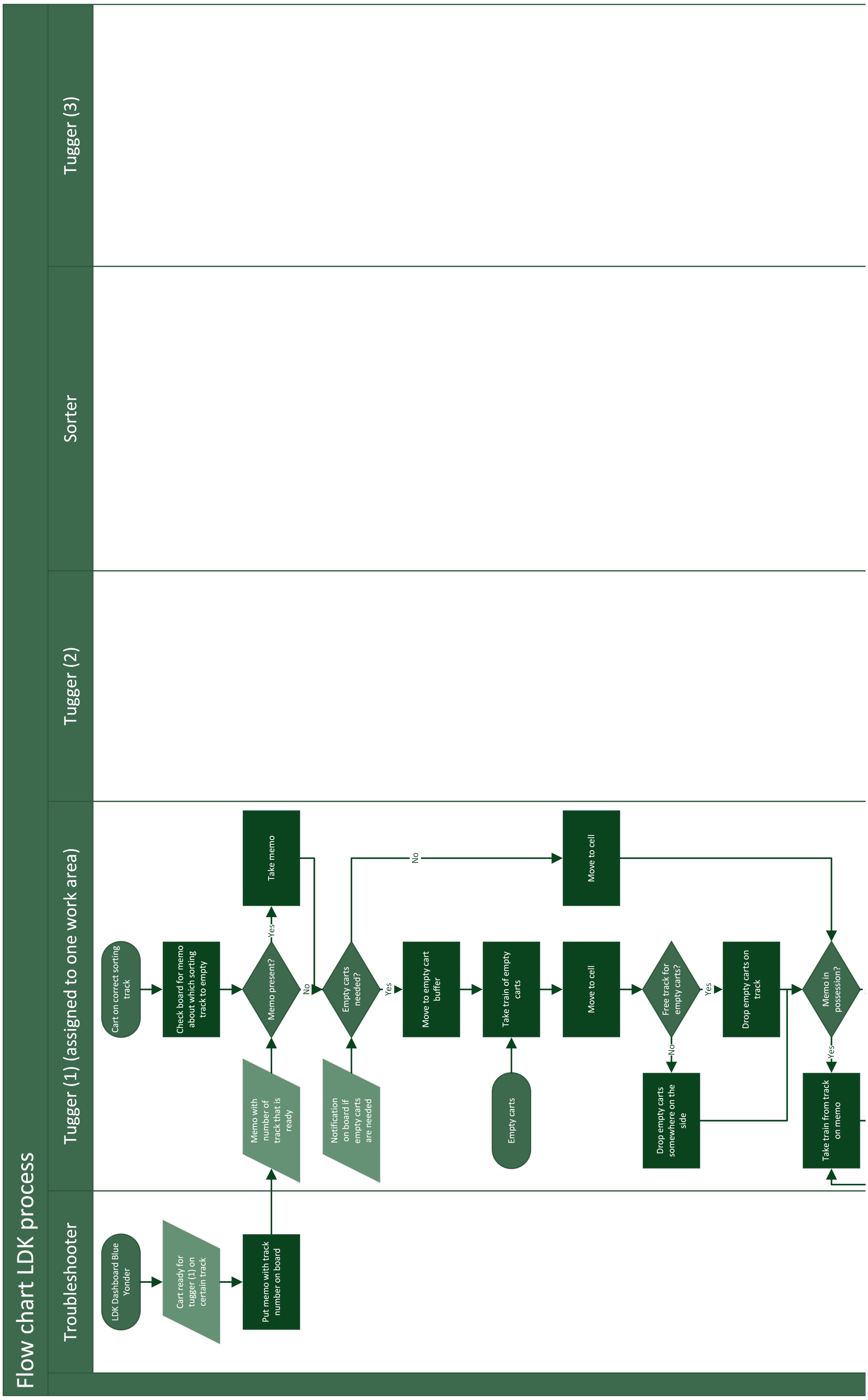


Figure E.4: Enlarged version of Figure 4.9 part 1/3

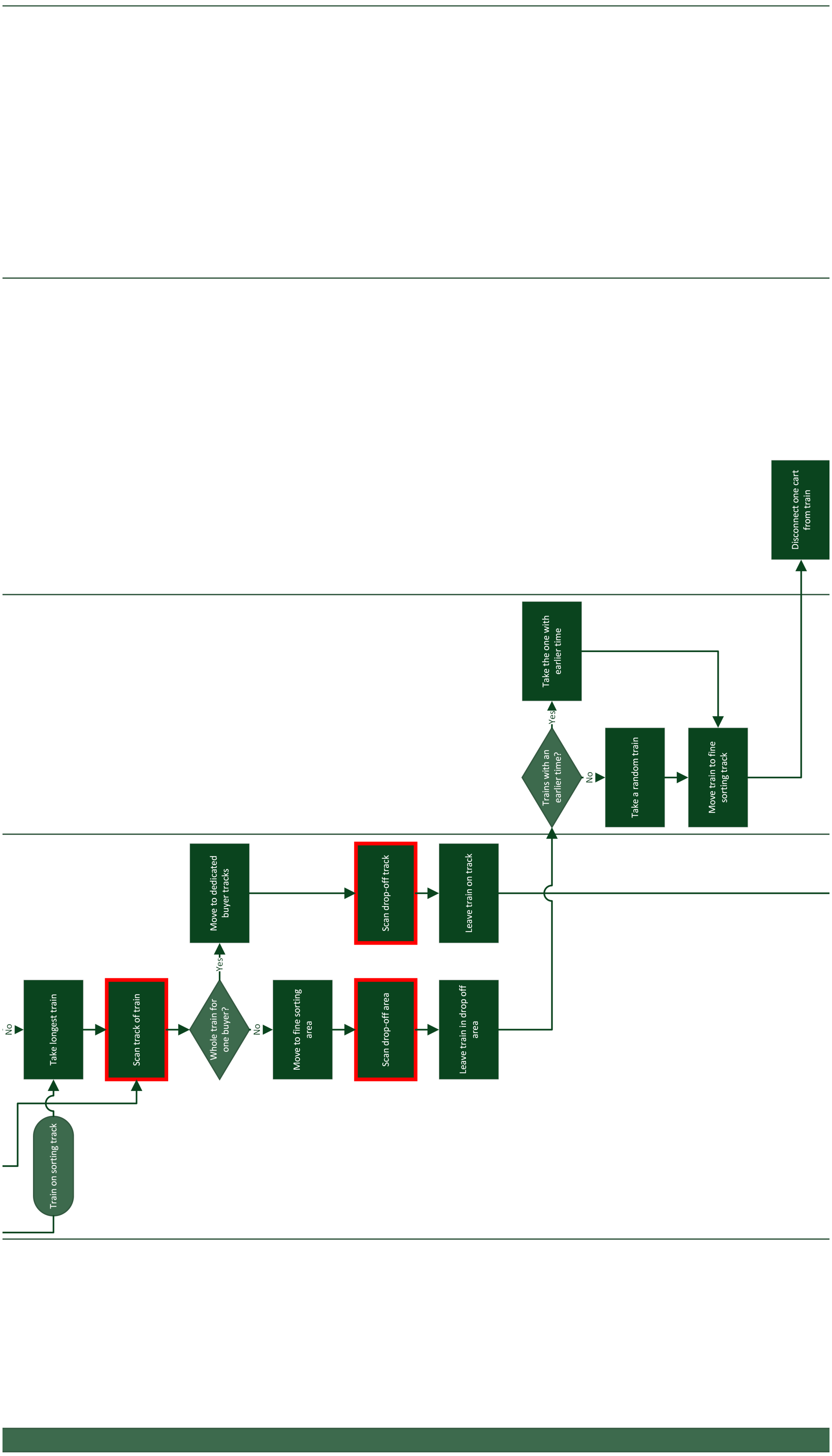


Figure E.5: Enlarged version of Figure 4.9 part 2/3

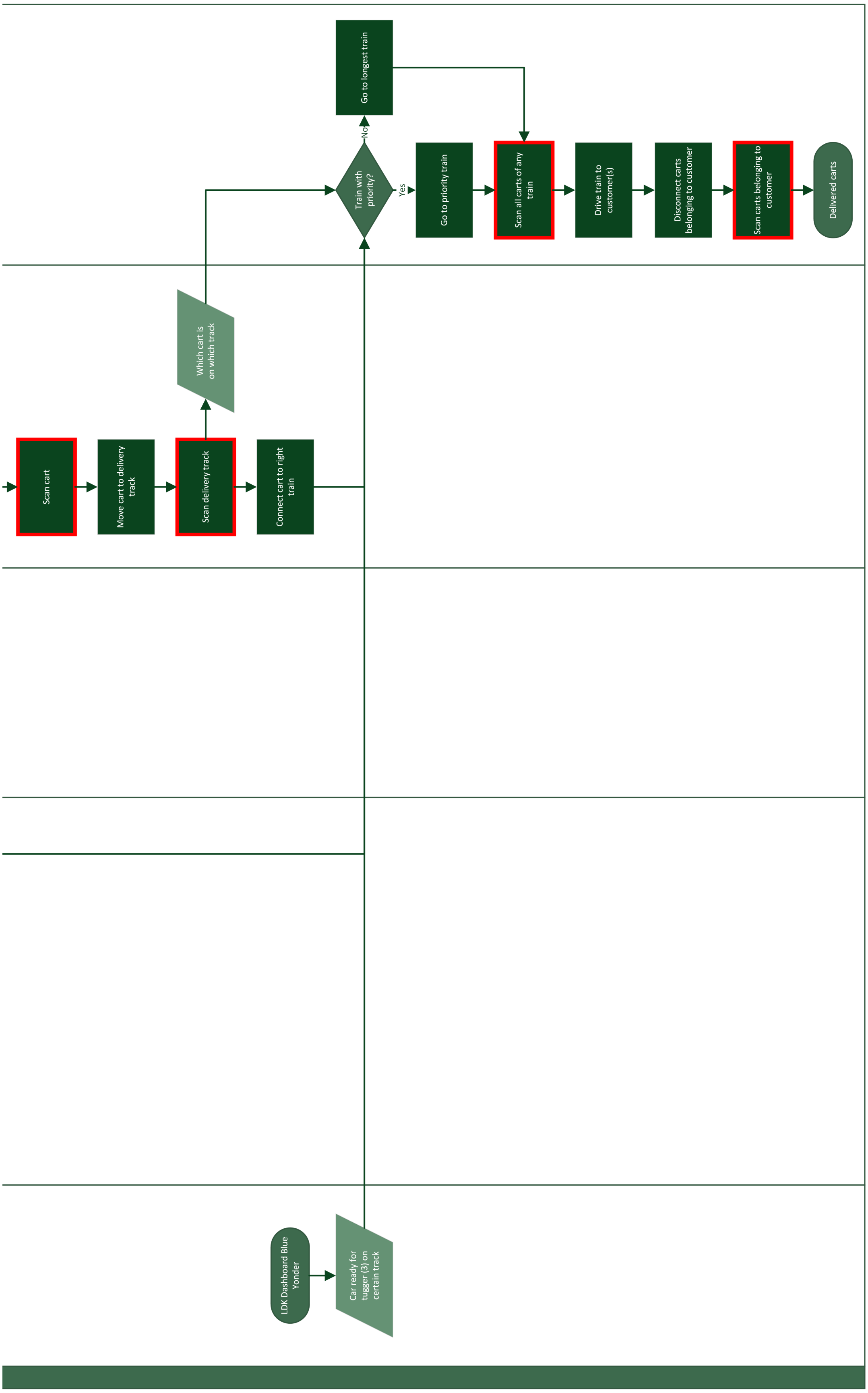


Figure E.6: Enlarged version of Figure 4.9 part 3/3

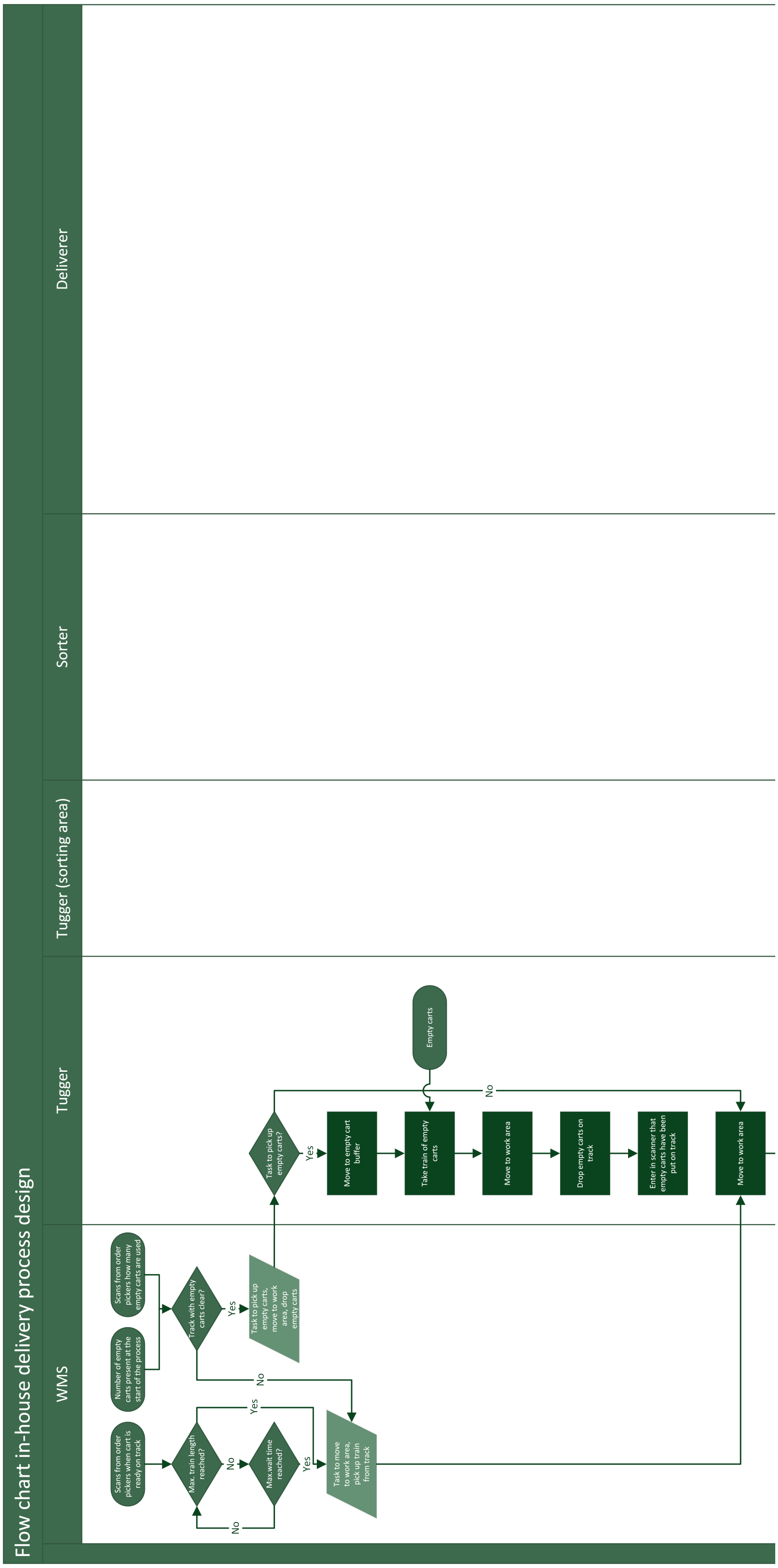


Figure E.7: Enlarged version of Figure 5.2 part 1/3

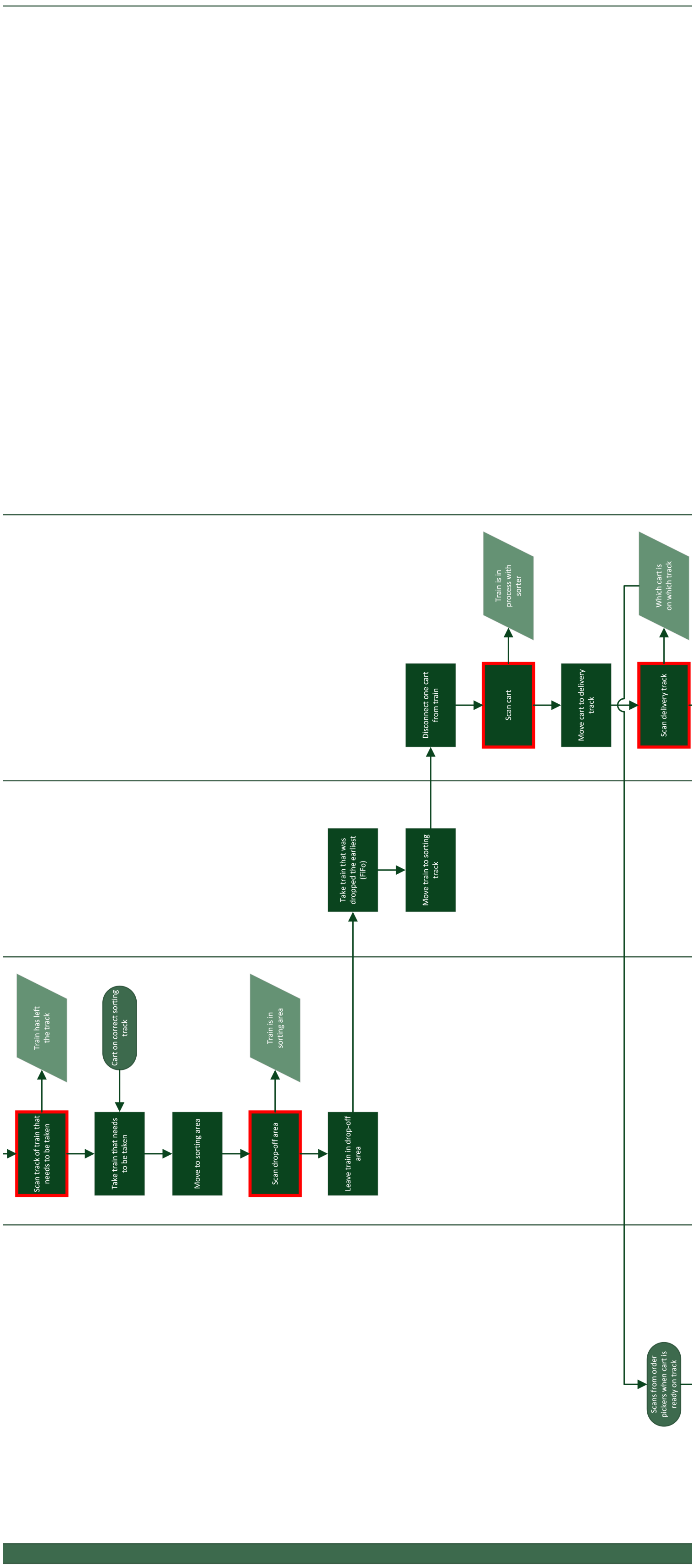


Figure E.8: Enlarged version of Figure 5.2 part 2/3

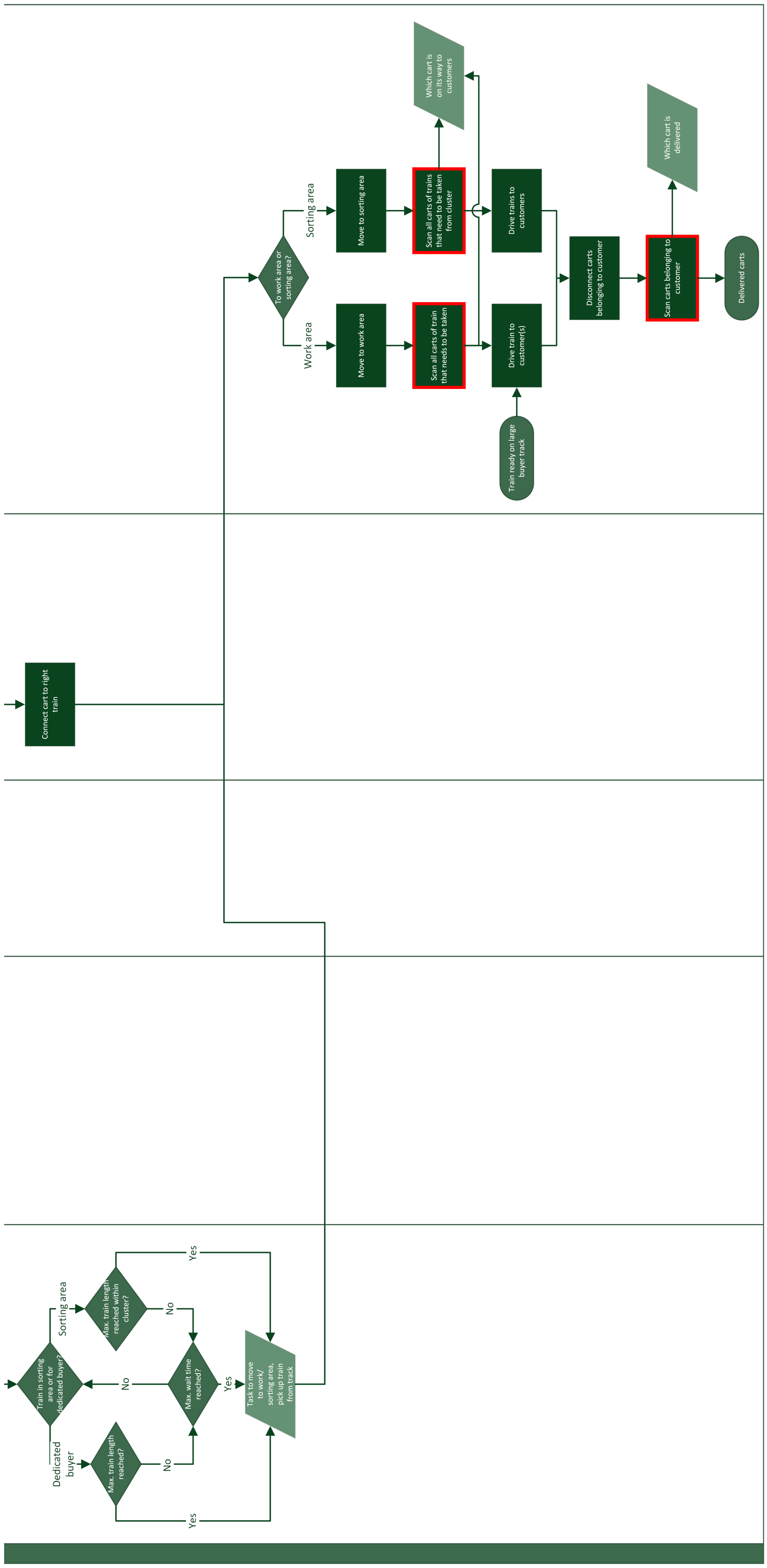


Figure E.9: Enlarged version of Figure 5.2 part 3/3