The Impact of Order Characteristics Uncertainty on Different Configurations of the Outbound Logistics of a 3PL Warehouse

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The Impact of Order Characteristics Uncertainty on Different Configurations of the Outbound Logistics of a 3PL Warehouse

A Contingency Approach Study

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Summary

Nowadays, warehouses are a crucial component in the supply chain, especially for Nedcargo, a third-party logistics provider for foods and beverages in the Benelux. With the emerging trend of e-commerce orders, it becomes less labour intensive for the customer to place an order. This e-commerce changes the size of the orders and increases the frequency of their placement. Considering this increase in complexity also entails uncertainty. In the case of e-commerce, this mainly concerns order characteristics. Currently, Nedcargo has only one warehouse which handles e-commerce orders in Tiel. However, a new warehouse will soon be built, focusing on handling e-commerce orders. This warehouse, called Haaften III, its configuration has not yet been determined. The configuration of a warehouse refers to a combination of operations, design aspects, and resources. Operations are divided into inbound and outbound logistics. The variety of the configuration choices and the uncertainty due to the e-commerce orders in the potential order characteristics leads to the following question: What is the impact of order characteristics uncertainty on different configurations of the outbound logistics of a 3PL warehouse? Which explains the title of this research and the overall purpose.

Now that the research background has been explained, it is necessary to focus on the main research question. This research question must emphasize knowledge gaps in the literature and contribute to future decision-making for Nedcargo's warehouse in Haaften. Warehousing is a much-discussed topic in research. The versatility of the subject gives opportunities to look very specific at some warehouse problems. There is a discrepancy between the warehouse processes' research and operational concerns and a lack of a framework to trial different solutions to specific issues. Next to that, to realize a framework that stresses the study and operational matters, warehouse modelling is a suitable approach. Reviews of literature about warehouse modelling studies led to the observation that a gap in warehouse modelling needs to be filled. Namely, the lack of uncertainty in warehouse models consisting of all the outbound logistics configuration choices. This study aims to fill that gap by modelling order characteristics uncertainty and different outbound configurations for Haaften. To answer the following research question: *What is the impact of context uncertainty of order characteristics on the different configurations of an order-picking warehouse?*

The method of this study is a contingency approach to configuring a potential warehouse for Haaften. The contingency approach emphasises that a warehouse must fit its context to perform efficiently. Since Nedcargo has insufficient information about the future context in which the new e-commerce warehouse of Haaften will operate. On the one hand, due to the emerging e-commerce trend, and on the other hand, the clients for Haaften are still unknown. This "it all depends" approach consists of three variables: contingency, response, and performance variables. The focus of the contingency variables is on order characteristics, which is a contextual factor of configurations of a warehouse. The response variables will be the configuration choices for either the current state of Tiel or the potential state of Haaften. The performance is the final result of the functioning of the configuration. These variables were all modelled in one experiment generation and three configuration models. To prove that the warehouse's order characteristics context differently influences the performance of the proposed configurations. Therefore, the study's method is a contingency approach and a proof of configuration combined.

Before the models were created, it was essential to analyse the current outbound logistics configuration of the operational warehouse in Tiel. Therefore Tiel is analysed using a recent state analysis followed by data analysis of the warehouse in Tiel. Tiel is a manual order picking warehouse that currently handles the e-commerce orders for Jacobs Douwe Egberts (JDE). First, all processes taking place were analysed by different techniques. This analysis gave a thorough understanding of all aspects of the outbound logistics of Tiel. We also established the configurational choices of Tiel. All of these configurational choices were further analysed by conducting data analysis. This data analysis

gathered data from the warehouse management system of Tiel. A new database was created using Microsoft Access. This database was filled with all the data of the past half-year. Existed out of the orders, movement of the pickers, time measurements- and the distance travelled data. Besides, the layout, product characteristics, and ABC analysis were also analysed for Tiel in the data analysis. This data analysis resulted in the current characteristics of orders of Tiel and insights into improvements that could be made for future configurations.

The first model, The Experiment Generation Model, was created. This model aimed to generate experiments that emphasize the uncertainty of the order characteristics. This model is the first step of the contingency approach by defining the contingency variables. Based on the data analysis, literature insights, and consultation with Nedcargo experts, the variables chosen were:

- SKU per Order, which is the number of orderlines per order;
- The ABC ratio, which determines the number of products that are fast-, medium, and slow movers in the warehouse;
- The amount of SKUs in the warehouse;
- And the amount of Colli per type of SKU.

These four contingency variables were classified into different levels and distributions. This classification made it possible to create 144 different context scenarios. Nedcargo was given a choice to select six plausible scenarios representing the future context in which Haaften will and could operate. The experiment generation model can generate various experiments based on these contingency variables. These experiments can be compared with an order list for a fictitious day; therefore, the output is a "dummy order data set." For each chosen scenario, five experiments were generated. This model was modelled using Visual Basic for Applications, a computer programming language within Microsoft Excel 2019.

One of the most crucial steps to answer the main research question is drafting potential configurations for Haaften. These configurations are established based on literature findings, consultation, data analysis, and the researcher's perspective. Before this can be achieved, a requirement analysis is carried out. This analysis stated several functional – and non-functional requirements to which the potential configurations had to comply. Next to that, assumptions are defined. These are divided into conceptual -, mathematical - and numerical assumptions. These denote the collection of explicitly stated premises, conventions, and choices. These analyses resulted in three new configurations, which each will be discussed separately.

Configuration 1 is predominantly focused on improving the current state. The previously conducted analyses provided insights into how configurations could be improved. These configurational changes will be dealt with per element. Concerning the **layout**, the primary concern that emerged was that the layout of Tiel was not compact. This layout was changed in configuration 1 so that as many aisles were used as SKUs needed.

Furthermore, the layout almost stayed the same; only the locations in which the SKUs were stored now consist of three SKUs instead of four. This changed storage assignment resulted in the rack locations becoming smaller. In terms of the **storage strategy**, an ABC-class-based strategy was adopted. ABC-class-based means that the A products are stored the closest to the depot. The **equipment** used is the same in Tiel, and the same goes for the **routing** strategy, which is the shortest route algorithm. The significant change in configuration 1 was the picking strategy.

The **picking strategy** in Tiel was based on the First Come, First Serve (FCFS) principle. This simple batch construction method is based that orders are sequentially assigned to batches depending on their arrival. So the first four orders (batches exist out of 4 orders) of an order day are batched together. Another batching strategy is the *SinglePick* strategy. The SinglePick strategy can be implemented if multiple orders consist of only a single SKU and a single Colli. All the orders with this characteristic are picked in bulk in one batch. A previously conducted design study at Nedcargo concluded that the packing operations would be more efficient if these SinglePick orders were batched together. The packer can then pack per customer instead of pack per order. This strategy has not yet been quantified in research. In addition to these two strategies, another strategy will be discussed. This strategy is called the *Star Aisle Batching* strategy. This strategy is previously explored in Aboelfotoh et al. (2018) paper. This strategy focuses on the batching orders based on a simplified aisle-by-aisle heuristic. In simple words, it batches the orders based on the aisles they need to visit. Configuration 1 has also incorporated the strategy of merging the *star aisle batching* strategy with the *SinglePick* strategy. So first, the SinglePick orders are batched, and the remaining orders are batched following the star aisle batching strategy. This combination of two strategies is a new strategy being investigated for the first time in this study. These choices together form configuration 1, which will be modelled as response variables.

The configurations are very similar to each other. It is chosen in this research to tweak them a little bit. Configuration 1 has made some significant changes compared to the current state. Configuration 2 will copy most of these changes but adds an extra element, namely, in the storage assignment of the warehouse. Configuration 2, therefore, uses a new storage strategy called "Dynamic SKU locations." The dynamic SKU locations are two locations in the warehouse where at the beginning of each working day, the stored SKUs could be different than the day before. This strategy is decided by first performing an affinity analysis, which checks if a pair of SKUs are often paired in orders on that specific day. And secondly, by looking at the daily demand of the SKUs. Suppose there are SKU affiliated or SKUs which have a high demand that particular day; they can be placed in the dynamic SKU location. This relocation should decrease the travel distance and therefore increase the productivity.

Configuration 3 focuses on decreasing the possibility of congestion, which is one of the non-functional requirements. This decongestion is achieved by changing the routing strategy of configuration 1. In configuration 1, the shortest route algorithm is implemented; this displays the shortest path necessary to pick all the SKUs in the batch. Configuration 3 uses a different strategy, namely the S-Shape routing strategy. The s-shape routing strategy leads to a route in which the aisles that need to be visited for completing the batch are traversed totally in a single direction. That is why it is called an S-shape strategy; aisles are visited in a shape of an S. This strategy is commonly used in a warehouse because: it is easy to understand for the picker and decreases the chance of congestion. As a result, the layout will also be slightly different from configuration 1. The cross-aisle is removed, and the aisle width will be narrowed down slightly.

Now that the configurations are apparent, it is necessary to look at the performance variables. This must be done before the configurations are modelled. The performance variables can also be seen as the output variables. There are various key performance indicators to evaluate the performance in a warehouse. Based on the current performance indicators in Tiel, findings in the literature, and consultation with Nedcargo; the following quantitative performance indicators were provided:

- the productivity, measured in Colli per hour;
- the total picking time, measured in hours;
- the total distance, measured in the meters travelled by the pickers;
- the total amount of pickers, which is the pickers needed to complete all the orders in a working day;
- and the average batching time and distance.

Next to these quantitative measures, two qualitative measures are possible: the possibility of congestion and automation. These are the performance measures that are used for this research.

The modelling of the configurations is programmed by using VBA Excel 2019. The experiments were processed by each configuration model and gave the proposed performance indicators as output. The configuration models are seen as the response variables and the performance indicators as the performance variables. This method tries to prove that the configurations perform differently in a specific order characteristics context scenario. Both within the configurations per scenario and between each scenario. Next to that, it is quantified if the proposed picking strategies of the *Star Aisle Batching* and the *SinglePick* influence the performance. These models gave both practical insights for Nedcargo and scientific insight by filling knowledge gaps and exploring new concepts. An overview of the method is shown in figure 1 below.

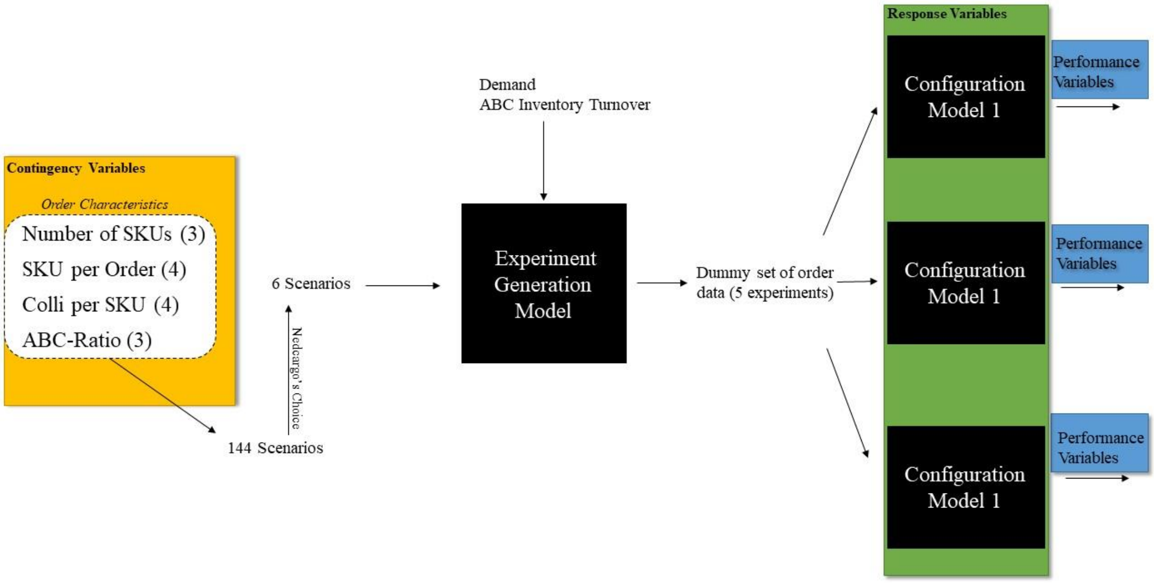


Figure 1 – Overview of the study method.

First, we will discuss the practical insights learned from the results of the output of the configuration models. The most crucial valuable insight was the configuration 1 comparison with the current state. This comparison resulted that if configuration 1was used with the same order set data of the context of Tiel, the FCFS strategy resulted in a productivity increase of 15%. If configuration 1 was implemented with the *Star Aisle Batching* Strategy, it would increase productivity by 20%. And if configuration 1 were implemented in Tiel with the *Star Aisle combined with the SinglePicks* strategy, it would increase by 30% in terms of productivity. Next to that, If we look at the results of the configurations models, it can be stated that Configuration 1 is the most optimal configuration investigated in terms of productivity and therefore decreases the total picking time. Next to that, it can be concluded that the *Star Aisle Batching Strategy* combined with the *SinglePick Strategy* has the highest performance in each scenario. Therefore, it needs this strategy is to be included in potential decision-making for the configuration choice of Haaften

The two proposed models can help Nedcargo investigate the specific context in which Haaften will operate. The Experiment Generation Model can help Nedcargo give insight into the uncertainty factor of order characteristics by defining how a potential client is characterised. This model can create experiments that can test configurations in terms of performance. The proposed configuration models include three different configurations where improvements to the current state are processed based on literature, expert insights, and data analysis. Proofs that certain choices, for example, the compact layout, ABC-class based storage, and the Star aisle batch strategy with Single Pick, improve the performance of the warehouse. Nedcargo must use this model to investigate, improve and quantify potential configurations for Haaften III.

Now we go back to the main research question of this research. Figure 1 shows the difference in productivity decrease per scenario compared to its most effective configuration and strategy. For each scenario, configuration 1 with the *Star Aisle combined with the SinglePicks strategy* has the best performance in terms of productivity. The table below shows the results of these experiments.

Table 1. Results of Configuration 1 and Star Aisle combined with SinglePicks strategy

Batch+SP	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Configuration 1						
Avg. Colli/Hour	163	124	178	208	160	156

Firstly, it is seen in table 1 that in each scenario, the productivity is different. How can this difference in performance be explained? The results showed that the ABC-Ratio contingency variable has a significant impact on the productivity of the chosen configurations. Respectively, high productivity is reached if the warehouse consists of a lower percentage of A-type SKUs and lower productivity if the warehouse has a high rate of A-type SKUs. This finding can be explained by comparing the high and low productivity scenarios with their corresponding contingency variables. Next to that, a context scenario where the amount of colli is high and the orderlines per order are low will result in higher performance. These contingencies can be explained since the picker can grab more colli during an SKU visit, which decreases the travel distance and thus increases the performance. Table 1 shows the difference in performance between the scenarios, but how do they react to configuration and/or strategy differences?

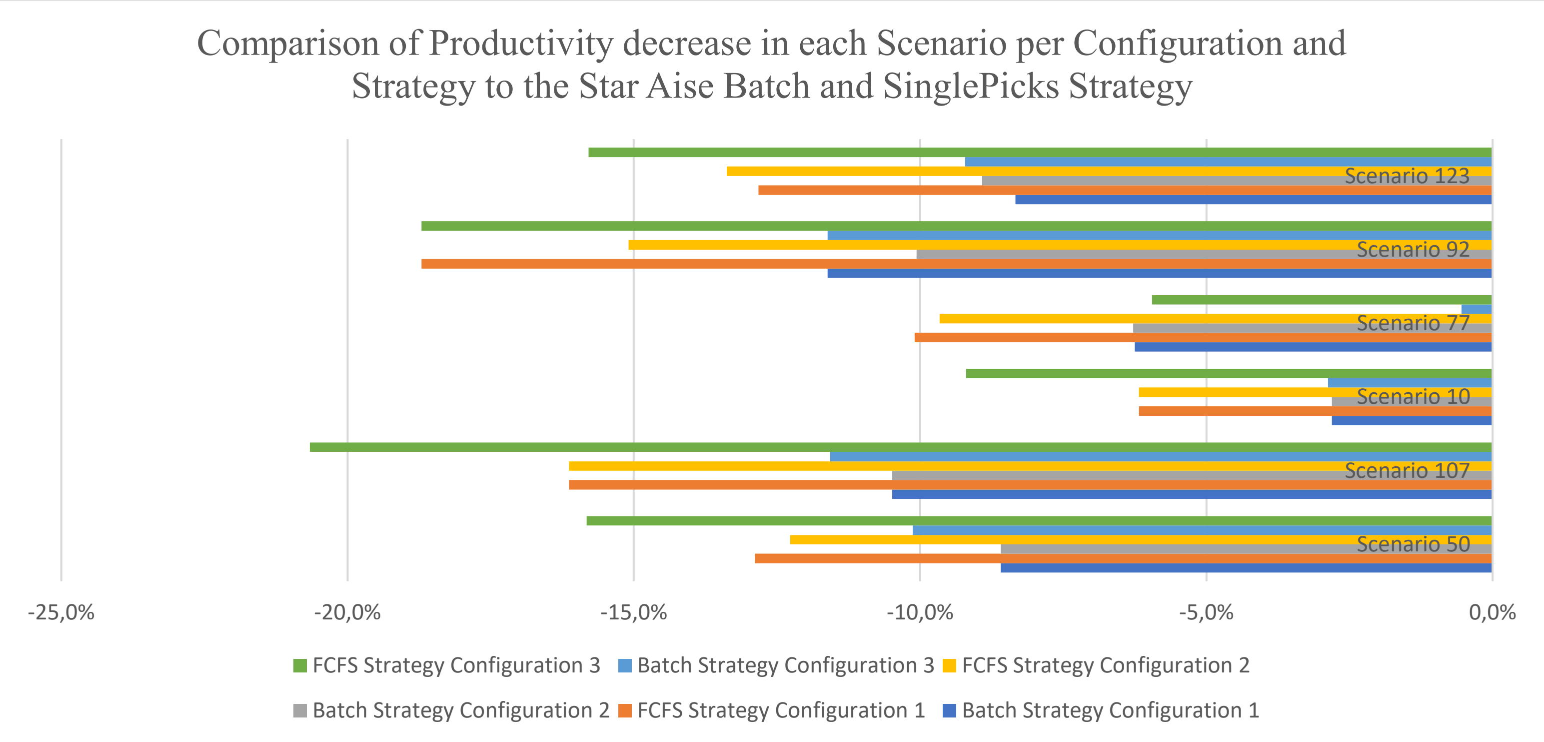


Figure 2 – Results of productivity percentage decrease compared with the best configuration and strategy per scenario

Figure 2 shows that the change between configuration and picking strategy has another effect in each scenario. In some scenarios, such as 10 and 77, another picking strategy or configuration does not have an as significant impact as, e.g., 107 and 92. In those scenarios, the percentage decrease in productivity is much higher when not the best configuration and picking strategy option is implemented. This is an essential insight because now it is shown that the order characteristics influence how well the warehouse functions per configuration and picking strategy. This analysis was done for each of the performance indicators proposed, and each gave the same insight. The contextual setting in which the configuration has been experimented with will influence its performance differently in each scenario. But looking at the performance, which configuration and picking strategy perform the best? To answer this question, we need to look within each scenario.

The proof of configuration concept that is being withheld in this research aims to demonstrate the feasibility of the chosen configurations. The results prove that configuration 1 performs better in terms of productivity for each of the scenarios than configuration 3 for each picking strategy and that configuration 2 has no significant effect on the performance irrespective of the context. Therefore the contingency approach proved that specific configurations perform differently in each context, and their performance is affected. On the other hand, configuration 3 has less chance of congestion due to the routing strategy, and pickers can only traverse the aisle in one direction. This should also be kept in mind if, in practice, i.e., configuration 1 causes a lot of congestion. It can be decided to switch to configuration 3.

The proposed three configurations were based on the requirements and assumptions that were urged. Each configuration was simulated within each scenario, and its performance was measured. A series of conclusions can be drawn from these results. First, it is seen in the performance that in each scenario, configuration 1 performs the best in terms of productivity together with configuration 2. Configuration 3, where the S-shape routing strategy is implemented, has lower productivity, reducing 2 to 11 percent. This is also affected by the context scenario it operates in. It can be concluded that configurations 1 and 2 in each scenario have higher productivity than configuration 3, but there is no significant increase between configurations 1 and 2. Configuration 2 uses another storage strategy that implements the idea of dynamic SKU locations, where SKUs can be moved based on SKU affinity and SKU demand. The model results in proof that configuration 2 does not significantly improve the performance of the warehouse if compared with configuration 1, from which it slightly differs in layout and storage. This proof in performance concludes that configuration 2 is not worth further investigation.

So, if we look back at the main research questions, the following can be concluded. The context in which an order-picking warehouse operates, based on the order characteristics uncertainty, has a significant impact on the performance of different configurations. Each configuration performs differently considering its context scenario. This is shown using the contingency approach. The contingency variables represent the uncertainty of the order characteristics, the response variables, which are the three configurations and picking strategies modelled, and the performance variables, which are the output of these models.

Based on the findings, Nedcargo has an insight into how a configuration would react in a particular context of order characteristics. The order characteristics of the future state for Haaften are uncertain, and therefore Nedcargo can use the findings of this study to be prepared. The experiments show that it is essential to test different configurations on their performance before you start designing. The results of this thesis function as a proof of configuration, which is that configuration performs better or worse in a specific context. Nedcargo must use these models as a tool to improve its decision-making.

Contents

Abstract

This thesis examines the impact of order characteristics on the performance of different configurations of the outbound logistics of a 3PL warehouse. A contingency approach combined with a proof of configuration method is used to answer this question. The contingency variables in this study are the order characteristics, which are uncertain for the future state of the newly built e-commerce warehouse Haaften III for Nedcargo Logistics, A third-party logistics provider in the Netherlands. Six contingency scenarios are chosen, and a model transforms them into experiments. Three different potential warehouse configuration models process these experiments, and their productivity performance is compared and analysed. Our results showed that the compactness of the layout, ABC-class-based storage and a new picking strategy, Star Aisle Batch combined with Singlepicks, provides the best productivity in each scenario. Next, between each scenario, the productivity is impacted differently. The productivity is higher if the order characteristics contain a low percentage of A-type products, the amount of colli is high, or orderlines per order are low. A change in configuration or strategy within each scenario also influences productivity differently. Lastly, it is also proved that the new proposed configuration and picking strategy can improve its current productivity by over 30%

I. State of the Problem

1. Introduction

There has been a growing interest in improving the operating efficiency of warehouses, which is one of the critical facilities used in the logistics sector. Warehouses are the hearth of integrated logistics operations, including storing, loading, unloading products, and information systems operations. Significantly since the emerging trend of e-commerce orders, which requires fast processing at warehouses to assure on-time delivery and enhance client satisfaction, the complexity of warehousing has increased. This new e-commerce trend is not a homogeneous concept and affects the order characteristics. For example, a reduction of products per order and low quantities are time-critical. Traditional picker-to-good (PTG) warehouses are frequently unsuitable for these requirements. Nedcargo is a third-party logistics provider (3PL) that recently started handling e-commerce orders in its warehouses. Currently, these operations are being handled in their warehouse in Tiel. But shortly, there will be a new warehouse built in Haaften, named Haaften III. One of the four compartments of Haaften III will mainly focus on e-commerce orders.

Warehousing is a much-discussed topic in research studies. In the last few years, it has become even more relevant due to the rise of e-commerce. Nowadays, warehouses are seen as an essential, maybe even the most important, component of any supply chain (Gu et al. 2007). Manual-order-picking warehouses are still the most common warehouse class; according to De Koster et al. (2007), 80% of the Western European warehouses are manually operated. The configurations of such warehouses refer to a combination of operations, design aspects, and resources. Joint warehouse operations include receiving, put-away, storage, picking, sorting, packing, and shipping (Kembro & Normann, 2020). Understanding the warehouse's current and future state and goals is crucial before selecting the suitable configuration. Considering that configuration elements are interrelated, a top-down approach is needed to get all the fundamental choices right (Rouwenhorst et al. 2000). Due to the complexity of the decision for a warehouse configuration usually, issues are considered separately. This obstructs the overall evaluation of warehousing processes. As a result, a holistic approach to the warehouse modelling challenge is necessary (Jacyna-Goda, 2015). The warehouse and configuration modelling may be adequately assessed with a comprehensive approach to the problem.

The new warehouse in Haaften allows Nedcargo to re-evaluate its current warehousing and improve its configuration to be efficient and robust. The performance of a warehouse is impacted by how it is configured, yet the pre-build development of warehouse systems has not been quantified. Besides, the context in which Haaften will operate is unknown. Context means the environment in which the warehouse operates, which could be internal or external. The uncertainty of handling the specific order characteristics of potential clients is a contextual factor. The fit between the warehouse's configuration and the context in which it operates is an essential driver for its performance. This study aims to investigate the fit between the context and configuration for Haaften, especially the uncertainty of the order characteristics. How would the performance be in a given context per defined configuration?

This study only focuses on the outbound logistics of the warehouse configurations. Therefore it will only focus on the configuration operations of the storage, picking, sorting, and somewhat on packing. The aim of this study can be divided into three parts, namely to produce a generic and analytical configuration framework to model order-picking outbound logistics of Haaften III, to define practical performance measures of these outbound logistics, and to provide tools for Nedcargo to set goals, measure performance and identify improvements. By emphasizing the uncertainty of order characteristics due to the yet unknown context, the potential warehouse configuration of Haaften-III will operate. If the research objective is accomplished, it should be able to answer the main research question of this study:

What is the impact of context uncertainty of order characteristics on the different outbound configurations of an order-picking warehouse?

This all with a short objective of having flexible decision-making for the future warehouse configuration of Haaften III.

This study uses a contingency approach in combination with the proof of configuration method to answer this question. The proof of configuration method, also known as the proof of concept but renamed for this study's purpose, is focused on determining if an idea is feasible or if an idea will function as envisioned. In this study, this so-called idea is the three proposed configurations of Haaften III. The contingency approach is a theory that suggests that a warehouse configuration must be tailored to its particular context (Donaldson, 2001). It is applied to connect decisions concerning warehouse configurations to match their context to improve their performance (Woodward, 1965). By looking at contextual factors, which in this study are the order characteristics, do they influence the performance of warehouse configurations in the rapidly advancing and changing e-commerce market? The contingency approach is distinguished into contingency, response, and performance variables (Sousa & Voss 2008). Contingency variables represent the order characteristics in this study. The response variables are the processes that respond to the contingency factors, which are the three different configurations in this study. The performance variables are the dependent measures and represent the effectiveness of evaluating the fit between context and warehouse configuration.

To quantify the performance of the configurations, two types of models are created in this study. The current state analysis is a crucial step in making these models. The existing warehouse at Tiel, which handles e-commerce orders, needs to be analysed. Data from the current warehouse management system (WMS) must be gathered to obtain contemporary order characteristics. This data will then be used to make a prognosis of what future context scenarios could be. Out of these findings, scenarios are constructed that contain the proposed order characteristics' contingency variables. These contingency variables must be transformed into experiments or, in other words, a dummy order list. This is achieved by an Experiment generation model, which transforms the contingency variables into experiments. These experiments will function as the input of the second model type, the three configuration models. First, the three configurations model must be determined, which is done utilizing literature findings, consultation with Nedcargo, and the data analysis of Tiel. The thereby compiled requirements and assumptions shape this determination process. The performance of each proposed configuration in each scenario is then presented and analysed. This should pave the way for answering the central question: if a specific scenario influences the performance differently given the configuration and if the order characteristics influence the configuration's performance. It should also analyse the difference in performance between the three configurations. Next to that, a current state model of Tiel is modelled. This is in order to compare the performance of the three new configurations with the current state configuration of Tiel.

To conclude, this study will aim to prove that specific configurations perform differently in a given context. This all provides scientific insights into the different configuration choices and how they affect the performance, the contextual importance of warehouses on their performance, and whether knowledge gaps from literature can be filled. In addition to practice, this study tries to create tools for Nedcargo to eliminate uncertainty in their decision-making for Haaften III. By experimenting with different scenarios regarding order characteristics uncertainty and how potential configurations perform in these scenarios.

The study will continue by defining the research design, followed by the literature review, current state analysis, data analysis of Tiel, the proposed method, scenario Modelling, configuration modelling, and results, and will end with conclusions and implications.

2. Research Design

This chapter presents a general plan about what this research will do to answer the research question. It is a framework for choosing specific methods. First, the problem is defined. The research objective is formed, and the adjacent research questions are created. All to answer the main research question. After this, the context is made clear in the study and Nedcargo. Then the research approach is presented, and it finishes with the research structure.

2.1 Problem Definition

Now that the introduction of the research study case is clear, a problem statement will be drawn up. In designing a warehouse, a lot of decisions have to be made. Nedcargo is the one who has to make these long-term strategic design decisions. This chapter will systematically point out problems that Nedcargo will or already experienced in designing the outbound logistics of the warehouse in Haaften.

Haaften III will be divided into four compartments. One of which is used for e-commerce purposes. The focus of the research will be on that one e-commerce compartment. The outbound logistics components, which will be further elaborated on in the literature review, are yet to be decided upon. These components all have different design options, and these choices also interact with each other. This interaction is currently unknown because the focus was mainly on analysing the different design components instead of synthesizing, which means combining the fragmented parts into an aggregated whole. The decision-making process is complex because of the numerous options for several components. Nedcargo wants its design to be as efficient and robust as possible. They want to substantiate their decision-making with quantified data to achieve those goals. But which design outperforms other designs in which situation, that is one of the main questions that Nedcargo is willing to get an answer to. Multiple factors should be considered, but the most interesting one is the potential client that will use the warehouse. How many design choices are there, and which design fits which client best?

This is all strongly related to the type of orders that the warehouse will handle. In the case of Nedcargo, the potential client who will use the services offered by the warehouse Haaften III is still unknown. In order to make the outbound logistics system as robust as possible, quantified research is needed. This is because Nedcargo can then adequately substantiate their design solutions for when they tender a potential client. Nedcargo bases its decisions nowadays mostly on its historical data and from experts' analysis. Most of this analysis is qualitative, and there is a need to quantify the systems design processes. The currently available data is from current customers' e-commerce orders in other Nedcargo warehouses, and these can be extrapolated for the design choices of Haaften. Nevertheless, this points out that a case study for different customers, e.g., order characteristics, is desired.

Concluded, the problem Nedcargo faces is that it needs insight into the consequences of confident design choices for outbound logistics process components, with the uncertainty aspect of the potential order characteristics the system will have to handle. This is to create a quantified tool for more efficient and robust decision-making. In the following chapter, an extensive literature review is performed. To give a better insight into what warehouse components for the outbound logistics are crucial in the design process. And to point out the knowledge gaps in current literature, which may make this research valuable.

2.2 Research Questions

The objectives of this research are as follows:

(1) To produce a generic and analytical configuration framework to model the order-picking outbound logistics of Haaften III. (2) To define practical and easy to adopt performance measures for the outbound logistics processes. (3) To provide the tools for Nedcargo to set goals, measure performance and identify areas of improvement in the warehouse configurations by pointing out the uncertainty of order characteristics in different context scenarios.

In this paragraph, the research questions are specified. To fill the research gaps, which were stated in the literature review discussion. First, the main research question is formulated down below:

What is the impact of context uncertainty of order characteristics on the different outbound configurations of an order-picking warehouse?

This main research question will be answered via several sub-research questions.

1. *What are the different components for outbound logistics when designing a warehouse for a third-party service provider like Nedcargo?*
2. *What are uncertainty factors when configuring a warehouse with regards to e-commerce?*
3. *What are the different performance measures of an order-picking warehouse, and how can they be quantified?*
4. *What are the current characteristics of the orders at Nedcargo's e-commerce warehouses, and how will they evolve in time?*
5. *What are the different process variables that occur in the outbound logistics in a current operational warehouse of Nedcargo?*
6. *In which context can a future warehouse operate, and can various scenarios be envisaged concerning the uncertainty factors that have been found?*
7. *Which new configurations are applicable for an e-commerce warehouse, and which requirements and assumptions will be made?*
8. *What method can model the proposed context scenarios and configurations of an e-commerce warehouse?*
9. *How do these new configurations perform compared to the current state?*
10. *What is the influence of the different context scenarios on the performance measures of the different new warehouse configurations?*
11. *How can the results be interpreted and used for decision-making in the future for Haaften III?*

To understand the context in which these research questions must be answered. Context analysis of Nedcargo is made in the next paragraph. After the research approach is elaborated, this chapter will end with the research setup about how each sub-questions is answered. This includes a further explanation and method.

2.3 Context Analysis

The focus will be on a B2B distributor/wholesaler in the Netherlands and Belgium market, which focuses on the food and beverage supply chain, namely Nedcargo. The specific type of processed goods depends on which customers Nedcargo wins for their operations. The case study in this research focuses on a newly built warehouse in Haaften III and will use data available from the already existing operating warehouses of Nedcargo. First, Nedcargo's position in the supply chain will be elaborated on, then a deeper look at the warehouse in Haaften is being made, and certain scope choices will be supported.

Nedcargo operates as a logistics service provider in the supply chain for food, beverages, and retail goods. They form the link between the manufacturers and the wholesalers or retail distribution centers by storing and distributing goods obtained from the manufacturers. Nedcargo does not (or hardly) add value to the goods. It makes sure the goods are picked up at the factories and delivered at the right moment to the manufacturer's customers. It is necessary to coordinate between different parties to achieve an excellent total supply chain performance. In figure 1, the position of Nedcargo is shown in the logistics supply chain.

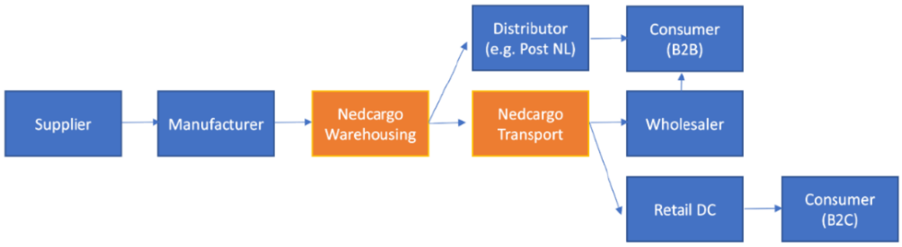


Figure I-1 – Nedcargo's position in the supply chain

Nedcargo operates mainly in the business-to-business market. The traditional B2B market is characterized by high lead times, high volumes, and strong relationships with the client. However, there with a contemporary shift toward the e-commerce market visible in the logistics service provider sector, and they show changes in these B2B market characteristics. Online ordering makes the order process a simple and efficient process that can be executed every moment of the day. This leads to smaller orders, more demand, and sets new expectations for reducing the lead time of order, picking – and packing efficiency, and more. How Nedcargo can implement this robust approach in their warehouse designs is a topic they would further explore.

To this day, Nedcargo is preparing for the arrival of a new large warehouse for its customers. In Haaften, there will be a 40.000 square meters warehouse built named Haaften III. It is expected that a lot of the daily operations of Nedcargo will be moved there. This is due to its central location in the Netherlands. The warehouse will be divided into four components. Figure 2 shows the construction plans of what the warehouse will look like. Nedcargo's focus is mainly on retail, and its expertise lies in the handling of full pallets orders as well as case orders transported on pallets. But nowadays, there is an increase in the client's need for e-fulfillment, which means an increase in the amount of smaller orders in terms of volume, the upcoming e-commerce trend. This e-commerce trend involves a different customer with possibly other preferences and reduced-order size. These e-commerce orders are not transported by Nedcargo itself but outsourced to an external distributor since it's not feasible to distribute these orders themselves. Nedcargo already copes with this wish, but designing warehouses for e-fulfillment is a relatively new topic for them. Nedcargo's goal is to cope increasingly better with these new upcoming circumstances. Therefore, it needs strategic design choices, process flows, qualitative and quantitative information, and external experience. Haaften III needs to be able to handle these smaller orders and different order characteristics next to its primary retail function.

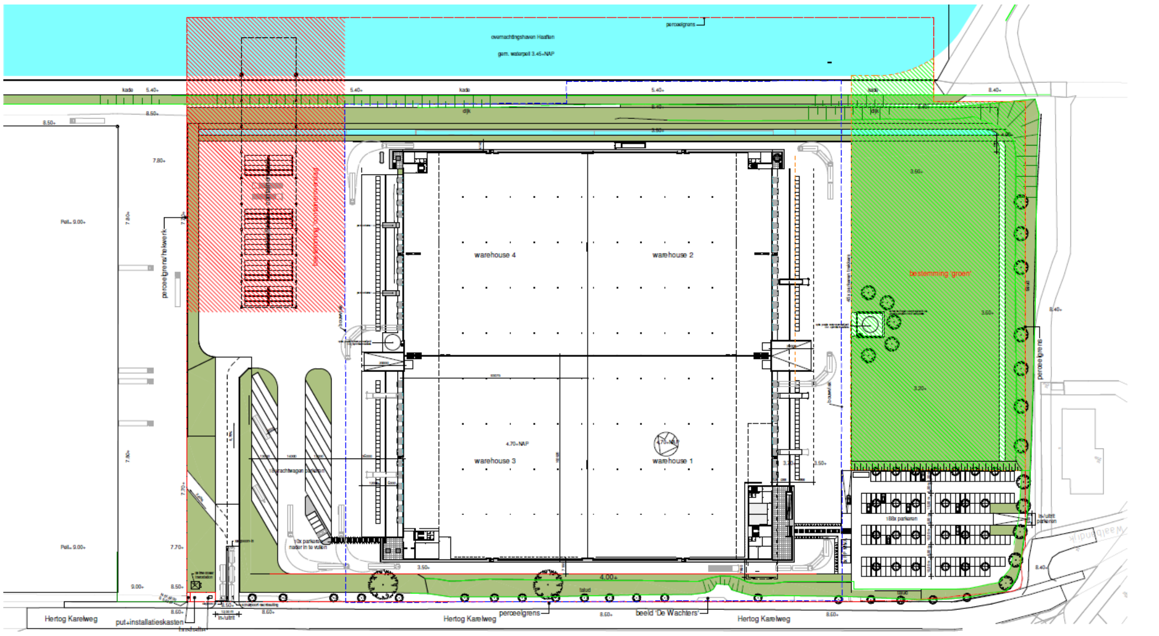


Figure I-2 – Construction plan of Haaften III

Haaften III will perform all the warehouse functions that will further be elaborated on in the literature research. In some of these functions, the strategic design choice has already been made and therefore been decided to keep out of context for this research. Figure 3 shows the simplified primary process of the warehouse in Haaften. The warehouse is planned to be designed so that an AS/RS system will store them in the different compartments for all their incoming products. This means that the inbound logistics of the warehouse can be regarded as a constant flow of products and be considered a given component in the research and design. Next to that, the warehouse of Haaften will be divided into four compartments. Each such compartment can be designed for any wishes of a client of Nedcargo. The prognosis is that three of the four sections will be used for retail purposes and one of them for e-fulfillment purposes. Figure 3 shows the scope for the research study case in the black dotted square, namely Haaften III's internal warehouse 1. In warehouse 1 (Haaften I in figure 3, warehouse 1 in figure 2), the e-fulfillment orders are being processed. It is assumed that the design choices have already been made for the inbound logistics, but for the outbound logistics, the design choices are still open for discussion. The design choices for the picking, packing, and loading are still to be decided upon. This is an uncertain and complex decision-making process, and Nedcargo wishes to substantiate its choices with quantified research outcomes.

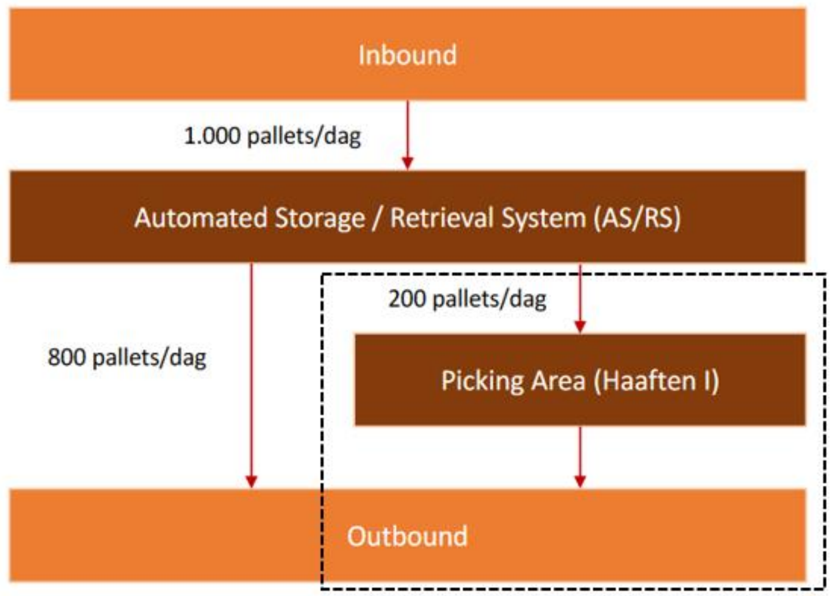


Figure I-3 – Scope of the research of in-house logistics Haaften III

Based on this information, the context of the research can be defined. Nedcargo still needs to make many decisions for the outbound logistics of the Haaften III e-commerce department. A lot of uncertainty and complexity are accompanied by these decision choices. One of the most important factors is the type of client that outsource their logistics to the service provider. The type of client determines the order characteristics and influences the processes in the warehouse logistics. Therefore a focus on different order characteristics will be researched (e.g., lines per order, SKU picks, product type, demand, idle time, etc.). Since customer orders can be very different in terms of order mix, order line, and order size, it is crucial to evaluate the profile of orders received in a warehouse in pursuance of good strategic decision-making for providing the best service. These factors very much impact the outbound process of an e-commerce warehouse, and the design choices should therefore be robust and efficient.

Therefore, this case study research will consist of a detailed investigation of the problem of many design choices in the outbound logistics for compartment 1 of Haaften III based on the uncertainty of different potential order characteristics. A contingency approach will help quantify the performance of specific (pre)-design choices of Haaften III.

2.4 Research Approach

In this chapter, suitable methods are presented in order to answer the research questions. The methods are discussed per phase of the research approach and visualized in table 1. The proposed framework and structure of the research approach will provide a guideline for this research. In order to answer the research questions and reach the study's objective, suitable methods must be used. Some of these methods have already been addressed in more detail in the previous chapters. Nevertheless, to execute the research and look into the problem definition of Nedcargo and the gaps found in literature, a methodology for the fundamental research must be defined.

The methodologies discussed are incorporated into an overall research approach, which is the adapted SIMILAR approach method. The SIMILAR approach is a System Engineering approach and can be seen as an iterative process roadmap. The SIMILAR approach is short for the following process steps: **S**tate of the problem, **I**nvestigate, **M**odel the System, **I**ntegrate, **L**aunch the system, **A**ssess performance, and **R**e-evaluate. The last three processes are combined in one Evaluate process step in this research. This is because this study is more based on proving the warehouse configuration than implementing a new system. In this way, this research approach can be seen as an abbreviated SIMILAR approach, denoted as SIMIE. This System Engineering approach is founded on system thinking, which is a mode of thinking that considers not the whole system but also how the pieces of that system interact. In this study, you can think of the different processes and choices that occur in the outbound logistics of a warehouse. INCOSE (2019) defines system engineering as a transdisciplinary and integrative approach that uses system principles, concepts, and methodologies to realize and apply engineered systems successfully. The descriptive parts per the research step below show the proposed SIMIE framework. Next to this, the research outline will be given, describing the content of each chapter.

<u>State of the Problem</u>

The research starts with the "State of the Problem" phase. The purpose of this phase is to define the problem of Nedcargo. This is done by identifying the problem, clarifying the scope and context, and setting the research goal. Only when there is a clear understanding of the overall definition of the research can it yield potential insights. In this phase, the research proposal is presented and should also introduce the first and second research questions.

<u>Investigate</u>

Furthermore, in the investigation phase, a literature review is carried out to obtain background information and find gaps in the literature that can be filled. The literature review primarily focuses on warehouse logistics, e-commerce, warehouse design components, and the proposed methodology conducted in previous research. In this manner, knowledge gaps are identified and can be used for the subsequent phases. This step is partly carried out by having written the research proposal. However, the literature study needs to be extended to substantiate confident choices in the following phases.

<u>Model the System</u>

The Model the System phase is the phase that focuses on how to model the current state. Before confident choices can be made for future state configurations, the current state must be clear and well understood. A clear view of all the current outbound logistics processes and design components can be reached by analysing. Therefore first, a current state analysis of Tiel is performed. During the current state analysis of the e-commerce warehouse of Tiel, the process of data collection is also started. In the data collection process, historical data from other Nedcargo warehouses and consultation with experts from Nedcargo are collected. If the available data is insufficient, new measurements have to be performed. With this data, the verification and validation of the future models become possible. It could also be beneficial to visit the building site of Haaften to get a better idea of the implementation plans. Then it could be clear which outbound logistics processes are included in the research and which design components are essential for Nedcargo. Next to that, many assumptions on which design components and processes are out of this research scope have to be decided. This is done in consultation with Nedcargo experts or of conclusions from the literature review. These assumptions must then be implemented with the requirements in the integrate chapter before the potential Haaften configurations can be modelled.

<u>Integrate</u>

This is the most time-consuming phase of the research, the integrate phase. The processes have been mapped, each warehouse component decided upon, and the current state model has been validated. This allows analysing of these processes and identifying the contingency variables that have to be simulated. The focus hereby will be on the order characteristics of potential clients for Haaften III, which is still uncertain. This is done by performing data analysis on historical data to see which levels of controllable variables for which design component are essential. The probabilistic functions of the different contextual variables are also determined. The last step of the analysis phase is the performance analysis in order to find out the effect of the warehouse configuration on the performance of the warehouse. This performance variable, which will be the output of the simulation model, will then be chosen in consultation with experts and based on the performance analysis results. This contingency simulation model must make it possible to generate different context scenario output. This means that each of those context scenarios can generate an experiment that a warehouse configuration model must process.

After this is done, another vital process of the research is carried out, the Modelling of the process variables of the outbound logistics. This is the backbone for the configuration models as it visually shows the steps of the warehouse activity and the entities involved in carrying out each step. The configurations can then be formed for the case study of Haaften III, which is simply stated as a series of logical relationships relative to the components, strategies, and structure of the system. Before the configurations can be modelled, the assumptions and requirements must be defined. Based on these assumptions and requirements, combined with the literature findings, consultation with experts, and data analysis, the new configurations can be formed and modelled. Three configurations are being modelled, and experiments are processed for each of the different contingency scenarios. These models result in different performance variables which can be analysed.

Evaluate

This is the last phase of the SIMIE framework and finalizes the research project. In this phase, the results of the models are evaluated. The chosen scenarios by Nedcargo are based on contingency variables, which are being processed by three different configurations and result in different performance indicators per configuration and scenario. It is looked at if the order characteristics impact the different configurations differently. Based on that outcome, the main research questions can be answered. Then the report is finished by writing a discussion and conclusion followed by recommendations for Nedcargo and possibly future research opportunities.

2.5 Research Setup

In this table, the analysis method and further explanation of the research question will be presented for each question. After the research setup is explained, the report structure will be made clear. So that there is an overall overview of what the questions mean, the method that will be used, and where to find them in the report.

Table I-1. Research Setup per question with each method, explanation, and approach

Question	Analysis Method and Explanation	**S, Inv**
1	*Literature review / Data collection / Review of current process documentation Nedcargo and proposed process documentation / Interviews / Gemba Walk* The different components applicable in a warehouse configuration for Nedcargo need to be defined. Therefore, it is necessary to have an extensive literature review. Multiple studies are performed on various design component choices and, therefore, insightful for the strategic choices for simulation. Next to that, the current policies applied in the operating warehouses of Nedcargo can be used to create the configurational model. This current data needs to be collected and analysed, which applies to current/proposed processes in outbound logistics. Interviews can also be a means of obtaining this.	
Question	Analysis Method and Explanation	**Inv**
2	*Literature review / Context Analysis* The following two techniques are needed to understand the purpose of the proposed approach and the requirements needed for successful implementation. Firstly, a literature review of previously conducted research about the contingency approach needs to be performed. This should be done for better background knowledge of the techniques, so wrong choices are avoided in the research process. A contingency approach is an approach that focuses on the context of the system. In the previous chapter, some of that context was made clear, but what could be an uncertainty of the context in the future? Is there uncertainty regarding the context while configuring a warehouse? Is it different for e-commerce warehouses? Those answers must be found by looking into previous research and deeper investigating a warehouse's potential contextual factors.	

Question	Analysis Method and Explanation	**Inv, M**
3	*Data analysis / Interviews / Process mapping* Before defining the different performance measures used in warehousing practices, it must be investigated which performance measures can be found in a 3PL warehouse. Based on the data analysis of the current state, it must be defined how the performance of the current operations is measured. This can also be achieved by conducting interviews with warehouse experts of Nedcargo. They can also give insights into measuring performance and decide which indicators are more important. Before these choices can be made, the current warehouse processes must be clearly defined. This can be done by mapping all the processes, which also helps answer the sub-questions.	

Question	Analysis Method and Explanation	**M**
4	*Interviews / Data analysis / Data Collection* This study focuses on the uncertainty of order characteristics while configuring a warehouse for Nedcargo. In order to make confident choices about the potential order characteristics, it is crucial to have insights into the current state of these. First, the current characteristics must be investigated. With the help of interviews with experts, it can be known where to find those data. By analysing the data, these insights can be made. Next to that, how will these characteristics evolve in time? Are there already specific insights for this future context, or must there they be generated?	

Question	Analysis Method and Explanation	**M**
5	*Process mapping / Data analysis* To prove that specific configurations perform better or worse in a particular context., first, it must be investigated what the current process variables are in a warehouse of Nedcargo. The outbound logistics of a warehouse consist of several process steps, and each can be configured differently. By mapping all these processes and quantifying them using data analysis, an answer to this question can be given. This can also be the basis for future configurations, which are the response variables in this study.	

Question	Analysis Method and Explanation	**M,I**
6	*Future State Analysis / Scenario Analysis / Simulation / Context Analysis* The uncertainty of the order characteristics is now elaborated on. The contingency approach focuses on a warehouse's contextual factors that influence the performance per configuration it operates. This question, therefore, proposes several scenarios which can be potential contextual scenarios for the future state of Haaften. Therefore, scenario analysis is fundamental to answering this question. These scenarios must point out the context and the uncertainty of order characteristics. How these can be envisaged can be reached utilizing simulation. The simulation must generate several experiments based on the chosen scenarios for the future state. To prove that configurations perform differently in disparate scenarios.	

Question	Analysis Method and Explanation	**I**
7	*Data analysis / Current state Analysis / Literature / Expert Consultation / Requirement Analysis / Assumptions Analysis* In order to prove that configurations perform differently in the context they operate in. It is necessary to investigate which configurations are applicable. This is an important question that needs to be answered for the research. How and which choices must be made. First, the current state is analysed by looking at the data with the expert consultation of Nedcargo. Their particular insights can be made for improvements to the new configurations. This can also be achieved by looking at literature and how they made particular choices. Next to that, the requirements of the configurations must be precise. This is done by performing a requirement analysis. The same goes for the assumptions. Not all the processes and choices can be simulated, and therefore, several of them must be assumed.	

Question	Analysis Method and Explanation	**I**
8	*Simulation / Parametric modelling* Now that the configurations and the scenarios are proposed, it must be decided which method can be used. The contingency approach is based on the three types of variables: contingency, response, and performance. How can we concretize these variables, and which method must be used? The objective is to create a decision-making tool for Nedcargo to quantify the	

	performance in specific scenarios. This can be achieved through simulation and parametric Modelling. This question proposed a specific method based on a combination between the contingency approach and the proof of configuration concept.	

Question	Analysis Method and Explanation	**E**
9	*Performance Analysis / Current State Modelling / Configuration modelling* To prove that the choices made in the previous questions for the new configurations work. It must be compared to the performance of the current state. This can prove that specific configurations perform better than the current state and must be quantified and substantiated. This is done by examining the results and the method's performance proposed in the previous question. Comparing the two models of the current state and the new configurations must answer these questions appropriately.	

Question	Analysis Method and Explanation	**E**
10	*Configurations Modelling / Results Analysis / Scenario Modelling* In order to answer the main research question, it must be investigated whether the chosen scenarios have a different impact on the performance based on their configuration. This question analyses the results from the scenario modelling and the configurations modelling by looking at the performance of each experiment. Does the context affect the performance, and does the configuration contributes to it? This also must fill the found knowledge gaps and provide the impetus to answer the main research question.	

Question	Analysis Method and Explanation	**E**
11	*Results Analysis / Configurations modelling / Scenario Modelling* Now that all the questions have been answered. The final step before the main question can be answered, and the objective hopefully is reached. Is the question how Nedcargo can learn from these questions. Due to the proof of configuration concept that is maintained in this research. The process of proof of configurations exists before the final design stage, and this question must be beneficial for Nedcargo, namely, how they can learn from all the findings and apply this to the decision process for Haaften.	

2.6 Report Structure

The research, as described in the previous section, is divided into parts. Each part contains different chapters. An overview of these chapters is stated below.

I. State of the Problem
   - Problem Definition
   - Research objective & questions
   - Context Analysis

II. Investigate
   - Literature Study
   - Knowledge Gaps

III. Model the System
   - Current State Analysis
   - Current State Modelling
   - Method

IV. Integrate
   - Scenario Modelling
   - Configurations Modelling

V. Evaluate
   - Results and Analysis
   - Conclusion
   - Discussion
   - Further Research Possibilities

II. Investigate

3. Literature Review

In this chapter, an extensive literature review is performed on all the essential warehouse logistics and design topics. This all to have a good background knowledge base to substantiate confident choices in research. Each issue will be elaborated on in terms of definition, previous research conducted, and still to be investigated knowledge. This is all to eventually point out the knowledge gaps to give the fundamentals for the proposed research.

3.1 Warehouse Logistics

In the supply chain of goods, it is essential to make warehouses as efficient as possible. According to the supply chain management definitions and CSCMP (2013) glossary, a warehouse is a storage place for products. Its principal activities include storage, receipt of the product, shipment, and order picking. The warehouse represents a significant role in the modern supply chain. Azadnia et al. (2013) state that 20% of the logistics costs of companies come from warehouse operations. In this manner, a warehouse's in-house logistics (or intralogistics) are an integral part of the organization's operations. Therefore, it can be seen as a vital opportunity to improve optimization, physical - and information flows, reduce inventory levels, and enable more agile distribution (Vrijhoef & Koselka, 2000). An appropriate strategy, layout, warehouse operations, and material handling system must be achieved (Lehrer et al., 2010).

The main objective of a warehouse is to satisfy its customers and clients with effective resource allocation and delivery of the right product, at the right place, at the right time in good condition (Frazelle, 2002). This leads to the fact that the main functions consist of temporary storage, protection of goods, fulfillment of individual orders, packaging of goods, after-sales services, repairs, testing, inspection, JIT sequencing, and assembly (Heragu et al., 2005). For warehouses, in the case of a third-party service provider like Nedcargo, the focus is only on the first five functions. These kinds of warehouses are a non-value added step in the supply chain as they store inventory but do not transform the product in any way before its completion. So the warehouses of Nedcargo have a more distributive role. Van den Berg & Zijm (1999) emphasize this by defining three types of warehouses: distribution warehouses, production warehouses, and contract warehouses. The warehouses' operations are classified into receiving, picking, storage, and shipping (Gu et al., 2007). Figure 1 shows an overview of warehouse operations and design (Kembro et al., 2018).

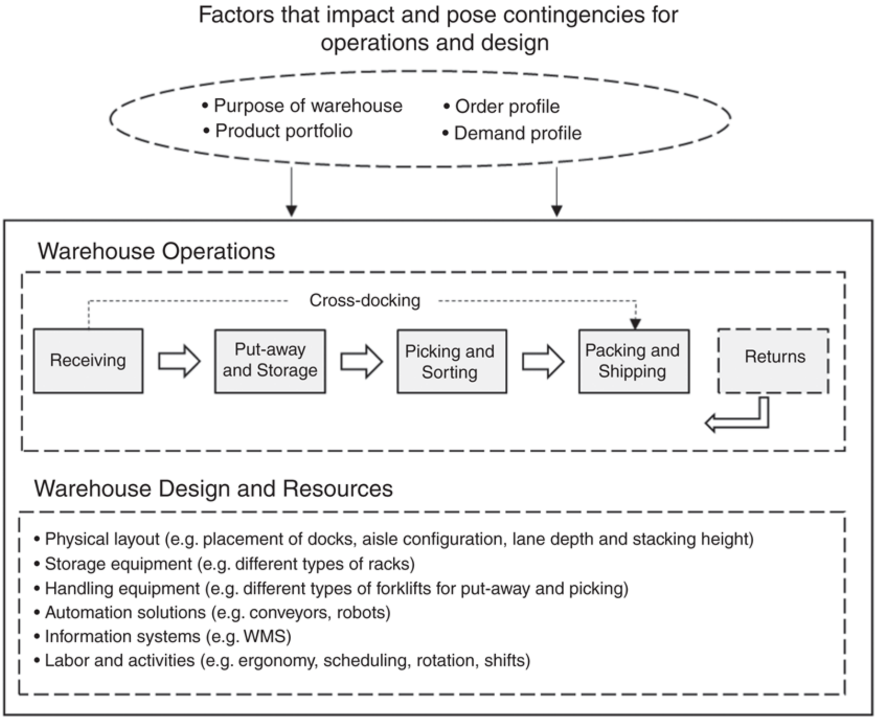


Figure II-1 – Overview of Warehouse Configuration (Kembro et al., 2018)

According to Roodbergen and De Koster (2009) and as mentioned beforehand, the in-house warehouse processes can be divided into four main phases. The first phase is called the receiving process, and this is where the inbound goods are unloaded from shipment vehicles, checked out and/or transformed, and then prepared to be transported on time to their corresponding storage location. The second phase is the storage phase, where the incoming products are stored in their designated storage location. The third phase is called the order picking process: this corresponds to retrieve the items from their storage location, primarily based on a customer's order request. Finally, the fourth phase is the shipping and dispatching phase. Here, orders are checked, packed, and loaded into the mode of transport to be shipped to retailers or customers. This literature review will focus on the picking, sorting, packing, and shipping phases of warehouse logistics, the so-called outbound logistics.

The outbound logistics of warehouses, especially with the focus on e-commerce, focus on operating as efficiently as possible to achieve profits. Klumpp and Heragu (2019) defined outbound logistics as moving and storing goods from the point of production to the point where they are delivered to the customer. As mentioned beforehand, the warehouse costs in the supply chain could be exceptionally high. So, efficient outbound logistics handling plays a vital role in reducing waste and decreasing costs for operations. The waste reduction factor occurs when a service provider examines the areas that are creating overproduction, waiting time, and stocks piling up in the inventory. If a warehouse's outbound logistics are efficient, it will be able to quickly satisfy customers and obtain a better reputation (Din et al., 2021). Important to mention that the outbound logistics are different for every warehouse. The chances of warehouses having almost the same outbound logistics process due to other order characteristics are minimum (Baretto et al., 2017)

Warehouse outbound operations performed at various material-handling nodes are a significant part of the distribution systems (Faber et al., 2013). For example, a considerable challenge is combining the handling and shipping of small e-commerce orders with large store replenishment orders, which were previously handled in different channels (Hübner et al., 2015). "The efficiency and effectiveness in any distribution network are substantially affected by the operations of the node in such network, i.e., the warehouses," asserts Rouwenhorst et al. (2000). Warehouse operations, which were previously viewed as a burden due to high capital and operating costs (de Koster et al., 2007), are now increasingly regarded as a strategic component of supply chains, particularly in e-commerce warehousing (Hübner et al., 2016). Therefore, the topic of efficient warehousing processes is attracting increased attention (Kembro et al., 2017).

Davarzani and Norman (2015) looked at the practitioner's view on warehouse issues. They revealed concerns about support aspects of warehousing, which implies a scarcity of decision support for daily warehouse operations for warehouse managers. Decision support relies on having the correct information about physical – and information flows at the right time to act at the right time to detect and improve bottlenecks. Human operators mostly make these decisions and are mostly ignored in research studies concerning warehouse architecture and design (Trentesaux and Millot, 2016). Nevertheless, these research studies show that most problems that arise are fixable. Therefore, research should look to support human decision-makers in improving and resolving daily warehouse operational issues.

To this date, a reasonable amount of research is conducted on strategic decision support in geographical location (Max Shen & Qi, 2007), design (Sprock et al., 2017), sizing of warehouses, and also in demand planning and forecasting (Dubey & Veeramani, 2017). There has also been a lot of research into various methods for optimizing warehouse problems like the storage location assignment problem (Gu et al., 2007). Figure 5 is shown which decisions are on a strategic level and which on a policy level (de Koster et al., 2006). However, the literature on decision support for daily warehouse operations is fragmented and not explored extensively. Klodawski et al. (2017) state that decomposing warehouse operations into separate problems, as has been done in literature research, makes it difficult to solve the warehouse bottlenecks in the context of the entire process in the supply chain. The information and analysis needed to help operational decision-makers complete the warehouse's daily amount of work is referred to as daily warehouse operation decision support (from receiving to shipping). In conclusion, the warehouse logistics environment management is complex and relies on accurate information about physical - and data flows, a series of processes and procedures, and human expertise.

3.2Warehouse E-commerce

The booming of e-commerce has dramatically influenced modern warehouses. Bayles and Bhatia (2000) even estimated that e-commerce logistics could cost 40 percent of the price that the customers pay for their product. The logistic chain of e-commerce consists of three stages: (1) replenishment of goods from manufacturers to warehouses, (2) order fulfillment phase (sorting, picking, packing, etc.), and (3) shipping from warehouse to customers. The third phase can differ in two types of business models, namely business-to-consumer (B2C) and business-to-business (B2B). The difference mainly lies in the destination of the product (customer or a business) and the transaction volume. The transaction volume is usually much higher in B2B than in B2C (Ta et al., 2015). Nedcargo is a third-party logistics (3PL) provider, and therefore, the e-commerce literature study will focus on the order fulfillment phase.

3PL service providers nowadays have been increasing their investments in expanding their warehouse capacities. In contrast, big e-commerce firms like Amazon and Alibaba have heavily invested in developing their own logistics facilities (Ellinger et al. 2003). This is because businesses have a common expectation for a paradigm shift in e-commerce to reduce the bottlenecks of an order. It is essential to understand the changing characteristics of e-commerce orders to find the bottlenecks in warehouse operations. 3PL service providers face the challenge of assembling large numbers of time-critical orders, which are typical of just a few order lines (SKUs) and low order quantitates (Weidinger et al. 2018). This trend influences several warehouse processes, and therefore efficiency and effectiveness of the supply chain have to be improved. This can be done by obtaining more insight into the processes and incorporating these findings into new design components or technologies (Wang et al., 2017).

3.3Warehouse Design

Warehouse design is a complex set of decisions made at the strategic, tactical, and operational levels to meet specific performance goals (Rouwenhorst et al., 2000). Warehouses can be considered as a way to optimize operations – and information flows, reduce inventory levels, and enable more flexible distribution (Vrijhoef & Koselka, 2000). The effectiveness of a warehouse is determined by its strategy, warehouse operations, and material handling systems (Lehrer et al., 2010). Gu et al. (2010) classified these warehouse design decisions into different categories: The overall structure of the warehouse, sizing, throughput, layout design, utilized number of workforce, equipment selection, and selection of operational policies. Next to that, a warehouse design project should include definitions of policies such as order fulfillment, picking, packing, stocking, and stock rotation (Chan & Chan, 2011). The fulfillment operation can be split into inbound and outbound operations. Inbound operations. Bulk items are broken down into stock units by the inbound processes, which are subsequently stored in the storage system. Orders are created by picking products from SKU into client totes and transferred to the packing operations in the outbound operation. Completed orders are kept in the storage area until they are received for shipping. This chapter will zoom in on the various design decisions and policies of a warehouse's outbound logistics since this work will mainly focus on the outbound logistics operations of a picker-to-goods warehouse.

<u>Overall structure</u>

The overall structure of a warehouse is the plan and overall design of the quantity, scale, geographical location, warehouse facilities, roads, and sites of a particular area where the warehouse is meant to be located (Huang, 2019). Next to that, Gu et al. (2007) stated that for warehouse design, the overall structure primarily focuses on the material flow of the warehouse, the department identification, and the relative location of those departments. In other words, the specification of functional areas and the flows between them.

Layout

Warehouse design involves sizeable capital expenditure, and after the warehouse has been built, it is tough to change it. The layout design is one of the most essential elements in the warehouse design. It consists of determining the length, width, height, aisle width, the position of the pickup/deposit depot (P/D), etc. This topic has received quite a bit of attention in research studies over the last few decades. Mohsen (2002) pointed out that designing a warehouse layout is complex for several reasons. First, the number of design decisions is numerous, and most of them are interrelated, which makes decision-making even harder. Secondly, many warehouse operations (picking, packing, etc.) and warehouse factors (demand, order characteristics, etc.) impact the warehouse's travel time, material handling, and throughput. These operations and elements of the warehouse should be accounted for in the comprehensive layout design in order to support them. This makes the layout design even more complicated. Third, these operations and factors interact, and such synthesis should be accounted for in the layout design. He came up with a framework derived from an analysis of different layouts and previous studies and cases that highlights essential design issues and steps to be taken for warehouse layout design. Bassan et al. (1980) used an analytical model to compare the decisions of the dimensions of the layout of a rectangular unit-load warehouse and a zoned warehouse. Berry (1968) looked at the impact of two configurations of warehouse racks, block-stacking, and pallet stacking, on the volume requirements and handling costs.

Sizing

In the design, warehouse sizing determines the storage capacity of a warehouse. In Modelling the sizing problem, there are two scenarios to consider (Gu et al., 2009): (1) inventory levels are determined externally, so the warehouse has no direct control of when incoming shipments arrive and their quantities. This is primarily the case for 3PL warehouses, like Nedcargo. And the warehouse must meet all exogenous storage space requirements. The other scenario (2) is that the warehouse can directly control the inventory policy, e.g., independent wholesalers. The significant difference is that in the second scenario, the inventory policies and expenses must be considered when resolving the size issue. The first scenario is typical for 3PL, like Nedcargo, and therefore assumed further. When the warehouse has no control over the inventory level, the warehouse sizing design must determine an appropriate storage capacity to satisfy the stochastic demand for storage space. Poor warehouse sizing planning can harm the efficiency of warehouse logistics. Pang and Chan (2016) stated that the uncertainty of the space demand and warehouse sizing is an essential step in the design process. Empty warehouse space results in higher storage costs due to an overabundance of storage space. On the other side, a shortage of storage capacity might result in additional costs associated with employing an overflow warehouse as well as higher response time. Therefore in, warehouse design frequently includes storage demand prediction and contract flexibility in the warehouse-size planning to mitigate the loss costs caused by space demand uncertainty. Storage demand is estimated from data analysis, i.e., sales plans or product demand forecasts, which aid in the reduction of sizing uncertainty. Therefore, the sizing design phase has been considered a dynamic component of having a robust warehouse design.

Equipment Selection

The equipment selection design decisions address the processes and systems to transfer and store products within the warehouse. In the case of Nedcargo, a picker-to-goods warehouse design is being researched. Therefore it will look at the strategic design decisions for equipment selection of a PTG warehouse. Equipment selection can, if properly carried out, have a significant impact on the profitability of a warehouse. Few researchers pointed out this equipment selection problem (Gu et al., 2010). The material handling equipment selection problem (MHESP) is a vital decision-making area for warehouse design. Material handling can account for 30-75% of the total operating costs because it influences many processes. Efficient material handling can be primarily responsible for reducing the warehouse systems costs (Kulak, 2006). MHESP can be divided into manual equipment and mechanization equipment, and both will be discussed.

Human operators perform manual material handling. The outbound logistics of a warehouse take place in the picking and packing operations. Therefore, the performance and costs profoundly depend on human availability and productivity, affected by the fatigue of operators and the probability of their injuries and gravity (Daria et al. 2015). Manual warehouses, like the ones of Nedcargo, rely on human operators for their order picking system (OPS). The equipment selection decisions in a manual warehouse are expressed, e.g., number of human resources, number of carts, utilization, etc. Order picking is one of the most time-intensive processes in outbound logistics, and human factors play a crucial role in OPS performance (Tompkins et al., 2010). Grosse et al. (2015) conducted a research where human factors aspects were highlighted in each OP process step. Based on the literature, they showed how perceptual, mental, physical, and psychosocial elements affect the performance, quality, and worker's health in OPS. Gong and Koster (2011) coped with stochastic models of warehouse operations. They discovered that human workers could introduce uncertainty into OP operations, e.g., by being absent from work, injuries, and the pick inaccuracy and errors.

Next to that, there is the usual machine equipment selection approach. This is to identify warehouse process requirements, match them with the available machine's specifications, and then select the solution with the least cost since that has been seen as the most critical immediate factor (Sujono & Lashkari, 2007). Thus, warehouse managers can reduce investment costs, maintenance and operation costs, increase machine utilization, improve machine layout and increase warehouse efficiency and productivity by selecting the correct number and type of machines (Tabucanon et al., 1994). Luong (1998) pointed out that one of the most essential aspects of MHESP is considering the implementation phase when selecting technology suited for warehouse operations and requirements. Decision-makers may encounter the following issues while adopting material handling equipment: (1) they have to select a technology that will provide the most significant benefit to the company while taking into account the company's objectives and operating characteristics, (2) financial justification of the investment and (3) developing an implementation strategy to guarantee that when the chosen technology is implemented and evaluated, the envisaged objectives are accomplished. The efficiency of the warehouse outbound processes is obviously related to the material handling operations. When the material handling equipment is poorly designed, the planning of the warehouse processes could result in low machine utilization, low material handling utilization, and a longer order cycle time (Sujono & Lashkari, 2007).

Level of Automation

Another aspect of warehouse design is the implication of reducing the lead time with increased automation of various warehouse operations to improve material handling speed (Hübner et al., 2016). Automation in material handling can be classified into three basic types, namely fixed automation, programmable automation, and flexible automation (Groover, 2007). Fixed automation, or hard automation, has little or no flexibility in order to accept a wide range of goods. Because the program of instructions is set according to the automated equipment's design and configuration, there is a lack of flexibility. As a result, processes have been set in a dormant state and are difficult to alter. This form of automation is utilized in the large-scale manufacturing of a single product (Craig, 2013). In programmable automation, the equipment is designed to modify the program of instructions. This allows for greater flexibility and a wider range of goods, although this adjustable characteristic results in lower production rates. Flexible automation enables continuous production of diverse components or product types by allowing any needed modification in the program of instructions (MacDuffie & Pil, 1997). This allows for cost-effectively responding to changes in volume requirements, product-mix requirements, machine status, and processing capabilities (Custodio & Machado, 2019).

The level of automation is increased in order to eliminate the routine manual tasks and administrative chores improvements in worker safety and product quality, reduce lead time, and the completion of processes that cannot be completed manually (Wiktorsson et al., 2017). The level of automation can be defined into three subgroups: automated storage, robotics, and transportation systems. Automated storage and retrieval systems (AS/RS) represent a parts-to-picker order picking system. It can be defined as a system that performs the storage and retrieval operations of the goods with speed and accuracy based on automated equipment (Groover, 2011). An AS/RS system can sort, sequence, buffer, and store a wide range of goods with high accuracy and efficiency. This leads to a reduction of labor requirements, increases productivity, and exploits unused storage space. Moreover, this technology can reduce the picking time because it eliminates the need to have a human operator pick products along the aisles. Robotics represents the technology that is most discussed in modern literature related to the category of automated equipment. This is because of the reason that robotics is related to the applicability of this automated technique in other areas of research. Robotics that increase the performance is mostly designed for palletizing, picking, packing, or as a human collaborator. Robots are deployed to perform repeatable processes with not much variation by constant precision and high speed; therefore, standardized products are preferred (Koobally et al., 2018). The flexibility of robotic operations is hence a popular research area. This means that a flexible robot should have the ability to be quickly re-tasked without the need to shut it down, the ability to recover its errors, and the ability to be deployable in different scenarios. The rapid growth of e-commerce increases the need for robotic assistance in massive warehouses. This increase in the level of automation can lower the human responsibility in the warehouse process. This increases the overall productivity and accountability of the warehouse (Petkovic et al., 2017).

Transportation systems are also a component in which the level of automation can be increased. Problems that occur in transportation in a warehouse are: that there are smaller order deliveries, challenges to meeting new demands of logistics warehouses, and the necessity to detect and transfer SKUs. This is all due to the factors mentioned before, like the e-commerce trend and the mass customization in manufacturing that forces warehouses to deliver smaller orders and the need for more flexibility and service quality while keeping the operations costs acceptable (Casado et al., 2017). Some studies point out that automated guided vehicles (AGV) technology can be used due to its flexibility benefits (Chung fu et al., 2017; Lopez et al., 2016). AGVs are vehicles equipped with an automated guidance system that can move pallets and containers in the warehouse. There are driver-less and programmed to follow a prescribed path. Therefore, they are not manipulators and differ from conventional robots (Shivanand et al., 2006). Next to flexibility: they can be reprogrammed quickly; AGVs are efficient: they can quickly be added as required to demand growth; AGVs are precise: if technology improves, a more precise space localization can be achieved; AGVs have economic benefits: they have an outstanding price/quality ratio. Next, AGVs are safe: they are predictable and avoid interfering with human operators.

Custodio and Machado (2019) performed an extensive literature review related to flexible automation in a warehouse and constructed a framework that could guide future designs for innovative conceptual models. They stated that in order to have a flexible warehouse environment, it should (1) increase productivity,(2) enhance flexibility and space utilization to accommodate the growth in SKUs, (3) and have higher throughput and faster deliveries. They pointed out that a flexible automated warehouse consists of a combination of automated technologies mentioned previously, data collection technologies, and management solutions. These three factors can be implemented to a lesser and greater extent. In order to implement, the warehouse needs to be able to collect data, increase transparency in its operations, improve its coordination and communication, and adapt to changes. This framework can help construct a conceptual model for a flexible automated warehouse.

Picking

For the outbound fulfillment of an order, several activities are performed: picking, packing, and order consolidation. Order picking is a crucial and demanding part of the outbound process, and it accounts for approximately 55-60% of the total operating costs of a typical warehouse (de Koster et al., 2007). The other factors of the operation’s costs are shipping, storage, and receiving. The picking process can be described as “the process of locating and selecting the ordered items from the warehouse's inventory” (Rouwenhorst et al., 2000). The picking process in a warehouse is the most labor-intensive and costly activity in its supply chain (Rushton et al., 2014). Order picking can be divided into goods-to-picker and picker-to-goods systems (de Koster et al., 2007). In the case study of a Nedcargo warehouse, the focus will be on a picker-to-goods system, and goods-to-picker will not be included in the literature study. Several design components of such a system will be elaborated on.

In picker-to-goods (PTG) warehouses, pickers walk or drive through the aisles of the warehouse. The pickers have to pick customer orders consisting of Stock Keeping Units (SKU), of which multiple are picked per picking. The most common method that a picker picks is the pick-by list, in which a picker receives a list where the product of the order is being placed. Less common methods are pick-by light, voice picking, and RF picking. This picking process utilizes 60% of the total labor force in a typical warehouse (Won & Olafsson, 2005). The total processing time of a picking tour consists of (1) *travel time,* which is the time spent on traveling between two pick locations, (2) *search time,* i.e., the time spent on locating the SKU to pick, and (3) *pick time,* i.e., the time spent on picking the goods from the SKU, and (4) *setup time,* i.e., the time spent on administrative tasks. Batholdi and Hackman (2008) stated, “travel time is a waste. It costs labor hours and does not add value”. However, Tompkins et al. (2003) figured that the travel time accounts for at least 50% of the total processing time of a picking tour. In the design phase, there are five different picking strategies to consider in order to minimize the total picking time: single order picking, picker routing, zoning, storage assignment, and order batching. These strategies will be elaborated on in the following paragraphs.

The first strategy is *single order picking*. Each picker in the warehouse is assigned to only one order at a time and undertakes the entire order's execution and the entire quantity's collection. The main advantage of this strategy is that the integrity of the orders is ensured; however, the picker may be obliged to travel long distances, especially when it’s a small order. Therefore, is this strategy more suitable for orders with multiple order lines so that the travel time per order line decreases (Pan et al., 2012).

The second strategy is *routing,* where the travel distance is minimized directly. This assumes that the travel speed remains constant. There are several kinds of routing strategies known and used. In the S-shape routing strategy (1), an aisle containing at least one of the requested SKUs is traversed entirely in an S-shape fashion. The last aisle that is traversed has to contain one of the requested SKUs seen from the depot. The picker will pick up the goods and return them to the depot without traversing the entire aisle. In the largest-gap strategy (2), the picker enters an aisle and can turn around and travel back. In a way, the non-traversed length of the aisle is maximal. Only the left- and rightmost aisles are traversed entirely (Henn & Schmid, 2013). Ratliff and Rosenthal (1983) developed an optimal routing solution strategy by using the traveling salesman problem (TSP). However, this solution is not often implemented in real life due to the confusion it causes among the pickers (Koch and Wäscher, 2016). Next to that, the two first methods reduce the in-aisle congestion instead of an optimal routing strategy (de Koster et al., 2007).

Under the *zoning* strategy, the warehouse is divided into several disjoint zones. Each picker is assigned to a zone and will only pick the SKU that belongs to his own zone. There are two types of zoning: progressive zoning and synchronized zoning. Progressive zoning is where the picker stays in the zone, and the pick totes are transferred to the next zone. Synchronized zoning is where the pickers from different zones pick in parallel, and the orders are consolidated afterward (de Koster et al., 2007). The main advantage of zoning is the minimization of travel time ab the acquaintance of the picker with his area. The negative side of zoning is that the time required to place the goods per order correctly is increased, and the risk of wrong order execution is higher. Although zoning has gotten more attention in the literature, the consolidation stage has garnered less attention (Boysen et al., 2018).

The fourth strategy is the *storage assignment.* The storage assignment exists out of several methods: dedicated -, random -, closest open location -, full-turnover-based -, and class-based storage assignment. Each of the methods will be discussed shortly. In the dedicated storage assignment, the goods are stored in a dedicated storage location in the warehouse. A disadvantage of this method is that it can lead to a lack of space utilization due to empty storage locations if a product is out of stock. The random storage assignment means that a product is stored randomly, which means that every empty SKU spot can be filled with equal probability. A disadvantage can be that if the storage assignment changes too rapidly, the pickers might not be able to learn the storage location (Grosse et al., 2017). This strategy increases the average travel distance, but the space utilization is high (Hsieh and Huang, 2011). The SKUs will be stored in the first and closest open location to the depot in the closest-open storage location. SKUs are stored according to their demand frequency in the full-turnover-based storage assignment. Fast-moving SKUs are kept close to the depot for convenient access. However, because demand fluctuates over time, this approach necessitates repeated relocation. Petersen et al. (2004) showed that a full-turnover-based storage strategy outperforms the random location storage strategy. Lastly is the class-based storage assignment. This policy divides the warehouse storage into several areas, each corresponding to a specific property of the SKU product. An example can be that heavy items are stored in the bottom layers of the racks. Within each property area, a random storage policy can be applied. ABC class-based storage is the most commonly used storage policy in practice and is widely discussed in the literature. ABC class-based divide the items into different classes (three is common) according to the ABC curve of the demand. A-class goods are a small number of high-demand products that are gathered together and kept in a warehouse zone close to the depot. C-class goods are stored in the zone farthest away from the depot because they are seldom ordered (Yu et al., 2015).

The fifth strategy is called the *order batching* strategy. Order batching means that customer orders are grouped into batches and picked in a single tour to save travel time. These methods are the ones most reviewed in literature studies (de Koster et al., 2007). Tsai et al. (2008) even considered it the most important strategy to save on travel time when picking. Each picker is assigned a group of orders in a single trip, minimizing its travel time and the average time per order line. However, because there needs to be an extra consolidation step after picking, the pick cart has to be sorted into individual orders, so the risk of wrong order execution is higher. Important to note is that batching can occur online and offline. In online batching, the orders are not known in advance and become available over time; offline batching means that the order is known beforehand (Henn, 2013). Order batching is an important aspect of PTG warehouses, and most research papers more or less try to tackle the same problem. How they solve the problem differs by (mostly) using a different algorithm. Cergibozan and Tasan (2019) made an overview of all the classification of these order batching operations studies. They concluded that storing and batching are interrelated to one and all, and therefore is storing an important issue for the effectiveness of the batching operation. So decisions about the determination of storage locations and layout design can also be considered a part of the success of a batching strategy. Next to that is that because of the new dynamic demand environment warehouses are part of now, the characteristics of the orders can change rapidly. They predict that in future studies on warehouse optimization, the most reactive and flexible companies will be the most successful ones in their area. Thereby, every effort to make the picking process faster and more flexible becomes the most willing subject in the current state of warehouse logistics.

As can be seen, is the picking process design an extensive and complex step in designing a warehouse. In figure 2, the different classification of order systems is shown. Many different decisions must be made to obtain an efficient order picking system, and most of the research findings are not generalizable to every case. Therefore, for the design of a warehouse, it is important that either data findings or previous literature thoroughly substantiate decisions.

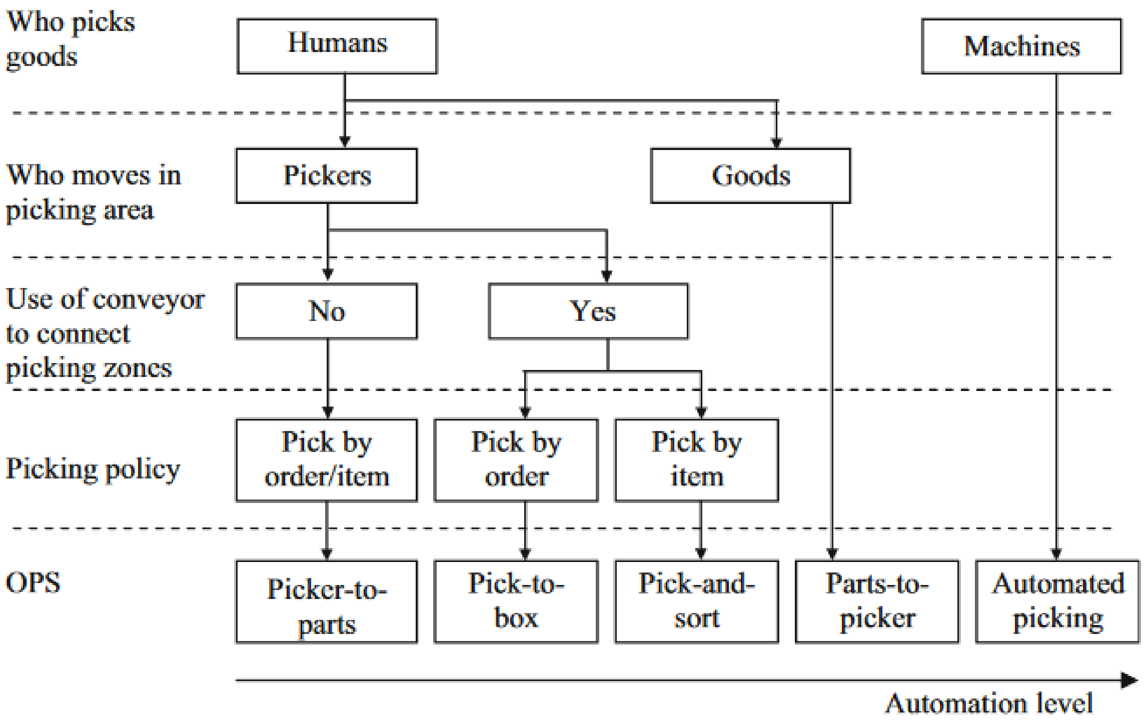


Figure II-2 – Classification of Order-Picking Systems (Dallari et al., 2009)

<u>Design Steps</u>

There is a lot of literature about the steps that need to be taken when designing a warehouse. A collection of research was evaluated and generally described the design process in terms of a series of steps. Heskett et al. (1973) concluded that warehouse design could be divided into three main aspects: determining the requirements, designing the material handling, and developing the layout. These three broad steps can be found in most of the subsequent literature. Apple (1977) observed that the designer has to process and analyse many different data of processes. This makes the design a complex task and therefore suggests a 20-step procedure for warehouse design. Oxley (1994) provides a more comprehensive list of steps. He begins by establishing the supply chain’s general system requirements, including service levels and implementation time. Data collection and analysis are crucial steps once again. He also adds a new process for determining the unit loads used. The following steps are about coming up with alternative operational methods, equipment types, and layouts. He emphasizes that the warehouse design should be centered on the storage and material handling requirements and that the rest of the warehouse should be built around this. Firth et al. (1988) and Mulcahy (1994) follow a similar approach as Apple (1977). However, they include features like recognizing the warehouse as part of a more extensive distribution network and comparing alternative approaches. Rowley (2000) and Rushton et al. (2006) added an extra element to the design steps, simulation. They were using the basic framework of the previously discussed steps and adding an extra step of computer simulation. They could test the impact of different volume throughputs and identify the consequences of specific changes on the rest of the supply chain. They stressed that although the steps are set out in sequence, the overall design process is an iterative process. Rouwenhorst et al. (2000) noted that a design process is usually divided into many consecutive phases. Therefore, they use a top-down method to organize these phases' actions into a hierarchical framework, identifying the strategic, tactical, and operational decisions. They propose that these three decision clusters should be evaluated in chronological order. Bodner et al. (2002) used ethnographic study techniques to identify how experts actually design warehouses. The focus of the study was on the methods followed by designers and experts in the area of warehouse design. To attempt to comprehend the decisions and techniques, they employ while developing a design project. They claim that the warehouse designers must weigh many complicated trade-offs. The paper proposes four to five steps and the requirement to reiterate these steps. These steps consist of data analysis, determining functional requirements, making high-level decisions, and performing a detailed system specification and optimization. The authors intended that following research, with the help of their proposed steps, could help develop computational aids for warehouse design. Bodner et al. (2002) also did an ethnographic study. They proposed an object-oriented model comprising five modules: base data, unit load and equipment details, movement within the warehouse, specified design, and the accompanying costs. Mohsen & Hassan (2002) and Waters (2003) also proposed a step-wise approach in similar ways to the abovementioned literature. However, their focus is mainly concerned with only one aspect of the design problem: the layout design. Waters (2003) even clashes with some of the previous authors that a warehouse design should not represent a stern sequence. Rushton et al. (2006) pointed out the importance of flexibility in the design process. This will be elaborated on further in the literature review.

So it can be seen that in warehouse design steps proposed in the literature, some common themes can be found back in their methodology. First, it is acknowledged that warehouse design is considered a highly complex process. Secondly, the authors try to tackle these complexities by using a step-based approach. Thirdly, these steps need to be interconnected, and reiteration is necessary. Lastly, they agree that there is not something as an optimal solution. This is due to the high possibilities that exist at each step and the uncertainty that goes along.

3.4 Warehouse Uncertainty

The increased competition among third-party logistics providers (3LP) has led them to make an effort to achieve the highest service level and, concurrently, decrease the costs. The following can be achieved in several ways: the increase in the correctness of order execution and the improvement in personnel productivity. These improvements to stay competitive are full of uncertainties and challenges, like the need for shorter lead times, real-time response, to handle a large number of orders with greater variety, and deal with the increasing complexity of warehouse processes in a flexible manner (Gong & de Koster, 2011). Especially e-commerce warehousing faces customers who more often purchase by impulse or change/cancel their orders. This upcoming real-time aspect creates uncertainty for warehouse managers. Therefore, it is necessary to consider uncertainties from various sources, both from inside the warehouse processes itself to outside the supply chain.

Warehouse systems are exposed to a wide range of internal and external uncertainty sources to the warehouse (Chopra & Sodhi, 2004). Gong & de Koster (2011) stated that a distinction can be classified into four types of uncertainties: (1) sources outside the supply chain, (2) sources in the supply chain but outside the warehouse, (3) Sources inside the warehouse, and (4) sources within the warehouse control systems. Next to that, there is also a variance structure of uncertainty, which they classified as (1) unpredictable events, like covid, which are rare, (2) predictable events like demand seasonality, (3) internal variabilities in activities, variance, or order waiting time, which could be caused by internal randomness. These uncertainty sources can affect the warehouse decisions at three levels: Strategic, tactical, and operational (Ghiani et al., 2004). Strategic decisions have a long-term effect, tactical has a medium (monthly/quarterly) term effect, and operational are daily-based decisions. Decisions based on the level of automation, layout, and system have a strategic effect. Storage, order picking, and shipping are examples of tactical decisions. Warehouse operational decisions include daily order-picking planning, daily resource planning, and daily warehouse information management.

Flexibility is a term that is inextricably linked to uncertainty. In order to maintain efficiency along the supply chain of the warehouse to maintain acceptable service prices, a lot of challenges arise. But the flexibility to deal with time-varying or dynamic demand could be even more important nowadays. Customer's orders are more likely to be increased, reduced, cancelled, or moved ahead or backward. Therefore warehouse operations must be more adaptable in various ways. This might involve the requirement to adjust capacity levels, different transportation modes, switch suppliers, deal with smaller order sizes, and have minimum changeover times. Flexibility is, along with cost, delivery speed, and quality, considered a critical component of competitiveness (Avittathur & Swamidass, 2007).

Aforesaid, a typical warehouse consists of multiple operations such as receiving, put-away, internal replenishment, order picking, accumulating, sorting, packing, cross-docking and shipping. In these different processes, internal variability can be observed (Gu et al., 2007). This internal variability creates uncertainty, and the warehouse has to learn to cope with this increase. This adaptation led to far more complex warehouse operations and the use of new warehouse innovations (Frazelle, 2002). The recent trend in e-commerce orders and the strength of its development have brought a new focus on warehousing operations and layout. In particular, the management of the order picking systems and packing, where fulfillment centers now need to process a far higher volume of smaller orders, increases the picking costs (Manzini et al., 2006). This e-commerce trend and the strength of its development lead to a new focus on warehouse activities and management. In particular, the management of order picking systems changes due to e-commerce. This is due to the increasing demand and the fulfillment process of a far higher volume and smaller orders, which eventually increases the costs.

3.5 Warehouse Flexibility

It is clear that warehousing is an essential business operation on a supply chain; it has to be able to adapt quickly and respond to changes in customer demand. A responsive warehouse should be flexible. In other words: flexibility must be designed into every function of the warehouse: receiving, material handling, picking and packing, shipping, management systems, and its personnel (Brockmann & Godin, 1997). Rushton et al. (2006) pointed out the importance of flexibility in warehouse design and refined the steps in their research. These steps include the concept of scenario planning, which leads to a concurrent step of evaluating design flexibility. The need for flexibility in the supply chain is growing and is becoming increasingly important as product life cycles shorten and global and competitive pressure lead to additional uncertainty (Christopher, 2000). In this environment, companies need to locate their inventory and capacity at strategic points in the supply chain to facilitate the flow of goods to market (Stratton & Warburton, 2003). 3LP firms want to provide this responsiveness for their clients by having flexible capabilities in several (design) areas of their warehouses. An example of competence at a warehouse level is shown by Stalk et al. (1992), which describe the case of Wal-Mart's cross-docking logistics operation. The case shows that this operation enables goods to be "pulled" by consumer sales data directly from the supplier.

The 25-year depreciation time of warehouses, in combination with the logistic equipment depreciation time of 5-10-year, the supply chain flexibility issue reconciling this long life cycle is a significant challenge. The long life of warehouse assets can either form a severe constraint on future flexibility or provide a significant advantage by making it easier to respond to market shifts that competitors may find difficult to adapt to (Baker & Perotti, 2008). A term associated with flexibility is a business-wide concept: agility (Aitken et al., 2002). Hoek et al. (2002) described it as a "management concept centered around responsiveness to dynamic and turbulent markets and customer demand." So, agility not only responds to changing market conditions but also can exploit and take advantage of the changing circumstances (Sharifi & Zhang, 1999). In warehouse logistics, agility is the ability to pivot direction quickly in your operations and nimbly respond to changing internal and external signals. This extra pressure on agile operations, especially 3PL warehouses, leads to additional uncertainty. The starting point for the requirement of flexible capabilities for warehouses starts, following Van Hoek (2002) and Baker & Perotti (2008), with the ability to respond to five types of agility that are described as follows: (1) *volume variance,* e.g., caused by seasonality, product life cycles and consumer demand fluctuations, (2) *time variance,* e.g., urgent orders, (3) *quantity variance,* e.g., small orders, item-level orders instead of case level, (4) *presentation of goods*, e.g., how the products are displayed, and (5) *handling of returns,* e.g., replacement of broken product. Nowadays, most of the actions to increase agility and adapt warehouse operations are performed on a trial-and-error basis. Consequently, the flexibility to adjust a warehouse system's behaviour depends significantly on the performance of the warehouse system.

Automation in the processes of a warehouse can help to improve flexibility. A so-called flexible automated warehouse should increase productivity, flexibility, and throughput (Custodio & Machado, 2019). Automation can help to achieve these factors. Fixed automated and – mechanized systems, on the other hand, are unable to react to changes in product mix and market demand. The clients need to be satisfied, so to do that, warehouse technology must be adaptable, quickly responding to difficulties such as the continued growth of warehouse fulfillment, new competitive threats, faster delivery, and unforeseen technological advancements. A flexible automated warehouse requires automation solutions that are simple to implement and adaptable and integrated intelligence to take advantage of machine learning and other technological innovations.

3.6 Warehouse Performance Measures

Performance evaluation is an essential aspect of warehouse logistics. Improving warehouse performance in global operations is a demanding and challenging undertaking, especially in the face of rising competition, consumer sophistication, and demand and supply volatility in significant supply chain networks. For warehouse design, there are several measures to be considered. The most commonly used in literature are order maturity time (OMT) (Petersen, 1997), or the travel time required to complete a given picking list, i.e., total picking time (TPT) (de Koster, 2010) or for especially automated systems the average equipment utilization (Ekren et a. 2010).

Warehouses not only serve as a critical link in the supply chain, but they also have an influence on costs and have evolved into complicated entities to manage. As a result, it is critical to keep an eye on how their performance is measured. Several studies were consulted to identify performance requirements in various warehouse management scenarios. The subsequent studies identified the following performance measures, De Koster and Warffemius (2005): productivity, flexibility, and outbound logistics; Cao and Jiang (2013): service capability through storage, transportation, and costs/time control; Nair (2005): productivity, delivery competence, and responsiveness; Johnson and McGinnis (2011): technical and economic-related performance measures; Gu et al. (2010): costs, throughput, space utilization, and service; Min (2006): responsiveness to outlier orders, value-added services, inventory accuracy, delivery time and order fulfillment; and Staudt et al. (2015): order picking time, picking accuracy, costs and throughput. Furthermore, Cuthbertson and Piotrowicz (2011) argue that performance measurement is a context-dependent process that is adjusted to specific supply chain requirements using a common framework for the empirical examination of performance management systems. As a result, it is suggested that good performance measurement incorporates three types of metrics: resource measures, output measures, and flexibility measures. Lu and Yang (2010) indicated that a warehouse could have two types of performance measures: financial and non-financial measures.

Traditionally research focuses on improving the system's throughput, so the total picking time and effective use of equipment, but the primary concern of customers is mostly how fast their orders are delivered (Won & Olafsson, 2005). On the other hand, improving one performance measure could impact the other. That is why Chackelson et al. (2013) researched how different picking policies affected which performance measure. This kind of trade-off in performance measures is a critical analysis to align warehouse efficiency with order (customer) requirements. The study of Nair (2005) showed that there is a positive relationship between the two by using a conceptual model of operational policies and performance. Furthermore, Beamon (1999) stated that a single-measure performance measurement system is insufficient, not comprehensive, and lacks the relationship between key supply chain characteristics and vital components of the warehouse's strategic goals.

3.7 Modelling of Warehouses

As aforementioned, warehouses experience uncertainties from various sources, both from outside their supply chain and from within the warehouse itself. Therefore, warehouse design is a complex process that relies heavily on the designer’s experience. The overwhelming quantity of technological equipment, strategies, components, etc., and the difficulty in assessing them motivates the search for better and more effective warehouse design tools (Heragu, 2016). In recent years, warehouse design has become even more complicated due to the tendency to create more extensive, automated warehousing facilities. Warehouse design necessitates the handling of a large amount of data and is frequently an iterative process that forces the designer to go through the different design steps before reaching a final solution (Brito & Basto, 2006). Therefore, to make the right choices for your design, models for warehouse design are desirable. Several methods to model warehouse design are mentioned in the research.

Deterministic warehouse models presume that the objective function is fully known and that this knowledge may be utilized to assess the search direction. Deterministic Modelling and algorithms for warehouse systems have been successfully applied in several research studies (Ratliff & Rosenthal (1983), van den Berg et al. (1999), Lowe et al. (1979), White & Francis (1971). Multiple studies focus on a warehouse's probabilistic nature. Probabilistic Modelling is a statistical approach for forecasting the likely occurrence of future outcomes by considering the influence of random events or actions. Next to that, there is stochastic modelling, which is almost the same as probabilistic Modelling. Only now does it take into consideration the time. So, a stochastic model is a tool that allows for random fluctuation in one or more inputs across time to estimate probability distributions of future outcomes. Those warehouse models in the literature focused on different warehouse components mentioned in the previous paragraph.

Even though there are always factors with some uncertainty, deterministic models can offer a decent approximation in a stable environment. In highly changeable environments, such as systems with strongly fluctuating order patterns and responsive processes, deterministic models may not always suffice. The following literature table shows several studies which focus on warehousing modelling. Each method is described and compared with this study.

Table II-1. Research Gap Table for Warehouse Modelling

		Method			*Component*					*External*
Reference	Focus	Deterministic	Probabilistic	Stochastic	Layout	Storage	Picking Strategy	Equipment	Routing	Uncertainty
Aboelfotoh et al. (2019)	Order Batching Optimization	X			X		X		X	
Altarazi et al (2018)	Different Warehouse Design Simulation		X	X	X	X	X	X	X	
Amorim-Lopes et al. (2021)	Probabilistic Simulation of Picking Warehouse		X		X	X	X			
Burinskiene et al. (2018)	Reduction of Waste in Warehouse Logistics	X		X	X	X	X	X	X	
Colla & Nastasi (2010)	Automated Warehouse Storage Strategy	X	X			X				
De La Fuente et al. (2019)	Staffing Strategy and Capacity of Warehouse simulation			X		X		X		
Gagliardi et al. (2008)	Warehouse Simulation to Allocate SKUs	X		X		X	X			
Gong (2009)	Stochastic Modelling Warehouse Operations			X		X	X			X
Gray et al. (1992)	Design of order-consolidation Warehouse	X	X		X		X			
Guo et al. (2007)	Narrow Aisle Pick Density		X		X		X	X	X	
He et al. (2020)	Uncertain Warehouse Layout Problem	X			X	X				X
Hwang & Cho (2006)	Performance model for Order Picking		X				X			
Kachitvichyanaku et al. (2005)	Batches of Customer Orders in Warehouse	X					X			
Le Duc (2005)	Design and Control of Order Picking	X	X		X	X	X	X	X	
Merkuryev et al. (2009)	Warehouse Order Picking Process	X			X	X	X	X	X	
Park & Webster (1989)	3D Warehouse Modelling			X	X	X				
Ratliff & Rosenthal (1983)	Order Picking in Warehouse with TSP	X					X		X	
Saderova et al. (2022)	Simulation modelling of Selected activity	X		X				X	X	
Sadownski et al. (2021	Contingent Nature of Warehouse Flexibility	X				X		X		X
Thi et al. (2021)	Optimizing Warehouse Storage Location under Uncertainty			X		X		X		X
This Research	The Impact of Order Characteristics Uncertainty on Performance of Warehouse Configurations	X	X		X	X	X	~	X	X

3.8 Knowledge Gaps

As a result of the literature review, some knowledge gaps emerged.

- It is noted from the literature that for effective planning and control of internal logistics operations of a warehouse, decision-makers should know the current state of the system, analyse different coherent scenarios, and assess the efficiency of these scenarios. Thus, to achieve this objective, decision support tools must be researched in order to assist decision-makers when managing distribution warehouse operations.
- There is a discrepancy between the research and operational concerns in the warehouse processes and a lack of a framework in which to trial different solutions to specific problems.
- Most related Modelling-based research focuses on the order-picking function without integrating the other main functions of warehouse logistics such as receiving, put-away, unloading, storage, and shipping.
- Most research on warehouse design via simulation considered single design components, mainly operational policies, layout, and/or sizing. Less focus on workforce/equipment, order characteristics, and throughput. Next to that, there is more focus on analysis than synthesis.
- Studies are focused on improving the overall picking efficiency in order to improve warehouse performance. This optimization approach is limited wherein an attempt to improve one performance may craft wastage in other warehouse processes. With the help of analytical parametric Modelling, a synthesis perspective can take care of such an imbalanced system. So, look at every component of the warehouse.
- There is not a single, one-size-fits-all solution. Optimal solutions can only be applied to particular settings and therefore are non-generalizable.

3.9 Conclusion

The literature study has shown that there is already a lot of research conducted on the warehousing logistics topic. Each of the studies emphasizes a different aspect of warehouse logistics, and this literature reviews several topics of this. The overall logistics in a warehouse, the e-commerce trend in warehousing, the designing of a warehouse, the uncertainty aspects in warehousing, warehouse flexibility, the performance measures for warehouses, how warehouse Modelling was conducted in previous research, and how this research will address this. From all the studies reviewed, several knowledge gaps emerged.

The following three sub-questions can now (partly) be answered based on the literature review carried out.

What are the different components for outbound logistics when designing a warehouse for a third-party service provider like Nedcargo?

Firstly, the different components that occur in outbound logistics when designing a warehouse for a 3PL provider. In the literature, the following components were identified as relevant to consider during the design process: the overall structure, the layout, the sizing, the equipment selection, the level of automation, picking strategies, and the packing operation. These components were integrated into the design steps of a warehouse. Because Nedcargo is still in its pre-stage design phase of the warehouse of Haaften III, it should be noticed what the current design choices are and how, with insights from literature, improvements can be made for the new warehouse. In Haaften? We concluded that all of these design steps need to be interconnected, and reiteration is necessary. So, each of the components for Haaften should be taken into account and must be integrated with choices still to be made.

Next to the previous research question, the following two sub-research questions could also be (partly) answered utilizing the findings in the literature.

What are uncertainty factors when configuring a warehouse with regards to e-commerce?

In these different processes, internal variability can be observed. This internal variability creates uncertainty, and the warehouse has to learn to cope with this increase. One of the uncertainty factors for Nedcargo is that it is still unknown which client will be handled in the new warehouse of Haaften. Therefore the order characteristics are an uncertainty factor in the future. This uncertainty factor is vital since, because of the emerging e-commerce trend, the characteristics of the orders are rapidly changing. This contextual uncertainty of order characteristics will be addressed in the following chapters and tried to integrate with the proposed method.

What are the different performance measures of a 3PL order-picking warehouse, and how can they be quantified?

The last research question that was partly answered in this literature review is the different performance measures that occur in a 3PL warehouse. The quantification will be carried out during the data analysis. During the literature review, it became clear that there are various ways of measuring the performance of a warehouse. The most important insight was that the choice of performance indicators is dependent on the environment and type of warehouse. A single performance measurement system is insufficient, not comprehensive, and lacks a relationship between the vital components of the warehouse's strategic goals. Therefore, it must be decided in consultation with Nedcargo’s expert and based on the current measurement system, and different performance measures should be used. This will be elaborated on in the following chapters and concluded before the new configurations are formed.

III. Model the System

4. Current State Analysis

In this chapter, the current state analysis is performed to develop new design improvements for the newly built warehouse located in Haaften. Nedcargo has to have knowledgeable insight into their current outbound logistics operations in their currently active warehouses. This research focuses on the outbound logistics of the e-commerce warehouse operations, and therefore, the current state analysis of the Tiel warehouse is performed. This chapter starts with some background information about Nedcargo's history and some basic information about the Tiel warehouse, in which the present e-commerce orders are handled. Then the processes that occur at the Tiel warehouse are systematically explained using several techniques. Then extensive data collection is performed in order to point out the weaknesses of the current state and gain insights into the order profiles that are handled nowadays.

4.1 Warehouse Background

Nedcargo provides sustainable solutions in a changing logistical world. Three specialized divisions work closely together, committed to creating the most sustainable and cost-efficient supply chain for customers in the food, beverage, and retail markets: Nedcargo Logistics warehousing and distribution by road in the Benelux for food and non-food products, wines, and beverages. They own several warehouses in the Netherlands in which they offer various services to their customers. In order to stay competitive and innovative, they invest a lot of resources in the research and development of their operations.

As mentioned earlier in this report, it is necessary to make the right choices for any conceptual design of new warehouse operations to have a clear insight into all the current warehouse operations regarding e-commerce at Nedcargo. Currently, these operations are being performed for one customer at their warehouse located in Tiel. In this chapter, some background information will be provided about the layout, operations, and customers handled at Tiel nowadays.

The warehouse of Tiel handles multiple operations in two different compartments. These compartments are called hall 6 and hall 5. In figure 3, the different active zones of the warehouse can be seen. Zone A and B are respectively hall 6 and 5, zones C and D are the loading areas, and zone C is the packing area for the e-commerce orders. This will be discussed in more detail later. The operations in Tiel can primarily be divided into cross-docking operations, bulk picking operations, and e-commerce picking operations. The pickers in the warehouse usually conduct these operations simultaneously in their shifts. This research only focuses on the e-commerce operations of Tiel. Thereupon, we only measure and focus on the performance of the e-commerce operations of the pickers and packers.

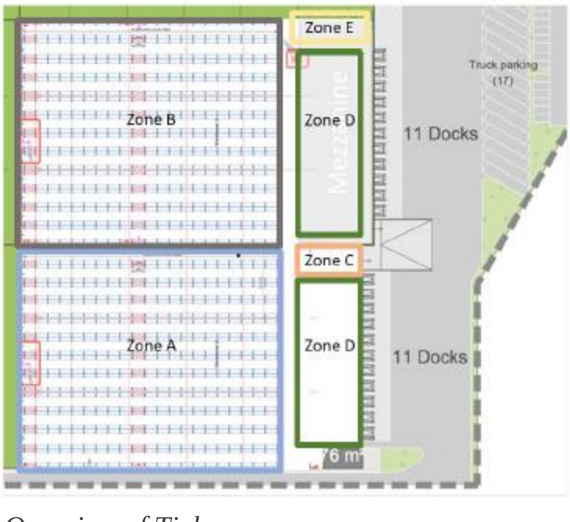


Figure III-1 – Warehouse Overview of Tiel

4.1.1 Zones

As said, at the Tiel site, two halls are used for warehouse operations. In each of those halls, a total of 12 aisles with racks on either side are placed. Each of those aisles consists of 23 ‘houses,’ also placed on either side, leading to a total of 46 houses in each aisle. These houses have a place for 3 or 4 stock-keeping units (SKU), which each can contain a different product. The e-commerce SKUs are only stored in the lowest rack house. The upper houses are used for bulk-picking and for replenishing the e-commerce inventory. There is room for a little over 24.000 pallet storage places. These pallet places are currently filled with products from two customers, Go-Tan and Jacobs Douwe Egberts (JDE). JDE covers with their products about 2/3 of the space in the warehouse. Now that there is a clear overview of the essential functions of Tiel, we will further elaborate on the different zones.

Firstly, zone A where all of the Go-Tan products are located. This zone is not used for picking up JDE orders, only for storage. The scope of this research lies in e-commerce order logistics handling. And since mainly other operations take place here, it is not essential to elaborate on them further. Therefore, the only thing that zone A means for the e-commerce operations is the storage locations of the load carriers, such as the pallet - and roll containers. Every picking tour starts with the picker obtaining two roll containers to put away the picked goods. This container storage is located across from the packing location in zone C.

Secondly, zone B. This is where the e-commerce orders are being picked. As of today, a total of 351 JDE products are being stored, divided over various ground-level houses into 9 active aisles. A more comprehensive overview of storage, strategy, and products will be given during the data collection and analysis. The picking operations performed in this zone will form the basis for potential new design choices for Haaften.

Thirdly, zone C, where the packing operations take place. An essential aspect of outbound logistics in an e-commerce warehouse is packing operations. The synthesis between the picking and packing operations is crucial for the smoothness of the overall outbound logistics. As of today, the packing area consists of three packing stations and an area where the picked roll containers are being stored. At the stations, the packers can pack the picked colli into shipping boxes for PostNL. PostNL is the distributor for e-commerce orders. Zone D and E are outside the research scope.

4.1.2 Resources

Furthermore, several different resources can be distinguished from the current operations at Tiel. The most important are the employees, which can be accounted for a lot of labor costs. At the warehouse of Tiel, two types of employees can be distinguished, namely the pickers and the packers. Order pickers are the employees who collect the orders. The picker's task is to collect the preferred colli out of the stock-keeping units. Order pickers are essential for the operation and also very cost-intensive. In the literature review, we have seen that 50% to 60% of the total picking time consists of the travel time of the picker. Next to that, almost 50% of the total labor costs in a warehouse go to picking activities. So they are crucial for a successful warehouse and very cost-inefficient if they are poorly managed. The pickers receive their order information from the warehouse management system (Boltrics), which shows them where the desired SKU is located. They use portable scanners to scan the collected colli. The following paragraph will describe how this process is carried out in more detail.

The packers are the employees who pack the collected orders into the outbound shipping boxes. That afterward is being transported by PostNL. These packing activities are relatively new processes for Nedcargo due to the upcoming e-commerce trend. They are provided with a working station at which they have to fold the shipping boxes themselves and pack orders into the shipping boxes, which are completed and palletized for transport.

Several means of equipment are available to perform these packing and, most of all, picking activities. We will discuss the resources that are important for the outbound e-commerce processes. First of all, the reach trucks are being used for the put-away and replenishment processes. These trucks are designed to carry one pallet and to be able to raise that pallet to high levels that a regular pallet truck cannot reach. Tiel has the availability of five such trucks.

Secondly are the pallet trucks. Each picker has access to move with a pallet truck through the picking circuit. There are long and short pallet trucks, and for e-commerce picking, only the shorter one is being used. The picker can stand on this truck and move to its picking destination. All trucks use batteries that are charged at the warehouse in zone A. There are more charging stations and batteries than required for the case to keep at all costs the carts available. We will further zoom in on its specifications during the data analysis. Furthermore, the pallet trucks carry the roll containers with them (or picking carts). They can attach two roll containers behind them in which the orders are being placed after collection. They can carry two roll containers simultaneously, and each roll container has room for 2 orders. So a picker can collect four orders during one tour through the picking circuit.

Going further into the roll containers. The roll containers, or as they call them in literature, the picking carts, are used to collect and transport the picked colli through the warehouse. At the beginning of the order picking process, two roll containers are attached to a pallet truck. Each roll container has a divider in the middle, which means that they have four different locations to place the collected colli on. In this way, the order picker can collect four orders in one picking tour. When the picking tour is completed, the picker detaches the fully loaded roll containers at the packing station waiting area. Then the cycle will be executed again. It can be assumed that there are more than enough roll containers available; a shortage of roll containers is therefore not an option.

Lastly, there is the picking scanner. Each picker uses the scanner throughout the whole warehouse operation. The scanners scan the barcodes on the colli, SKU, and boxes. The scanners are directly linked to the warehouse management system, so their actions are immediately stored as data in the WMS environment when scanned. Although the scanners might differ per process for which it is used, they all serve the same purpose of communicating and confirming information through the WMS.

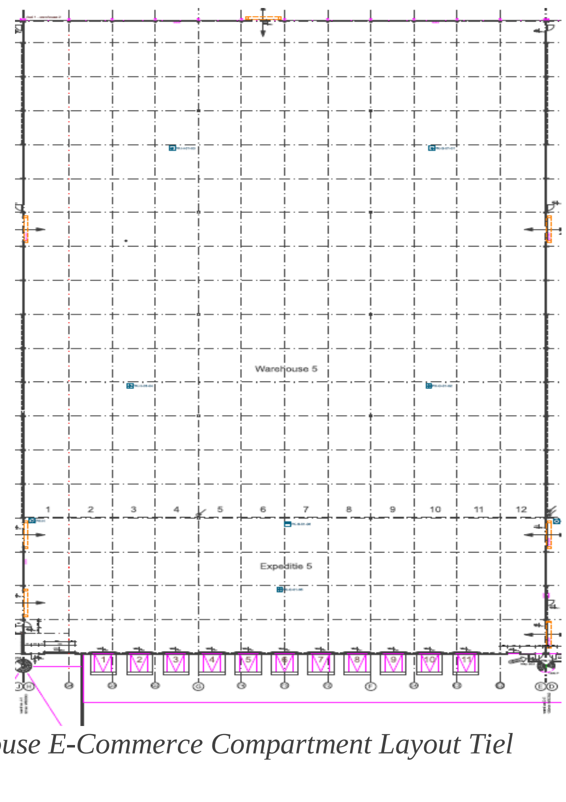


Figure III-1 – Warehouse E-Commerce Compartment Layout Tiel

Now it is known in which warehouse Nedcargo currently operates its e-commerce orders operations, and the configuration of Tiel is elaborated on. It is crucial to go deeper into the various processes and decisions at the warehouse which is currently being made. Next to that, when the current state is known, the historical data of Tiel is being collected to extract significant value from it during data analysis in the next chapter. This is in order to substantiate specific potential configuration improvements.

4.2 Context Analysis

First, the context in which the warehouse of Tiel operates will be investigated. This context analysis will point out the most important contextual factors which are mainly dealt with.

Warehouse configuration is influenced by many contextual factors representing both the external and internal environment. Configurations refer to the combination of operations, design aspects, and resources (Rouwenhorst et al. 2000). The warehouse configuration is a critical component for meeting the customer's demands. Notably, it is interesting where specific configurations might fit better and which future path to pick. As a result, it is essential to comprehend how numerous contextual factors impact the choice of a warehouse configuration, which in this case refers to a mix of warehouse operations, - designs, and – resources.

In warehousing theory, the contingency method (Donaldson, 2001) receives increased attention. Especially when tweaking the operations towards a configuration to the particular context in which the warehouse operates. The contingency approach, or situational approach, is a theory that suggests the most appropriate management style depends on the context of the situation and that adopting a single, rigid style is inefficient in the long term. In the early stages of the logistics use of the contingency approach in warehousing, the contextual factors were related to the complexity and dynamics of the flow of goods and information and the external environment. Afterward, the quantities and volumes of inbound and outward product flows, suppliers, manufacturers, customers, and their geographical distribution, were used to operationalize the contextual elements further.

The importance of context in which a warehouse operates is of great significance. Several researchers emphasize the importance of context in warehousing. Van den Berg and Zijm (1999), Rouwenhorst et al. (2000) and Karagiannaki et al. (2011) conducted research towards the implementation of RFID in warehouses. They stated that there are three dimensions of aspects that influence the type of warehouse configuration: (1) the structure, e.g., level of automation and storage system; (2) the workflow, e.g., picking policy and order accumulation; and (3) resources, e.g., space capacity and labor. Hassan et al. (2015) identified 54 factors that influence the warehouse configuration and argued that operational factors and organizational are the most crucial to consider. However, he affirmed that the importance of each factor might vary from one situation to another and would mainly depend on the sector the warehouse operates in. Faber et al. (2013) studied external factors that influence the planning and control of WMS systems. They consider two sets of variables: the external warehouse environment (i.e., the market it operates in) and the internal warehouse system. They argue that a foundation in complexity and dynamism is necessary for understanding and optimizing the warehouse configuration. Next, they address five contextual factors: the number of SKUs, assortment fluctuations, demand unpredictability, number of SKUs per order (or amount of orderlines), and process diversity. These factor claims are backed up in several other warehouse studies. The need for handling and storage equipment is influenced by SKU features (Rouwenhorst et al., 2000). the picking process is influenced by order characteristics (Bartholdi and Hackman, 2016). Each type of warehouse requires different operations (Van den Berg and Zijm, 1999), and the characteristics of the current and future demand influence capacity decisions regarding storage and labor activities (Frazelle, 2016).

Now that the awareness of the influence of contextual environment on warehouse operations is evident. A further look is required towards the context of the Tiel warehouse and what can be learned from that. Thus, some of the previously stated challenges in warehouse design could be seen as contextual factors that affect configuration elements. And these elements are customer characteristics, demand profile, order characteristics, assortment, volume, and product characteristics. This is visualized in figure 3. Due to the upcoming e-commerce orders trend currently handled in Tiel for Nedcargo, a different context in which the warehouse must operate is changing. And most of all, the order characteristics are uncertain because the clients are still unknown. This context must be investigated to understand how the configuration can be improved or changed and what the impact could be on its performance.

These contextual factors representing both the internal and external environment influence the warehouse configuration. Figure 3, the adapted framework from Kembro et al. (2018), explicitly emphasizes how the match between context and configuration affects the ultimate performance. Therefore, the contingency approach can be used to give direction to the still-to-be-made warehouse configurations.

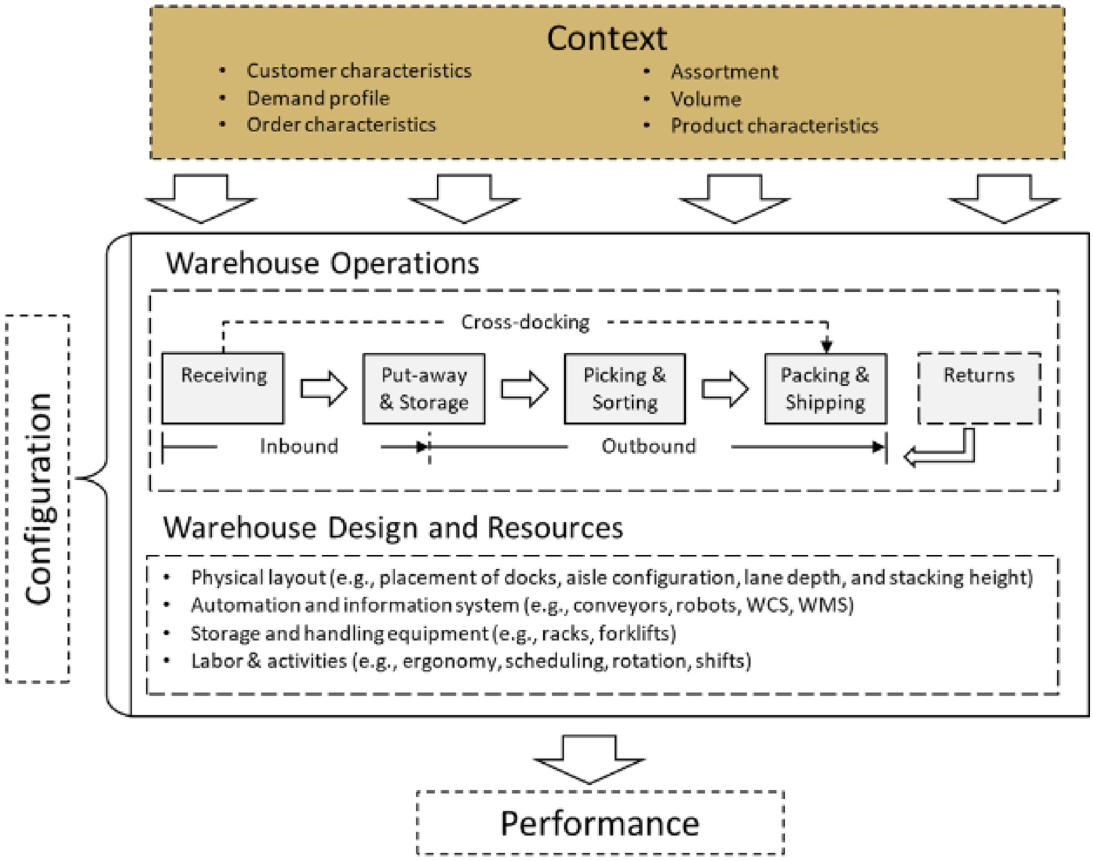


Figure III-3 – Conceptual Contingency Framework for Warehouse Configuration (Kembro & Normann, 2020)

In the warehouse of Tiel, the importance of its context has several factors that impact these operations. First, in the next chapter, the outbound processes of the warehouse operations of Tiel will be explained and analysed using different techniques. Afterward, the data collection of its operations will be presented. This data collection forms the basis for the data analysis. This data analysis will point out the most important contextual factors of the warehouse's experiences and quantitates the warehouse operations of Tiel. This qualitative and quantitative current state analysis will be used to shape the future state of the new warehouse in Haaften for Nedcargo.

4.3 Process Description

This chapter will discuss the processes of the outbound logistics of the current warehouse processes of Nedcargo. This part will more concretely analyse the current situation in which Nedcargo operates. Having seen the logistical context of the warehouse in Tiel, the processes that take place are outlined in this chapter. The different processes as seen and explained in the warehouse of Tiel itself are described. In this paragraph, we will further zoom in on the different outbound processes that occur in the e-commerce operations in Tiel. This information is used to shape the IDEF-0.

4.3.1 Inbound Process

The inbound process consists of the receiving and the put-away & storage operations. This is out of the scope for the future state, but for the understanding of the whole warehouse system in Tiel, it is included in the current state analysis. The inbound process starts with the truck arriving from the clients' factory at Tiel. The truck with the load needs to be parked at general parking, after which the driver signs in at the inbound office. The inbound office appoints the driver to a specific dock where the trucks need to unload. After parking, the unloading process can begin. A warehouse employee at the dock unloads the shipment it has been appointed to. Since the COVID-19 pandemic, this was only performed by a Nedcargo employee before it was in cooperation with the driver of the truck. After successful unloading, the number of pallets and type of pallets is checked to see if they match the received CMR consignment note. If this is correct, the driver can leave.

After these steps, a second check is performed by another employee of Nedcargo to see if the number of pallets and the type of products match the expected shipment. The state of the order is then communicated to the manufacturer or for Nedcargo, its customer. When there are any sudden deviations, the extra – or wrongful pallets are put away at a separate location in the warehouse, and the customer needs to be contacted about the deviations. If the shipment passes the second check, confirmation about the completeness of the shipment is sent to the customer.

The completed approved inbound shipment is then put away at its allocated SKU location in the warehouse. This is done manually with a reach truck which has a scanner and a computer, which tells the employee exactly where to locate the different storage locations.

4.3.2 Outbound Process

The outbound process consists of three stages: storage, picking & sorting, and packing & shipping. For the scope of this research, we will mainly focus on the picking and sorting stage of the outbound process. As mentioned beforehand, there are different types of operations in the warehouse of Tiel. This process description is that of the handling of e-commerce orders in Tiel. The warehouse office receives the planned outbound orders from the planning department every day at approximately midnight for the next 24 hours. This includes the specific arriving time slot of the transport and the orders associated with that transport. Each transport ride is allocated and appointed to a specific dock by a warehouse employee. There is a clear distinction between the early arrivals and late arrivals of trucks. For the e-commerce orders, there is only one slot of transport each day, so a distinction between early and late order sorting is out of scope in Tiel. The orders that are placed early have more priority than those that are booked later. There are, therefore, first in, first out appointed to the picker. This information Is passed by the system present at the scanners the order picker carries.

<u>Picking</u>

As previously stated, an order picker each has a pallet truck with two roll containers attached. Every roll container has a divider in the middle, which means that two different orders can be separately collected on each roll container. Therefore, the picker has a capacity of four orders per picking tour. At the start of the picking tour, the order picker must collect the two empty roll containers from the site. The 4 trips that the picker has to conduct during its tour are batched randomly from all the orders that have to be collected on that day. The order picker receives its orders on its scanner, which tells the location and the amount that needs to be picked. The picking route is based on the shortest route algorithm, which shortly will be emphasized. When the pickers accept their picking tour and the roll containers are collected, the picker departs from the packing area towards the picking zone.

The picking tour is based on the shortest route algorithm and the SKU locations. What does that mean? It means that of all the SKUs from the four orders to be visited, and the picker starts with the SKU that is the least distance from its initial location. The aisle least distant from the starting point is aisle 2. So the picker will first move to the aisle with the lowest aisle number. Within the aisle, the picker will move chronologically from the lowest number of the SKU houses to the highest within that specific aisle. When the pickers need to move to another aisle, it has two options. The picker can move through the crossing aisle, which is located at houses 25 and 26 in the warehouse, or goes back to the current aisle's beginning and move from there towards the designated aisle. Which options are chosen depends on the shortest route from its initial position towards the following location. What the exact choices and decision moments for the picker are in the picking tour will be more specified in paragraph 4.3.5. Next to that, the pickers' decision chart is shown in appendix A table 10.

When the order picker arrives at the first SKU location, a barcode of the location is present and is scanned with the scanner. The order picker has to collect the number of collo of that product needed for the specific orders. So, the picker starts picking the number of collo needed for one of the four specific orders out of its stock-keeping unit, inserts the number of collo picked in the scanner and places it on the roll container scanned as well. This means that a specific order is allocated to a specific location on the roll container. Logically, this means that (optional) later picked colli from the same order must be placed in the exact location in the roll container. If multiple orders contain that product, the picker repeats this sequence for the other orders with the exact SKU location. If all the colli is collected at the SKU location, the scanner shows the following SKU location with the associated product on its interface. The order picker goes to the following SKU location, scans the barcode of this product location, inserts how many products are picked from that location for the specific orders, scans the barcode of the location on the roll container related to the specific order, and places the products on the exact location on the roll container. This goes on till all the locations of the products for all four orders are visited by the order picker, and then the picking tour is complete. The picker then moves back to the packing area with four completed orders on the roll container. The order picker will pick up another pair of roll containers to start picking up four other orders.

It can occur that the product is not available at its SKU location. The order picker can indicate this on her scanner and continue with picking the rest of the products on the list. If a pick location needs to be replenished, a reach truck gets a primary task to do a replenishment. The order picker will then collect the skipped products at the end of her picking route.

Another situation that can occur is as follows: the size of the order can be larger than the available space on the roll container. If an order has a lot of colli per pick, which needs to be stored in the depicted location on the roll container, it can be the case that it exceeds the roll container's capacity. The protocol is then that the order picker puts a sticky note with the correct order number written on the product that does not fit and puts it on the available space of other order compartments of the roll container. This means that the packer needs to collect colli from other compartments than the one assigned to the order of the roll container.

When all four orders are completed and collected, the picker takes the shortest route toward the packing area. It parks the roll containers in the designated area for completed picked orders and prepares to collect a new batch of orders.

Packing

The following process of the outbound logistics of the e-commerce orders at Tiel is the packing process. It starts with the packer employee scanning the barcode of one of the four orders on the roll container. The computer present at the packing station shows the order with the list of the type and amount of products it contains. The packing employee estimates how many shipping boxes are necessary to pack all products of that order. The employee collects the right amount of boxes in the right size of a pallet with empty unfolded shipping boxes. The packer registered the first box with its associated size in the computer at the working station. The boxes are folded and taped so the products can be scanned one by one and placed in the shipping box. Products without a barcode can be selected on the computer. After the first box is filled, the second box is registered in the computer until the order is complete. When the order is completed, and all the shipping boxes are filled, the packing list is printed and put into the shipping boxes. The shipping boxes are then closed with tape, and the labels for all boxes are printed and put on the boxes. Now the shipping boxes are positioned on the pallets which are destined for the PostNL transport. When such a pallet is complete, the pallet is sealed and set up on a collection point for the total shipment of PostNL. A new empty pallet then replaces the entire pallet.

A few possible situations require additional actions of the packing employee. First of all, it can be the case that the order picker did not pick everything correctly. For example, he did not pick every product belonging to the order or picked the wrong product. In this case, the packing employee will walk to the SKU location of the missing product and pick up the product himself. Next to that, the packing employee can incorrectly estimate the necessary shipping boxes. In this case, the packing employee needs to change this on the computer and take an extra box to put in the remaining colli that belong to the order.

When all the orders for the shipment for PostNL are processed, the last pallets will be set up at the collection point. After the arrival of the PostNL truck, on the time slot that is determined in advance (only one time a day), the shipment is loaded into the truck with a forklift by the driver of PostNL. This ends the cycle in the warehouse for the e-commerce orders.

4.3.3 IDEF-0

In appendix A, the full IDEF-0 chart can be found. The IDEF-0 summarizes these processes by using an integrated framework of the inputs, control, outputs, and mechanisms. The IDEF-0 technique is used to model systems and their processes to be understood and improved.

4.3.4 Swim Lane

More insight into the specific order picking processes at Nedcargo must be obtained, so a swimlane diagram has been constructed. Swimlane is a process stream diagram in which the process is divided into several ‘swimlanes.’ These swimlanes indicate what a specific department or employee has to do in a process (Janse, 2019). The swimlane of Tiel can be found in appendix A.

4.3.5 Outbound Logistics Flow Chart

In appendix A, the logistic flow chart of the human picker resource of the Tiel warehouse is shown. This chart shows the different decisions the human picker has to perform. Although the scanner supports these actions, it gives a comprehensive insight into how a picker moves through the SKU locations. This way of moving can also be easily adapted by changing specific processes or configuring new methods or strategies of picking.

4.3.6 Information System and Flow

Nedcargo has its own warehouse management system (WMS), named Boltrics, in which each warehouse has its own environment. These systems are used during the whole process, from the inbound of goods to the final outbound of orders. Each employee receives the necessary information on their scanner or computer. All actions or movements are all directly updated in Boltrics.

In the Tiel warehouse, the information flows started when the transport planning is provided for the next 24 hours by the planning department. The team leader of the warehouse will assign the orders to the different docks available at the warehouse and releases them based on the priority in planning. The IDEF-0 also shows what information is provided for the different sub-processes.

The WMS includes different strategy algorithms for warehouse operations. In Tiel, this WMS determines the storage location for the inbound goods and the picking strategy to pick the different orders. The product placement strategy of the incoming goods is based on the sort of goods, the weight and height of the pallet, and the distance from the dock at which the goods are unloaded. In this way, after scanning the inbound pallet, the best fitting location is assigned to the pallet and shown on the computer of the reach truck. The second algorithm determines the strategy for picking the different orders. As said beforehand, it defines the route of the picker using the shortest route algorithm. It looks, therefore, to the stackability of the goods related to the order and the SKU locations of these goods. The algorithm integrated with the WMS tries to find the shortest path to pick all colli included in the accepted orders. When arriving at an SKU location, it also considers that the more fragile product in that SKU location is to be picked last when stacking the roll container.

The control of the operations also is managed by WMS. The employees who handle the operations use their scanners as a means of control. The incoming pallets need to be scanned before they are relocated into the storage. Confirmation is given by the reach operator at the computer when the pallet is correctly stored at the right SKU location. The WMS also keeps track of the inventory levels of each SKU location. When the pallet of a specific product is almost empty, the system automatically sends a priority task to one of the reach truck operators, who gets the assignment to replenish the SKU with a full pallet from the storage and relocate this to the specific SKU location. The pallet is then scanned as well and stored in the database of the WMS.

When picking the colli from the pallet, the picker scans the barcode of the compartment located on the roll container. It confirms the number of colli pickers per order relocated to the specific compartment of the roll container. Therefore, the WMS knows where all colli is situated in the warehouse. Since all the pickers need to scan the SKU location, roll container compartment, and confirm the number of colli picked, the margin of error for the order picking is narrowed. Furthermore, the WMS system interface on the scanner shows which products still need to be picked and prevents an order from being confirmed as picked by the picker while not all products are present yet in the roll container.

For the e-commerce orders, after the picking, there is an extra check by the packing employee. The packer checks if the order is complete and rightfully picked. An empty shipping box is registered via the computer at the working station to the WMS. The colli of the products are placed in the shipping box and are chosen from the list presented at the computer and linked to the shipping box. In this way, all colli an order need must be registered by the packer before the order can be confirmed as entirely packed. Nex to that, the WMS distributes a packing list that is printed and added to the shipping box and the label with a barcode per package.

Before loading the pallet for PostNL transport, the last scanning moment occurs. Namely, to discard the pallet as being active in the warehouse. It can be concluded that multiple warehouse operations and employees are dependent on this warehouse information system. The use of the WMS is nevertheless always a point of discussion if used correctly or efficiently. The error margin is reduced by using multiple checks by different types of employees. But to conclude if the use of the WMS is efficient, a further look at the produced data from the WMS is necessary. So, this data has to be collected and analysed for a better qualitative and quantitative understanding.

4.4 Data Collection

Data collection is a systematic process of gathering observations or measurements. This research focuses on the contextual factors in which a warehouse operates and how its design choices react to uncertainty in a future state. Before these types of decisions and questions for the future state can be answered, the observations and measurements of the current state are crucial for a better understanding of the actual state of the warehouse operation. Therefore, data on the current outbound logistics of the operations in Tiel have to be collected before it is analysed in the following chapter. The previous paragraphs mainly focus on the qualitative aspect of the Tiel warehouse, and this chapter will be explained how quantitative data is obtained and used.

The warehouse management system Boltrics monitor the current and historical state of the warehouse in Tiel. For this research, the data was collected from all the e-commerce orders from 1-3-21 to 8-10-21. In this half-year period, a total of 36.552 orders were processed. These orders consisted of 103.969 order lines, all of which have their movements of the associated picker of the orderline. 351 products were used in 136 SKUs by the customer JDE for e-commerce purposes. The following paragraph explains how this data was imported and stored in a database.

4.4.1 UML

The collected data from the warehouse management system of Tiel is used to create a database. These data are linked using different queries and relations between multiple datasheets. In order to make these relations, a software package is used. The data from the WMS systems are exported to Microsoft Excel and later imported into Microsoft Access. Microsoft Access is a popular relational database management system for creating and managing client database applications. It is packaged with Microsoft Office Professional, which combines the relational Microsoft Jet Database Engine with a graphical user interface. It allows reasonably rapid development because all database tables, queries, forms, and reports are stored in the database. From a programmer's standpoint, one of the advantages of Access is its relative compatibility with various programming languages that may be utilized within its environment to add new functionality to the programs, such as SQL, Macros, and Visual Basics for Application (VBA). For this research, Microsoft Access is used to store and link the data provided from the WMS of Tiel. In this way, queries can be formed to link the different tables and eventually make analyses.

UML, a unified Modelling language, is used for visualizing, specifying, and documenting the components of data systems. UML is a standard way to diagram computer systems or databases. It helps the developer visualize the different relationships between different pieces of software to more efficiently plan development. The input data from the WMS of Tiel is used to form a database in Microsoft Access. The database structure is seen in figure 4 as a UML to the extent of the object-oriented analysis. The database that forms the parametric model of Tiel contains the data of the distance travelled (Booked Movements), orders, orderlines, time measurements (Booked Movements), pick locations, and product characteristics. The data tables from WMS are all modified and connected through different data relations. For example, each order had one OrderID, consisting of multiple orderlines. Each orderline of the according order can be linked through the OrderID from both tables. In this way, a database is created in which multiple queries in SQL are run to give new data insights the WMS did not provide. In the next chapter, we will discuss these findings regarding the operations and context of the warehouse in Tiel.

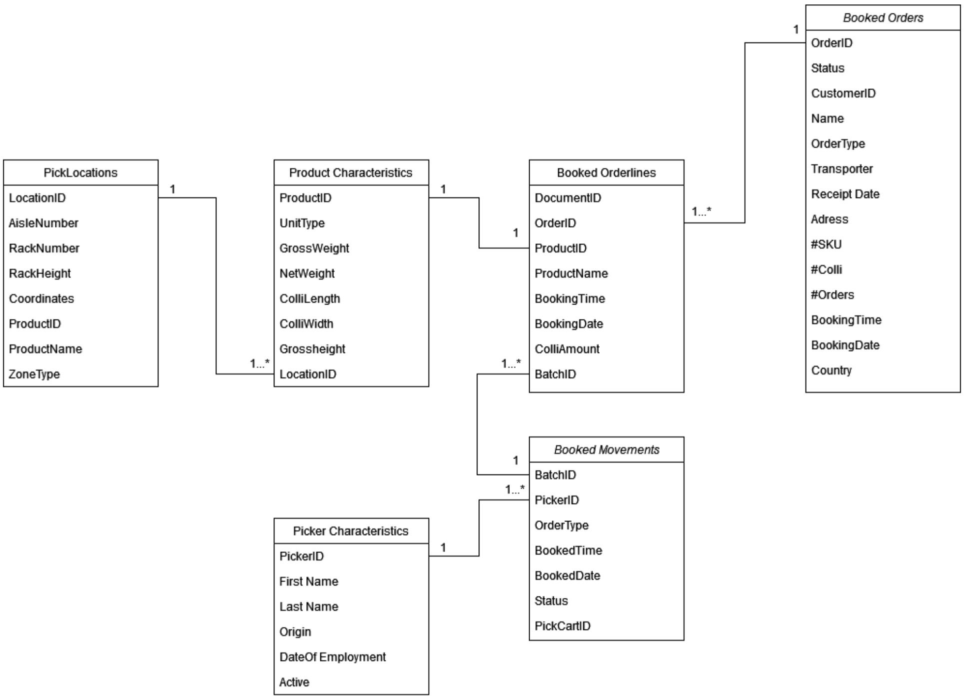


Figure III-4 – UML of the Access Database of Tiel

4.5 Conclusion

In conclusion, the current state analysis gave a lot of insights into the current operations and processes that occur in the warehouse of Tiel. The background of the warehouse in Tiel was discussed. This explained confident choices in strategy and operations. Next to that, an additional context analysis pointed out that the warehouse's context depends on several variables. One of these variables was the order characteristics that the next chapter will investigate using data from Tiel. The contingency approach, which was briefly mentioned, will also be further discussed when proposing the method of this study.

Furthermore, the processes were elaborated using several analysis techniques, such as IDEF0, the swim lane diagram, and the outbound logistics flow charts. These techniques make it possible to visualize and assemble all the processes that occur during the outbound logistics in Tiel at one glance. The warehouse management system (WMS), which Nedcargo uses, was explained and made it possible to collect the data in a database, which collects all the warehouse data, order data, and picking activities. This data should provide the input for multiple analyses, which quantify the retrieved processes. So, now that we analysed the current state of the e-commerce warehousing in Tiel. We can start by answering the following question:

What are the different process variables that occur in the outbound logistics in a current operational warehouse of Nedcargo?

It is noticeable that the outbound logistics at the current operations exist out of picking and packing. Researchers of Nedcargo previously redesigned the packing operations, and one of the conclusions of that design study was that the picking operations must be in symbiosis with the packing. The functioning of one depends on the other. This is visualized using process Modelling techniques and gives an overview of all the processes that occur in Tiel. This current state analysis gives the possibility to improve the processes and realize new strategies and operations. The first step to concretize these goals is to quantify the process variables and obtain more insights from the collected data on the current state of e-commerce operations at Tiel. This will be performed in the next chapter using the compiled database presented in paragraph 4.4.

5. Data Analysis

The previous paragraphs gave an extensive overview of all the processes and the data collection of the operations in Tiel. This research focuses on the context in which the warehouse operates, and its purpose will be more explicit in the next chapter. But first, data analysis must be performed on the context and operation data of the warehouse in Tiel. This is to obtain more insight into how the handling is performed and the environment Nedcargo operates. This can be used to figure out or substantiate confident new design or strategy choices for the new warehouse configurations of the Haaften warehouse. Several aspects of the order data will be discussed per paragraph.

5.1 Order Characteristics

In the previous chapter, the context in which the warehouse operations operate was emphasized. One of these context factors was the order characteristics that the warehouse must handle. For a further understanding of the current state, the order characteristics of Tiel are being analysed. The analyses are being made by using the software packages of Microsoft Excel in combination with PowerPivots, Microsoft Access, Java, and SPSS. The data has been collected from the WMS ‘Boltrics’ from 01/03/21 till 08/10/21

Table III-1. Amount of SKU picks in Tiel warehouse operations

Total Orders	Total SKU Picks	Mean	Mode	Minimum	Maximum
36551	104090	2,85	1	1	33

Table III-2. Amount of Colli picks in Tiel warehouse operations

Total Orders	Total Colli Picks	Mean	Mode	Minimum	Maximum
36551	254498	6,72	2	1	260

Table III-3. Amount of Colli per SKU in Tiel warehouse operations

Total SKU Picks	Total Colli Picks	Mean	Mode	Minimum	Maximum
104090	254260	2,36	1	1	260

In the above tables, the different order characteristics of the e-commerce orders in Tiel are shown. In table 1, the amount of SKU picks are displayed. Here can be seen that the mean of the SKU picks per order is almost three, but the mode is only 1 pick. The data set mode is the number that occurs most frequently in the order set. This can be explained by looking at table 4, which shows the exact amount of picks per SKU and the associated amount of colli, which is then collected per SKU visit. Table 2 shows the characteristics of the amount of colli that has been picked during the measured period. Per order, an average of 6,72 colli has been collected, but the mode is two colli. Therefore, the gravity of the orders is much lower than the maximum amount of colli once picked of 260. This will be shown in more detail further in this chapter. Table 3 shows the amount of colli that is picked per SKU visit. With a mean of 2,36, and yet again with a mode of 1. To have a more detailed look at the colli per SKU picked, we have to look at table 4.

Table III-4. Order characteristics Tiel with the amount of SKU and Colli picks

	Amount of SKU picks										
Amount of Colli	1	2	3	4	5	6	7	8	9	10	Total
1	5984										5984
2	4105	2209									6314
3	1629	1426	1126								4181
4	1260	1004	746	565							3575
5	501	542	600	466	261						2370
6	700	428	480	391	262	166					2427
7	63	232	286	299	248	145	110				1383
8	278	234	256	244	189	157	96	75			1529
9	28	105	192	210	178	130	105	55	46		1049
10	357	134	155	156	161	134	86	58	36	23	1300
Total	14905	6314	3841	2331	1299	732	397	188	82	23	

In table 4, the number of SKU visits per order and the number of colli that the order consists of are contrasted. It’s been chosen to only look at 10 colli picks because the gravity of the colli per order consists of only 1 to 10 colli. From the amount of SKU picks perspective, it can be seen that the mode (as seen in table 1) is 1 SKU visit. This means that the picker for those specific orders only has to visit 1 SKU location and pick an amount of colli. Also, for the e-commerce orders in Tiel, the most common order consists of only 1 colli per 1 SKU location, namely 5984 orders. From the amount of colli perspective, it is seen that most orders consist of 2 colli, namely 6314 orders. Mostly picked from only 1 SKU location. Next to that, it can be assumed that an order is less likely to consist of a higher amount of colli than that of a less amount. To give a better overview of the likelihood of the amount of SKU visits and colli per order, tables 5 and 6 are provided.

Table III-5. Characteristics for SKUs per Order

SKUs	Amount of Orders	Percent	Cumulative Percent
1	15426	42,20	42,20
2	6789	18,57	60,77
3	4422	12,10	73,88
4	3060	8,37	81,25
5	2024	5,54	86,79
6	1467	4,01	90,80
7	1045	2,86	93,66
8	754	2,06	95,72
9	492	1,35	97,07
10	356	0,97	98,04

As we can see in the above table, the number of orders that only consist of one SKU visit account for over 42 percent. Next to that, it can be seen that also over 80 percent of the order consist of only 4 or fewer SKU visits. It is, therefore, less likely that a picker has to visit more than 4 SKU locations for one picking trip. Nevertheless, a picker tour consists of four picker trips (or orders), and we will discuss that later on in the data analysis of Tiel. This can be explained due to the e-commerce environment the Tiel warehouse operates. E-commerce orders trigger a trend that is more likely to consist of fewer products and, therefore, fewer SKU visits for a picker. Figure 5 shows the cumulative percentage of the number of SKU visits in a line graph. Here is seen that very few orders consist of more than 16 SKU (99,86% of the orders consist of 16 or fewer) visits, and as mentioned beforehand that 80 percent of the orders will not exceed the amount of 4 SKU visits.

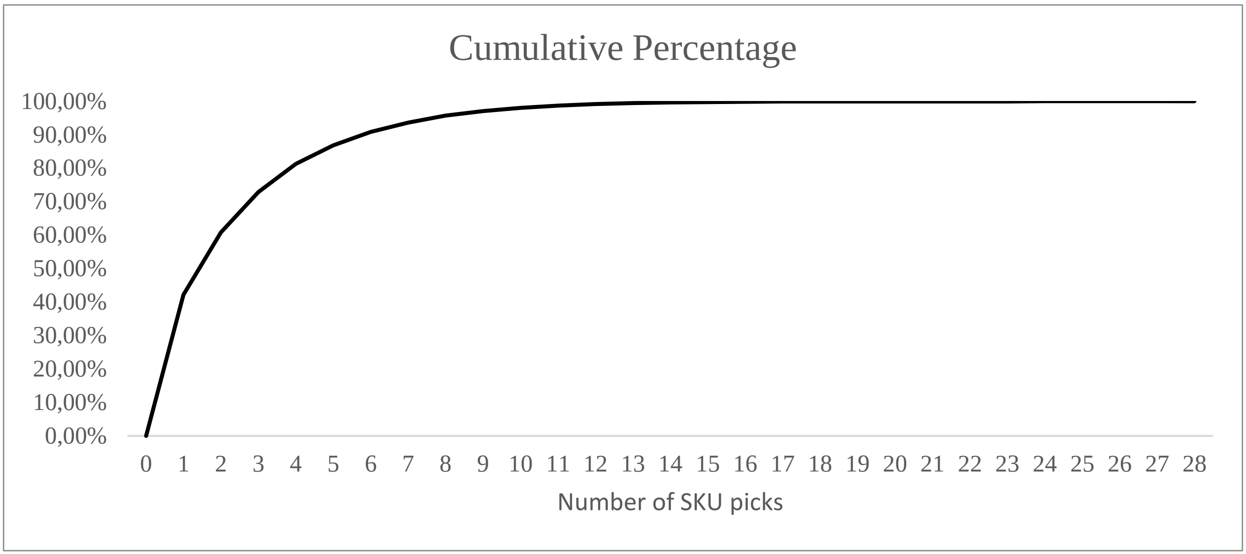


Figure III-5 – Cumulative percentage of Number of SKU picks per Order

The below table shows the percentage share of the number of orders that consist of that particular number of colli. Table 2 taught us that the mean of the colli per order is 6,72, and its mode is 2 colli per order, just as can be seen in the above table. Also, more than 80 percent of the orders consist of only 10 or fewer colli per order. If that is combined with the characteristics of the SKU per order, it can be concluded that over 80 percent of the total orders will be less than 4 SKU visits, with most of the time not more than 10 colli picks. Another interesting finding is that almost seventeen percent of the orders consist of only one colli, which does not differs much from the mode of colli picked 2. This characteristic can be used to provide a more efficient batching strategy for the future state.

Table III-6. Characteristics for Colli per Order

Colli	Amount of Orders	Percent	Cumulative Percent
1	5984	16,37	16,37
2	6314	17,27	33,65
3	4181	11,44	45,08
4	3575	9,78	54,87
5	2370	6,48	61,35
6	2427	6,64	67,99
7	1383	3,78	71,77
8	1529	4,18	75,96
9	1049	2,87	78,83
10	1300	3,56	82,38

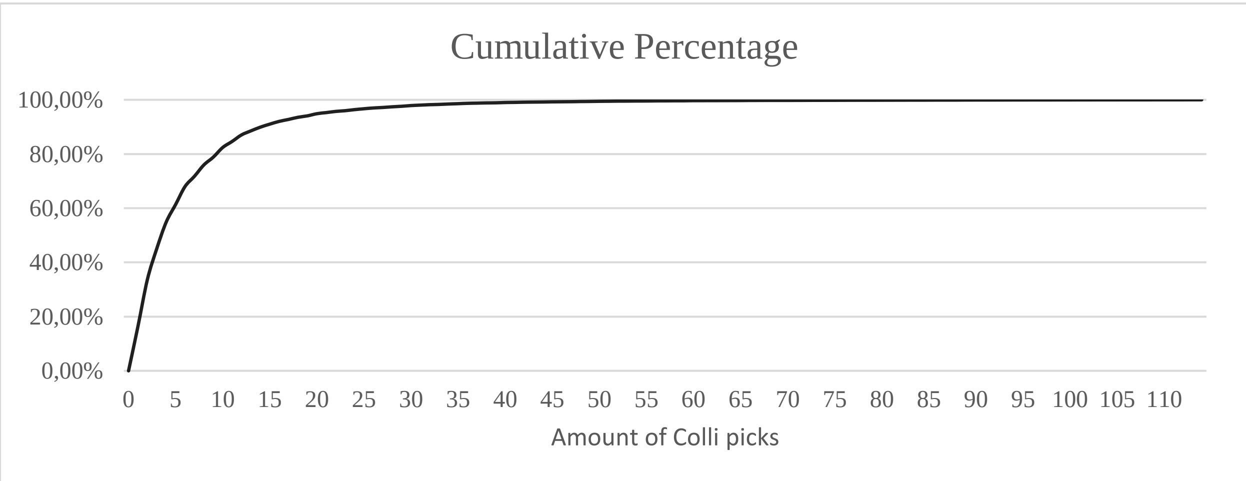


Figure III-6 – Cumulative percentage of Amount of Colli per Order

Table III-7. Order characteristics Tiel with the amount of SKU and total Colli picked

	Amount of SKU picks										
Amount of Colli	1	2	3	4	5	6	7	8	9	10	Total
1	5984										5984
2	8210	4418									12628
3	4887	4278	3378								12543
4	5040	4016	2984	2260							14300
5	2505	2710	300	2330	1305						11850
6	4200	2568	2880	2346	1572	996					14562
7	441	1624	2002	2093	1763	1015	770				9681
8	2224	1872	2048	1952	1512	1256	768	600			12232
9	252	945	1728	1890	1602	1170	945	495	414		9441
10	3570	1340	1550	1560	1610	1340	860	580	360	230	13000
Total	37313	23771	19570	14431	9337	5777	3343	1675	774	230	

Table III-8. Characteristics of total Colli picked

Colli	Amount of Colli	Percent	Cumulative Percent
1	5984	2,44	2,44
2	12628	5,14	7,58
3	12543	5,11	12,69
4	14300	5,82	18,52
5	11850	4,83	23,34
6	14562	5,93	29,27
7	9681	3,94	33,22
8	12232	4,98	38,20
9	9441	3,85	42,05
10	13000	5,30	47,34

The total amount of colli picked per type of SKU and Colli combination is shown in the above tables. Here, the mode of the total colli picked is with an order where 6 colli needs to be picked. This table can be used to determine which type of order could take the most amount of time to be completed.

5.2 Product Characteristics

Table III-9. Average colli per pick of fast-movers of total SKU Picked and total Colli picked

Product Name	Ranking SKU	Avg. Colli/Pick	Product Name	Ranking Colli	Avg. Colli/Pick
DE MELKPOEDER ZAK	1	1,38	DE ESPR MED ROAST	1	2,63
DE CACAO FANT BLUE	2	1,27	DE ESP DRST100%ARA	2	2,38
DE ESP DRST100%ARA	3	2,38	PICKW GR TEA LEM PRO	3	3,28
DE ESPR MED ROAST	4	2,63	DE MELKPOEDER ZAK	4	1,38
DE CAFE MILC LIQ	5	2,34	DE CAFE MILC LIQ	5	2,34
DE WOODEN STIRRERS	6	2,37	DE WOODEN STIRRERS	6	2,37
DE SUIKERSTICKS	7	1,90	PICKW ROOIB ORIG	7	3,03
DE P. CUP BLCK	8	1,78	LOR PROMESSO MILC	8	4,46
PICKW GR TEA LEM PRO	9	3,28	PICKW ENGLISH PROF	9	3,18
PICKW FOR FRT PROF	10	2,60	PICKW FOR FRT PROF	10	2,60

In table 9, we see the product characteristics of the fast movers in Tiel. The 10 most visited SKUs are displayed on the left, and on the right, the SKUs were the most colli picked. As you can see, there is a difference in ranking per SKU visit and in colli picked. Tables 1 and 2 in appendix A compare the SKUs on their ranking per SKU and Colli for both fast movers categories.

Table III-10. Affinity analysis of SKUs in Tiel Warehouse for Amount of Completed Orders

SKU-1	SKU-2	Amount of Orders	Amount of Completed Orders	% of Completed Orders
	Total Amount of Unique SKU Pairs	*1048576*		
DE CAFE MILC LIQ	DE SMOOTH RST LIQ	346	197	56,94
DE MELKPOEDER ZAK	DE CACAO FANT BLUE	2049	133	6,49
DE ESP DRST100%ARA	DE ESPR MED ROAST	697	129	18,51
DE MELKPOEDER ZAK	DE ESPR MED ROAST	703	122	17,35
DE MELKPOEDER ZAK	DE ESP DRST100%ARA	741	113	15,25
DE MELKPOEDER ZAK	DE INST GO OR UTZ	654	107	16,36
TP SUMA CAFÉ MLK	TP SUMA CAFÉ AUTOTA	194	103	53,09
DE CACAO FANT BLUE	DE CAFE MILC LIQ	204	95	46,57
TP FR.VLG VOLLE MELK	DE ESPR MED ROAST	281	66	53,09
DE INSTANT CLASSIC	DE MELKPOEDER ZAK	361	64	46,57

The above tables show the affinity analysis of the SKUs in Tiel. What is meant by affinity? Product affinity analysis shows which SKUs are most often ordered together. Knowing which SKUs are mostly picked or ordered together can give a better idea of how to optimize product storage in your warehouse (Kofler et al., 2014). The affinity analysis tool by John Bartholdi III (2016) gave the possibility to do such analysis for all the orders that have been processed in Tiel. The results are given in the tables above. Table 10 shows the SKU pair with the highest percentage of being ordered together and also completes the order. This means that the order exists out of two orderlines. This is the case for 197 orders out of the 346 times they were being ordered together. Table 11 shows were more than 1 million combinations of SKU pairing and that DE MELKPOEDER ZAK and DE CACAO FANT BLUE were the most often picked together in orders. In over 6% of these orders, the order was completed. There is a choice of slotting these SKU locations near each other in order to reduce travel distance (Garfinkel, 2005).

Table III-11. Affinity analysis of SKUs in Tiel Warehouse Amount of Orders

SKU-1	SKU-2	Amount of Orders	Amount of Completed Orders	% of Completed Orders
	Total Amount of Unique SKU Pairs	*1048576*		
DE MELKPOEDER ZAK	DE CACAO FANT BLUE	2049	133	6,49
PICKW GR TEA LEM PRO	PICKW ROOIB ORIG PRO	1022	4	0,39
PICKW ROOIB ORIG PRO	PICKW FOR FRT PROF	1018	3	0,29
PICKW GR TEA LEM PRO	PICKW FOR FRT PROF	1004	2	0,20
PICKW ENGLISH PROF	PICKW GR TEA LEM PRO	836	5	0,60
DE MELKPOEDER ZAK	SUIKER AUTOM. ZAK	828	17	2,05
PICKW ENGLISH PROF	PICKW FOR FRT PROF	822	0	0,00
PICKW ENGLISH PROF	PICKW ROOIB ORIG	799	5	0,63
DE SUIKERSTICKS	DE LICHT&ROMIG MELK	796	43	5,40
PICKW EARL GREY	PICKW ENGLISH PROF	785	5	0,64

5.3 Picker Movement

An analysis has also been made about the pickers' movement in the warehouse. Each picker tour has been analysed, and the results of that analysis are displayed in Table 12. As can be seen, the mean SKUs that are visited in each batch is 11,29, and the mean amount of colli collected in those batches is 26,82. The scan time shows the time between the first and last scan of colli. The tour time is the total time that the tour has costs. The drive time back to the packing depot is added to the scan time, which gives the tour time. The last two columns show the average speed at which the pickers move through the system. It stands still to pick the colli at the specific SKU most of the time.

Table III-12. Picker Tours Data Results Tiel

Total Tours:	*5468*	*Total Orders:*	*22278*	*Picker Cart Speed (km/h):*	*5,78*
Total SKU Visits:	*61678*	*Total Colli:*	*146469*		

	SKU Visits	Colli Picked	Scan Time (s)	Tour Time (s)	km/h Scan	km/h Tour
Mean	11,29	26,82	676,49	752,32	1,84	1,54
Median	10	22	501	571	1,61	1,41
Mode	8	15	251	608	2,27	1,28
Std. Deviation	5,75	18,82	595,81	616,961	1,12	0,83
Skewness	1,14	2,87	2,22	2,12	1,80	1,29
Minimum	1	2	21	31	0,07	0,07
Maximum	44	298	3556	3558	9,91	7,38

The table below shows the distance travelled per picking tour. The mode of this distance is more representable because it shows the distance travelled that occurs the most per picking tour. Long and shorter picking tours more influence the mean, and therefore, the mode is more representable for comparing it in the future state. As can be seen in the table, the mode of the picking tours in Tiel is 264 meters.

Table III-13. Distance travelled per Picking Tour

Total Measurements:	*5468*
	Distance travelled (m)
Mean	243,79
Median	248,22
Mode	264,00
Std. Deviation	92,63
Skewness	0,50
Minimum	29,17
Maximum	969,91

5.4 Time Measurements

The time measurements focus on the picking activities of a picker. The picking time per SKU can be distinguished into two-time measurements: the fixed time per SKU and the variable time per colli. The fixed time per SKU is the time the picker needs at every SKU stop. For example, the scan time of the SKU, disembarkation time, and search time. Table 14 shows the results of the fixed time per SKU of the valid data in Tiel. Valid data means the times that the picker performs the stops correctly, so no loss of time due to, i.e., forgetfulness of scanning.

Table III-14. Fixed Time per SKU of Valid Data

Total Measurements (SKU picks):	*92903*
Total Colli:	*199435*
	Fixed Time per Colli (s)
Mean	23,50
Median	17,23
Mode	16,00
Std. Deviation	20,19
Skewness	1,94
Minimum	1
Maximum	120

There is another time measurement in the warehouse of Tiel measured. That is the time between picking tours or *idle time*. Idle time incorporates the sign-off time of the picking cart, de-, and attachment of old and new picking cart, etc. In the data of Tiel, the breaks were incorporated in this measurement. In this manner, a full picking day of 8 hours was analysed. The average time between two picking tours is almost 6 minutes.

Table III-15. The time between Picking Tours

Total Measurements:	*7638*
	The time between tours (s)
Mean	325,84
Median	207,00
Mode	159,00
Std. Deviation	415,16
Skewness	3,95
Minimum	1
Maximum	3542

5.5 Performance Measurement

The performance of the pickers in the Tiel warehouse is measured for each month and is reported in the average amount of pickers and average colli picked per hour, their total colli picked, and the total picking hours. The productivity of the pickers of Nedcargo is measured in the average colli picked per hour, and as we can see, it is on an average of 113 colli per hour. This productivity is achieved by an average of 4 pickers for all analysed picking days.

Table III-16. Performance per Month

Month	Amount of Picking Days	Avg. Amount of Pickers	Avg. Colli Picked per Hour	Total Colli Picked	Total Picking Hours
Mar	23	5,04	90,64	25141	282,21
Apr	20	5	110,20	19378	180,71
May	20	4,15	117,04	17796	160,45
Jun	22	4,14	106,37	26070	254,27
Jul	21	3,33	112,22	17684	158,87
Aug	22	2,90	126,07	15752	130,73
Sep	22	3,18	122,19	19630	163,65
Oct	5	4	128,49	5184	41,93
Total	*155*	*3,96*	*112,46*	*146815*	*1372,83*

In tables 3, 4, and 5, the average performance for three different picking days is shown in appendix A. These tables prove that the number of pickers active for a picking day is very randomly determined. This can explain the disparate average number of pickers seen in the table above. The total colli picked should determine how many pickers should be active in combination with the productivity reached in the warehouse. This analysis, therefore, makes it clear that this should be considered in the new configurations. Thus, to decrease the number of pickers by increasing productivity and have insight into the number of pickers needed.

5.6 ABC Analysis

The final analysis of the acquired data of Tiel is the ABC analysis. The ABC analysis helps to classify each SKU and how often it is picked. This classification is made by defining if an SKU is an *A-product, B-product, or C-product.* Group A products are the most critical warehouse products, namely the best sellers. Followed by B-product and C-products. The inventory turnover of Nedcargo's products is determined on respectively 75%, 20%, and 5%, which means that A-products provide 75% of the total turnover in the warehouse. This can be seen in table 16. Here can be seen that 64 products cause almost 75% of the inventory turnover in the warehouse. Insight into the ABC distribution allows the warehouse to create and implement a strategic strategy to optimize its layout. The ABC-analysis table below is based on the SKU visits. The ABC analysis can also be made for the amount of colli picked, which is displayed in the appendix.

Table III-16. ABC-analysis of SKU visits per product in Tiel

	A-Products	*B-Products*	*C-Products*
Total Products	64	95	192
Share of Products	18,2%	27,07%	54,70%
Share of SKU Visits	74,8%	20,13%	5,09%

Next to that, it can differ per type of category how many colli is picked. IT could occur that, for example, the A-products are picked in less quantity than the C-products. Therefore the analysis is made on the colli picked per category of SKU in tables 17, 18, and 19. As seen in the tables, there is a clear distinction in the amount of colli picked per category. It is more likely in Tiel that A type of SKUs is picked in larger quantities than that B and C. The chance that only 1 colli is picked increases significantly when an SKU belongs to a "lower" category than A. This product share of colli is a characteristic of the order.

Table III-17. Colli picked share for A-products SKU visits

Colli Picked	1	2-3	4-8	9-15	16-50	50-250
Total Picks	37436	27022	11155	1557	549	28
Share	48,15%	34,76%	14,35%	2,00%	0,71%	0,04%

Table III-18. Colli picked share for B-products SKU visits

Colli Picked	1	2-3	4-8	9-15	16-50	50-250
Total Picks	10975	6803	2718	299	124	9
Share	52,44%	32,51%	12,99%	1,43%	0,59%	0,04%

Table III-19. Colli picked share for C-products SKU visits

Colli Picked	1	2-3	4-8	9-15	16-50	50-250
Total Picks	3012	1494	622	116	50	0
Share	56,89%	28,22%	11,75%	2,19%	0,94%	0,00%

5.7 Current State Model of Tiel

Before proceeding with this research method, the current state as described must be implemented as a model. This should be done as it allows for comparing whether new strategies, designs, layout, or operations choices for Haaften are valid and verified based on the current state model. Therefore a simulation model representing the current state warehouse of Tiel has been made to make it possible to measure the effects of future state configurations for Haaften. This paragraph explains how the process of creating an accurate model is described.

The outbound logistics processes and data analysis of Tiel is now precise, and this must be transformed into a simulation model. To obtain the performance of the real-world operations, only then in the form of simulated data. The model has been implemented using Microsoft Excel Visual Basic for Applications (VBA). This object-based programming language for Microsoft Excel 2019 allows the Modeller to automate processes and control them with multiple application aspects. This powerful built-in programming language allows you to write your functions or commands in an Excel spreadsheet.

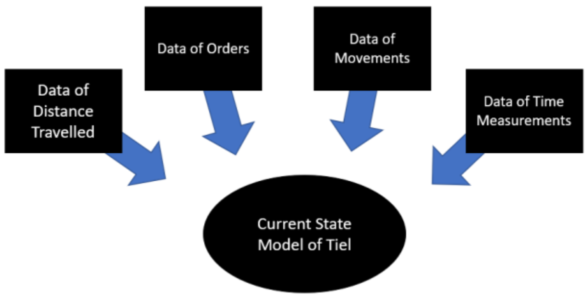


Figure III-7 – Data from Tiel Access Database,which shapes the Current State Model

Figure 7 shows the data that is gathered in order to form the current state model of Tiel. The data of distance travelled is compiled by the database in Access 2019 of Tiel and showed that this is a mode of around 264 meters per picking tour. The data of all the orders have been analysed and can show there is a mean of 2,85 SKU per order and an average of 6,72 colli per order. The average number of orders for a picking day in Tiel is around 180 orders with 1006 colli. The data of movements is how each orderline is picked. The data analysis showed that this is performed using the shortest route algorithm when switching aisles. As stated, the pickers first pick all the colli that need to be picked per aisle before switching to the next aisle with the shortest route. This is collected in the data of movements, and based on that data, the velocity of the picking cart is determined at 5,7 km/h. The time measurement is the last data that is gathered in order to establish the current state model. The time measurements are the fixed time per colli, the variable time per colli, and the idle time per picking tour. The fixed time and idle time can be seen in paragraph 5.4. These data of time measurement are used to form the current state model. The variable time is the time needed per colli, which Nedcargo’s Supply Chain department conducted research into. They stated that Nedcargo’s pickers that for each colli that needs to be picked, the “extra” time is continuously distributed between 6 and 9 seconds.

They are based on the data gathered during the data analysis and the current state analysis. Where the processes, strategies, designs, and resources were analysed. The model of Tiel can be modelled, and real-life average orders can be simulated into the model. This gives the following results for the productivity of an average picking week with every 10 iterations.

Table III-20. The results of the current state model based on the performance of an average Tiel Day

	Simulated Day 1	Simulated Day 2	Simulated Day 3	Simulated Day 4	Simulated Day 5
Performance in Colli/Hour	116,6	114,4	117,2	117,1	118,1
Avg. Batching Distance (m)	331	303	297	278	288

Table III-21. The average results of the Tiel warehouse.

	Average Day Tiel
Avg. Performance in Colli/Hour	112,4
Avg. Batching Distance (m)	264

5.7.1 Verification and Validation

Model verification and validation is an enabling technique for the development of computational models that can be used to generate warehouse predictions with a high level of certainty. In order to apply the current state model for configuring the future models, it must be verified and validated. *Verification* is determining that the simulation model performs as intended. *Validation* is concerned with determining whether the conceptual simulation model accurately represents the real-life model. It can be stated that *verification* aims that the current state model has no programming error, so it is made efficient and more user-friendly. Therefore it must accurately represent the Modeller's conceptual description of the current state of Tiel. *Validation* aims that the model is an accurate representation of the real world from the perspective of Nedcargo.

Now the current state simulation model has been programmed. It must be checked whether the model can be verified. This can be done by (1) checking if the model generates any errors. (2) comparing the final simulation outputs with analytical findings for the real-world system, and (3) via animation. Firstly, the code is checked to see whether any errors are made in the code. Because it represents the Tiel warehouse, the data of time movement and time measurement is known. It s checked whether these two aspects were programmed the same in the current state model as in the WMS. This process is relatively easy because both models use the spreadsheet's same order layout. Next to that, it must be checked whether the analytical findings from the current state analysis were implemented in the model. This includes the storage, layout, and strategy characteristics. They must be the same in the model as in Tiel. This includes the same storage of SKUs, the same width and length of the aisles, FCFS strategy, etc. This was verified when a walk-through of the model was performed. This corresponding confidence of the simulated data compared with Tiel can be used to verify the results. Lastly is the animation, for the reason that Excel can visualize what happens with the data. IN this manner, a reference can be made to the model implementation to see if it is implemented in the same way as the WMS of Tiel.

The validation process of the current state model is based on discussion and interaction with experts during the phase of modelling the simulation model. Validation can be achieved when the experts discuss the model while designing it. If it interacts with the client throughout the process, and if it can be supervised. This is done by weekly meetings with the supervisor expert of Nedcargo, which could validate if specific processes were implemented correctly. Next is the comparison of the simulated data with the real-world data. It was chosen to simulate an average working day in Tiel. And as can be seen in the tables above, first of all, the data of the simulations are in the same range, and no outliers are detected. This means that the model does it the same way for each iteration. Next to that, if compared to the real-life performance and batching distance, it can be seen that all of the simulated data is a bit higher in performance, but not more than 5%. This means that the obtained results lie within the reliability of the 95% confidence interval of the average performance in Tiel (106.8-112.4-118.1, see tables 20 and 21).

5.8 Conclusion

This chapter focused on the data analysis of the current state. To find out how the different characteristics of the warehouse in Tiel are categorized. First, to quantify the processes that were discussed in the previous chapter. Secondly, to investigate whether specific findings out of data can help for configuring the future state. Thirdly, a current state model was configured with the help of the data analysis. Based on the current state analysis, the collected data, and the data analysis, a model could be created which represents the warehouse of Tiel. This current state model can simulate the processes that occur in the warehouse and gives them according to performance. This performance is verified and validated so that the model is accepted as a simulated representation of the Tiel warehouse. This model attributes to the following sub-question to be answered.

What are the different performance measures of an order-picking warehouse, and how can they be quantified?

The performance indicators were discussed earlier in the literature analysis. In this chapter, we have quantified them for the warehouse in Tiel. As stated, the performance of the warehouse is measured in productivity per hour, or the average amount of colli that is picked per picker. The data analysis quantified this productivity, resulting in the average productivity of 113 colli per hour in the warehouse of Tiel. The other performance measure that was simulated and analysed is the average batching distance. This is the distance covered by the picker for each batch consisting of four orders. This was also verified, validated, and considered plausible.

In the next chapter, we will further elaborate on more performance indicators and how these will be used in the new configurations of Haaften.

Lastly, the data analysis aimed to give an insight into the current order characteristics of the e-commerce operations of Nedcargo. To partly answer the following sub-research questions

What are the current characteristics of the orders at Nedcargo's e-commerce warehouses, and how will they evolve in time?

The data analysis gave us multiple insights into the current characteristics of the orders at Nedcargo's e-commerce warehouse in Tiel. This by looking at the order characteristics, product characteristics, picker movement, performance analysis, and ABC-analysis of Tiel. The data analysis gave the means to obtain insights, which can help to improve new configurations for Haaften. These paragraphs answered the current characteristics of Nedcargo's e-commerce warehouse in Tiel. The next chapter will elaborate on how these will evolve in time.

6. Method

This study aims to research the uncertainty aspect of the order characteristics on different design configurations of the warehouse in Haaften. A contingency approach is used to connect different decisions concerning warehouse configurations in the e-commerce concept of Haaften. The contingency approach focuses on the importance that the processes and structure of the design should match with the internal and external environment it operates in, in other words, the context in which it is placed. This is all to improve the overall performance.
The proposed method will be explained in the following paragraphs.

6.1 Contingency Approach

The contingency research approach is based on two assumptions. First, there is no ideal way to organize, for warehouses that can mean that there is no universally acceptable management structure or system that applies to all warehouses in every scenario. Secondly, the most successful organizational structure, or in this case, configuration, should be appropriate for the environmental operating conditions. Contingency theory is the central theoretical perspective on such organizational contingencies. Lawrence and Lorsch (1967) were the first to point out that organizations whose structure fitted their environment had higher performance and created the theory. Central to the theory is the concept of the fit between structural and environmental characteristics of organizations (Donaldson, 2001). Sousa and Voss (2008) pointed out that contingency studies consist of three types of variables: (1) contingency variables, which represent the context, (2) response variables, which represent the organizational actions to respond to the context, (3) and performance variables, which measure the effectiveness of the operations of the system. Thus, applying the contingency theory in this study, we propose that a warehouse system's performance depends upon the fit between its configuration structure and the context the warehouse operates.

Kembro et al. (2018) stated that it is emphasized in many recent studies that the role of a warehouse in meeting its customers' expectations is growing. Mainly due to the shorter lead times and e-commerce trend, it has become more common to rely on the functioning of a warehouse to fulfill the client's wishes. Kembro et al. stress that more research is needed to analyse and test managerial practices and solutions. Particularly "the need to understand where certain configurations might fit better and which future path to pick" Warehouse configuration refers to the combination of operations, design aspects, and resources (Kembro and Norrman, 2020; see also, e.g., Rouwenhorst et al., 2000; Tompkins et al.,2010; Bartholdi and Hackman, 2016; Frazelle, 2016).

In the figure below, it is visualized what is meant by the configuration of a warehouse as discussed in the context analysis in 4.2. It is a combination of its operations, design, and resources. This figure is well known in research studies about warehousing, but what Kembro et al. (2020)added to the figure is the context in which a warehouse configuration operates influences its handling. Those contextual factors are shown in the green box and consist of the customer, product and order characteristics, demand profile, assortment, and volume. They stated that if a warehouse wants a steady-state and robust system, it needs to understand and highlight the various contextual factors that influence the selection of a warehouse configuration.

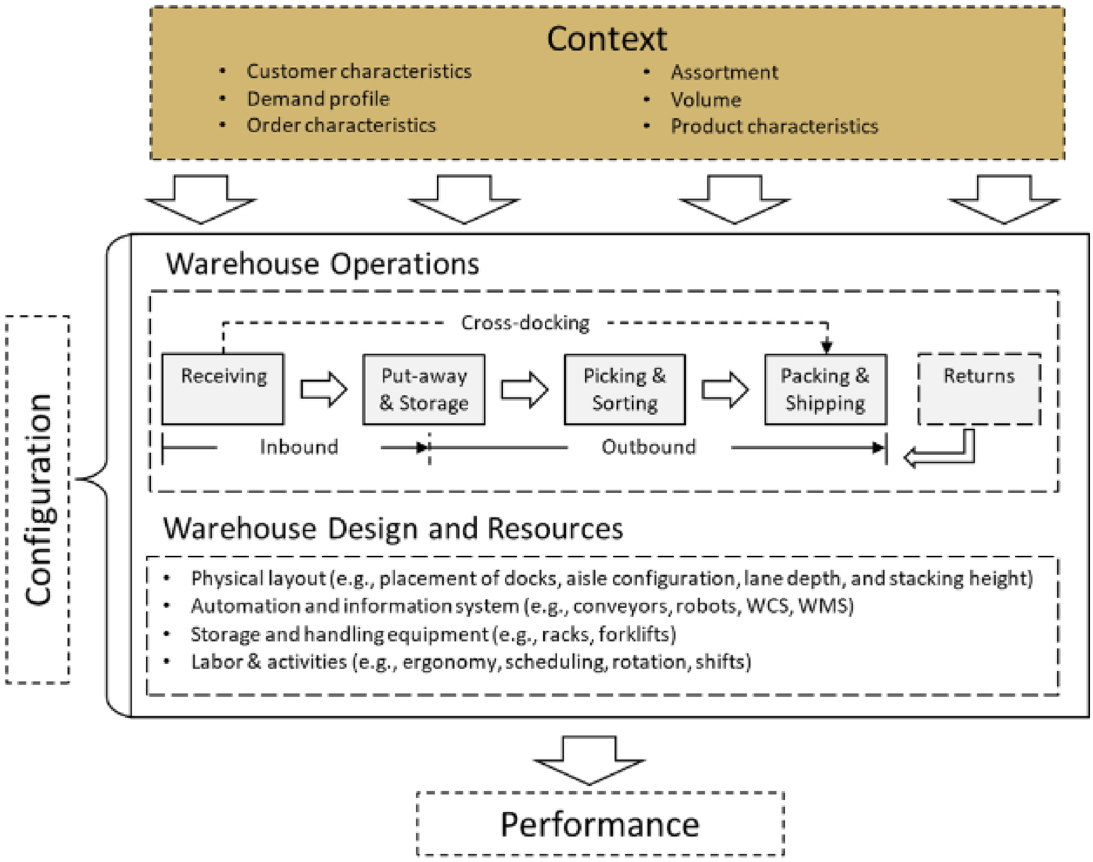


Figure III-8 – Conceptual Contingency Framework for Warehouse Configuration (Kembro & Normann, 2020)

This research tries to implement this way of thinking in a case study for Nedcargo. The contingency approach will help in this regard. The main research question is based on the outbound logistics of a warehouse and order uncertainty. How can we link these two to the figure above? The outbound logistics are seen in the warehouse operations of the configuration. It is seen that storage, picking, sorting, and packing are part of outbound logistics. These processes will be involved in the contingency approach as the configuration of the warehouse in combination with the design and resources used for these processes. Next to that is the order uncertainty mentioned in the main research question. Therefore, this can be seen as a contextual factor that should fit. As seen in the figure, order characteristics are seen as a contextual factor. Therefore, this study will focus on the contextual factor of order characteristics and how the performance will react to different warehouse configurations operating in these contexts. The following section will explain how these context of order characteristics is quantified and used.

6.2 Experimental Plans

In order to investigate the effect of contingencies on warehouse configurations performance, scenarios are created of different variables of order characteristics. Each scenario can be used to create a dummy order data set or a fictitious order set. The dummy data set contains records with the same content and layout as an accurate production data set, but all the data is fictitious. The contingency variables will shape the data according to the scenario.

Order characteristics are a contextual factor in the operations of a warehouse. The warehouse's operations and design together form the configuration of the warehouse. The choice of configuration in a specific context consequently leads to a specific performance. Therefore, it is explicitly stressed that there is a match between context and configuration that influence performance. This dummy data set can test whether a particular context scenario of order characteristics works better in a chosen configuration.

The configurations are based on literature findings and on observations of the current state in Tiel for Haaften III. But the scenarios are chosen by using Nedcargo's expertise. The variables of the scenarios are all based on probability. The different contingency variables that are being used for the scenarios are:

1. *SKU per Order*
2. *ABC-Ratio*
3. *Number of SKUs*
4. *Colli per SKU*

These variables together form the context in which Haaften III can operate. Confident configuration choices can perform better than other configurations based on the order characteristics' contextual factors. So for a better understanding of potential configuration choices, it can be beneficial to look at the context in which it has to operate in.

6.2.1 Contingency variables

All these scenario variables are based on probability. These probabilities are based on the current state of Nedcargo's e-commerce operations in Tiel and chosen deviations from this study's perspective and those out of literature. We will discuss them one by one.

SKU per Order:

SKU per Order	1	2 -- 3	4 -- 8	8 -- 10	11 -- 20	20 -- 50
Distribution 1	25%	20%	28%	17%	7%	3%
Distribution 2	42%	31%	18%	7%	2%	0,05%
Distribution 3	50%	34%	11%	4%	1%	0,02%
Distribution 4	45%	19%	21%	10%	4%	1%

The above table shows the 4 levels of distribution of which one can occur in a scenario. Distribution 2 is the current characteristics of the probability of SKU per order in Tiel. It is based on the probability of how many orderlines an order exists.

ABC-Ratio:

ABC-Ratio	A	B	C
Level 1	10% of SKU	30% of SKU	60% of SKU
Level 2	18% of SKU	27% of SKU	55% of SKU
Level 3	25% of SKU	32% of SKU	43% of SKU

After the SKU per order characteristics of the order are determined, the next step is to look if the product is an A, B, or C product. ABC analysis is an inventory management technique that determines the value of inventory items based on their importance to the warehouse. The ABC-ratio and ABC inventory turnover is based on previous data from the Tiel warehouse, which is level 2 in the table. The share of SKU visits for this characteristic is 75/20/5, which means that 18% of the SKUs account for 75% of the SKU visits. The characteristics of 75/20/5 will be given as a constant.

Number of SKUs

Number of SKUs	
Level 1	350 SKUs
Level 2	500 SKUs
Level 3	750 SKUs

After determining if the orderlines consist of an A, B, or C product, it has to be chosen which, according to SKU, has to be picked. In order to acknowledge this information, it is necessary to know how many SKUs are available in the warehouse. It is chosen to vary the number of SKUs on three levels, namely 350, 500, and 750 SKUs. Currently, Nedcargo has an e-commerce warehouse with 350 different products, so 350 possible SKU locations. It is chosen not to vary to a level less than 350 due to the current strategy of Nedcargo of extending its e-commerce warehousing selection.

Colli per SKU

Colli per SKU	Distribution 1	1 -- 2	3 -- 5	6 -- 10	11 -- 20	21 -- 50	51 -- 100
	A	37%	37%	17%	5%	2,50%	1,50%
	B	44%	34%	15%	4%	2%	1%
	C	54%	27%	12%	4%	2%	1%
	Distribution 2	1 -- 2	3 -- 5	6 -- 10	11 -- 20	21 -- 50	51 -- 100
	A	48%	35%	14%	2,00%	0,71%	0,04%
	B	53%	33%	13%	1,38%	0,50%	0,04%
	C	57%	28%	12%	2,19%	0,94%	0,00%
	Distribution 3	1 -- 2	3 -- 5	6 -- 10	11 -- 20	21 -- 50	51 -- 100
	A	53%	36%	9%	1,5%	0,50%	0,01%
	B	59%	34%	6%	0,80%	0,19%	0,01%
	C	69%	27%	3%	0,5%	0,10%	0%
	Distribution 4	1 -- 2	3 -- 5	6 -- 10	11 -- 20	21 -- 50	51 -- 100
	A	60%	22%	15%	2,0%	1%	0,05%
	B	51%	31%	16,2%	1,50%	0,30%	0,01%
	C	30%	29%	28%	6%	5%	2%

After all the previous 3 steps, the final characteristics of the order are determined by how many colli the orderline consists of. Based on the data analysis of Tiel, it is chosen that the amount of colli per order is based on whether the orderlines consisting SKU is an A, B, or C product. It occurred out of the data analysis that there is a difference in the amount of colli picked per type of product, so in this manner, the probability also differs for the scenarios. There are 4 levels of distribution of probabilities for the type of product seen in the above table.

6.2.1 Dummy Data Set

Each order set will consist of 300 orders. This is chosen to be constant because the used performance measure is colli picked per hour. So if we increase the order total, this will only increase the picking time and not the colli picked per hour. How an order is characterized is dependent on the scenario. The algorithm of how the order is formed will be based as follows:

First, an order is created – i.e., this is order 212 of 300 – first, the number of orderlines (SKU per order) in the order is determined – then for **each** of the orderlines, it is determined if it is an A, B or C product, this is dependent on the ABC-ratio - after this, the algorithm will decide which exact product it is. This depends on how many SKUs are in the warehouse – the last step to complete one orderline is to determine how many colli has to be picked for that product. This is based on the accompanying probabilistic distribution of the type of product. – this process is repeated for every orderline until all 300 orders are completed.

This should create a dummy order data set, which can be used to test different deterministic configurations on how it responds to a particular context. Based on this, it can be said that the scenarios are being used as experimental plans. Further elaboration on the model's work will be given in the next chapter.

6.2.2 Experimental Plans

As mentioned beforehand, in order to form such experimental plans or scenarios, four different variables are used to point out the contextual factor of order characteristics in a warehouse. Two of those variables, ABC-ratio, and total SKUs, consist of 3 levels, and the other two, SKU per order and colli per order, consist of 4 different levels. Thus, a total of 3*3*4*4 = 144 experimental plans can be established. They are displayed in the table in appendix B.

The choice has been made only to perform a dummy order data set for 5 different experimental plans. Nedcargo is choosing these 5 scenarios. They have to decide which scenario they find the most plausible or exciting to investigate and test on different configurations for Haaften III. These contextual experimental plans are scenarios 50, 107, 10,77, 92 and 123

6.3 Proof of Configuration

The proof of concept, or in this thesis' case configuration, constituted the scope of this research project. As part of a robust systems engineering process, it is critical to conduct a proof-of-concept initial study to identify potential system limitations in order to develop an understanding of the expected usefulness of the system before incurring additional costs (e.g., software development efforts). As told in the contingency approach chapter, we address a warehouse concept as a configuration. So from now on, we will talk about a proof of configuration approach.

In the figure below, the method proposed in this research is visualized. On the left, the contingency variables of the order characteristics are shown. The scenario experiment generation model is shown in the first black box, and on the left, the three configuration models are shown. The previous paragraphs pointed out the importance of this study of the contingency variables translated into experiments. The contingency variables together are formed into various scenarios, out of which the experts at Nedcargo chose six plausible scenarios for them. These scenarios are transformed in experiments by using the scenario experiment generation model. The outcome of this model results in 5 experiments for each scenario. This can also be seen as a week of orders which are the input for operations at a warehouse. The output of the scenario model will function as the input of the configuration models.

The proof of configuration approach in combination with the contingency approach is pursued because it can prove that specific configurations better fit and perform in certain contexts. Therefore Nedcargo can use that knowledge for their decision-making in design, operations, strategies, etc., for their new warehouse in Haaften. These configuration models must represent the outbound logistics of a warehouse; thus, storage, layout, picking strategy, routing, and equipment must be modelled within the models. Each of the configurations differs from the other. The aim is to prove whether a particular context performs better or worse, given the configuration it operates in. This can be called proof of configuration.

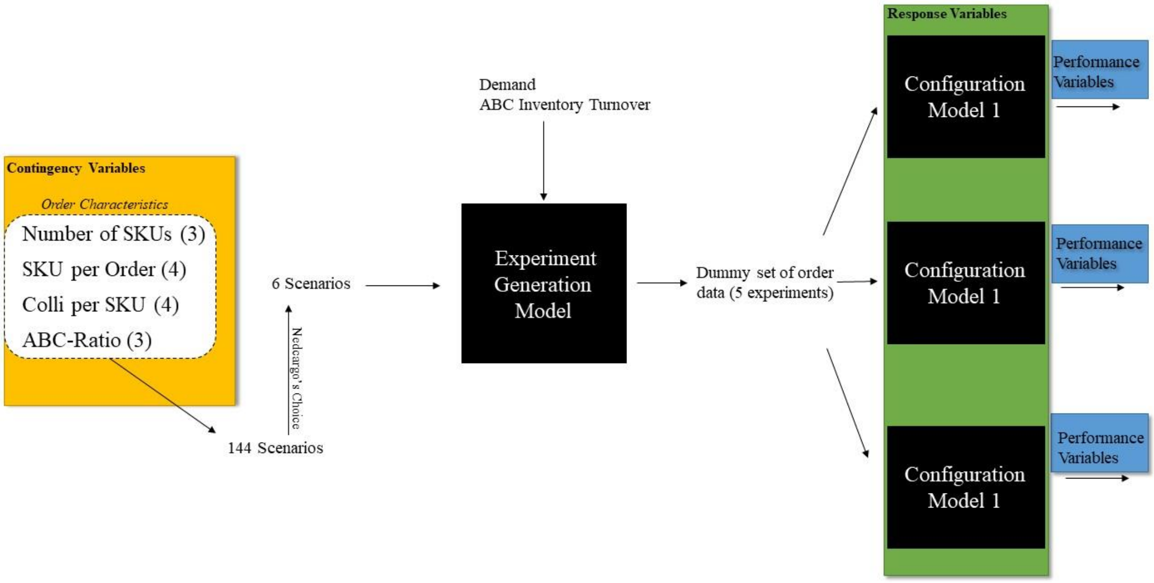


Figure III-9 – Overview of the Method of this Study

6.4 Performance Measures

Figure 9 also shows that the output of the configuration model is the performance measure. As is stated during a contingency approach, there are three types of variables. The contingency variables are being used to model the experiments. The response variables are defined in the configuration model. And the performance variables, or key performance variables (KPI), are metrics associated with measuring the warehouse's performance in outbound logistics. These KPIs can be used to monitor the efficiency of the operations and can uncover potential problems, manage risks and find ways to optimize the workflow. There is a distinction between quantitative KPIs and qualitative KPIs in this study.

6.4.1 Quantitative KPI's

KPIs measure performance and quantitative are the most straightforward KPIs. They are measured solely by a number. In warehouse logistics, there are a lot of performance indicators available for measurement. This way, it is necessary to choose the right indicators for the proper analysis. This study aims to see if specific configurations perform better under certain contexts. But which indicators can provide the correct answer to this question? With a combination of consultation with the expert of Nedcargo and what is found in literature about performance indicators of warehouses, a couple of KPIs have been selected. Because the picking operation can primarily be measured in numbers, most of the KPIs involve picking.

The first quantitative KPI is the **picking time**. Picking time means the number of hours, minutes, or seconds the picking operation account for a specific order day. This is the total amount of time needed to complete every order. This differs per scenario because more SKUs have to be visited or more colli have to be picked. Therefore, this picking time is influenced by multiple factors in the system and is a result of it. Factors that can influence the picking time are the pickers' picking speed. Pickers have a fixed amount of time and a variable time per order. The fixed amount of time is the time that is needed to get out of the reach truck and scan the SKU in order to start picking. Each time a picker visits an SKU of an order, this is a fixed time. The variable picking time of a picker is the time that is needed per colli. This is less than the fixed picking time but increases if more colli needs to be picked. Nedcargo did some research to quantify these numbers, which will be further discussed when the model's working is covered in the next chapter. The last factor that influences the picking time is the driving time of the picker. This differs per routing strategy and batch. It covers the time needed to complete the trip to collect all the orders in the batch.

That brings us to the following quantitative KPI, which is the **total distance** covered. Each experiment consists of 300 orders that need to be picked in batches of four. The total distance that the pickers need to cover to collect all the orders is measured in the model. It is beneficial for Nedcargo that this distance is as low as possible. This can mean that an efficient picking strategy is adopted and that there is not much loss of time due to a greater travel distance.

One of the most critical indicators of efficiency in a picking warehouse is the **productivity** of the pickers. This is measured in the amount of colli picked per hour. Each picker has a performance that is measured in colli per hour. If this productivity increases, the same amount of colli can be picked in less time. Therefore, it is very beneficial to have a colli per hour as high as possible. This can be achieved by having an efficient picking strategy, a more favorable layout, a better storage strategy, and much more. Is this also affected by the context of the warehouse? Which this study aims to show. Higher picking productivity can also result in fewer pickers needed to complete an order day.

The following KPI is the **number of pickers** that are needed. In a Nedcargo warehouse, pickers work 8-hour shifts which means that if there are two pickers, they can pick an order day that requires less than 16 hours of picking time. The model also aims to give an insight into the number of pickers needed, which does not happen in today's operations. This can mean that a prognosis can be made for future operations as to how many labor hours will be needed in a certain period. This can be translated into costs and thus provide cost estimation and possible savings from these insights.

The last quantitative KPI that is measured is the **average batching time**. As mentioned in the current state analysis, is that Nedcargo batches their order in quantities of four. This is to reduce the distance that needs to be travelled. It is, therefore, interesting to have. As a result, an insight into the average time needed for each batch. This is influenced by multiple factors such as distance and productivity. But it can also reflect for a warehouse manager to check if the pickers are collecting the orders in the right way. It gives a possibility that when the model is translated into real-life to check if a picker reaches its productivity or not. But also gives an insight if the batching strategy is working or not.

These are the five quantitative KPIs that will be investigated. They will function as an output of the configuration models. The next chapter should envision how they are influenced and differ per context when the models are described in more detail.

6.4.2 Qualitative KPI's

Qualitative KPIs are typical characteristics of a process of business decision and are not measured by numbers but expressed descriptively. They tend to focus more on expert experiences and feelings and the value placed on them. A couple of qualitative KPIs are being used in this research.

Firstly, the possibility of **congestion** is a qualitative performance indicator that is looked into. When a warehouse is congested, it is so crowded with traffic or people that it hinders freedom of movement. If there is a lot of warehouse congestion, it can affect the ability to take care of fulfilling customer orders promptly. Multiple causes can lead to an increase in congestion. In this study, congestion was considered to be a qualitative indicator. This is for the reason that congestion has to be measured using flow analysis. Flow analysis can be modelled using agent-based Modelling and is not in the scope or method for this research. Nevertheless, using several insights from practice and literature, congestion can be detected early. The potential congestion can be visualized by reflecting on the heat maps of the SKU visits and the demand per SKU seen in appendix A, figures 11, and 12.

The second and last qualitative performance indicator is the possibility of **automation**. Warehouse automation is the process of automating the movement of inventory within the warehouse without (or minimizing) human assistance. For outbound logistics, this can be achieved through AGVs or other innovations. Nedcargo would like to retain the option of switching to more automation in the warehouse in the future. Therefore, the configurations developed in this study will have to take this into account.

6.5 Conclusion

Now that the method of this study is known, the research questions need to be reflected upon. The proposed method is based on combining the contingency approach and proof of configuration. The contingency approach focuses on that warehouses must fit their context. The contingency approach consists of three variables: the contingency variables, the response variables, and the performance variables. The contingency variables represent the warehouse context, and in this study, the context is the uncertainty of the order characteristics. An experiment generation model is developed to create dummy order data (experiments) to use as an input for the configuration models. The configuration models can be seen as the response variables. The design, operations, strategy, layout, and storage together form these configurations. The configuration models must show if a different configuration setup leads to other performance in specific context experiments. These performances are measured in quantitative and qualitative performance indicators. This all to give proof that specific configurations fit better in a particular context. This proof can help Nedcargo in future decision-making concerning their new projected warehouse in Haaften. Based on the proposed method, the following sub-research question can be answered:

What method can model the proposed context scenarios and configurations of an e-commerce warehouse?

Therefore, the method is a contingency approach to prove that specific configurations perform differently based on their context. Four models will be drawn up, one experiment generation model, which transforms the scenario's into a dummy order day. And three configuration models, each representing the outbound logistics of a warehouse. The output of those three models will be the performance indicators, which will be analysed and drawn to conclusions upon. Figure 10 shows the knowledge gap which can be filled with this research. As can be seen, there is a strong link between organizational concerns and the contingency theories that have been found in theories. But it lacks to translate these concerns and ideas into practical applications, which this study aims to accomplish (Betts 2003).

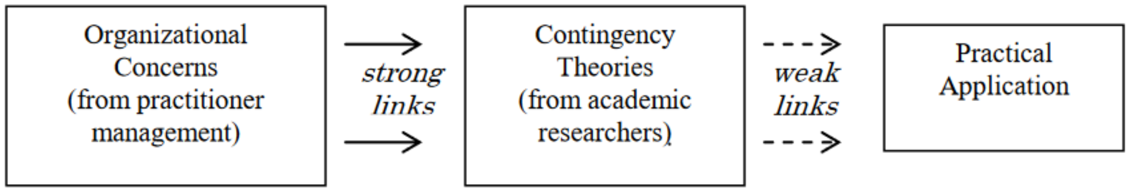


Figure III-10 – Visualisation of the knowledge gap to create a practical application which is in line with the contingency theory of warehousing

IV. Integrate

7. Scenario Modelling

This chapter will take a closer look at the chosen scenarios and how these scenarios are converted into experiments. In order to achieve this, a model is needed to generate the experiment. First, the chosen experimental plan of the scenarios will be discussed, and then the model's functioning will be explained. As mentioned earlier, the scenarios will be based on simulating the possible context of where the warehouse in Haaften will operate. In appendix X, all of the experiments are being described and will be referred to if needed.

7.1 Experimental Plans

In chapter 6.2, the different scenarios were discussed and visualized in the appendix. Nedcargo was given the task of selecting the six most plausible and exciting scenarios for the Haaften III warehouse. They had the possibility to choose out of a variety of scenarios (appendix B) and chose scenarios 10, 107, 10, 77, 92, and 123. These scenarios will be transformed into an experimental plan to create a dummy order data set for each scenario. These dummy data sets are being generated by a model that is made to create a dummy order list from the chosen contextual factors of each scenario. Five of those experiments will form the experimental plan of the scenario and will each be simulated through the configuration models, which will be elaborated further in this thesis.

In this paragraph, first, the different experimental plans of each scenario will be discussed, and after this, the model will be explained. The results, namely the experimental plans, will serve as an input for the configuration models. This is to eventually look at if a particular context of a warehouse has any influence on its performance.

7.1.1. Experimental Plan of Scenario 50

The first scenario for which experimental plans are generated is scenario 50. The different variables a scenario consists of to point out the warehouse context are SKU per order, ABC-Ratio, number of SKUs, and Colli per SKU. The first scenario that the experts of Nedcargo have chosen is that of scenario 50. The SKU per Order is distribution 2 (see chapter 6.2.1), the ABC-ratio is level 2 (see chapter 6.2.1), the number of SKUs is 350 (see chapter 6.2.1), and the Colli per SKUs is based on distribution 2 (chapter 6.2.1). Nedcargo chooses this scenario because it is based on the current order characteristics the Tiel warehouse operates in. As can be seen in the current state analysis, the distributions and the levels of the scenario variables are aligned with Tiel's in scenario 50. Thus, it can be seen as transferring the current client of Tiel towards the new potential configurations of Haaften to quantify whether new configuration choices have any effect and how much they will be. The model will each generate five experiments that form the experimental plan of scenario 50.

7.1.2. Experimental Plan of Scenario 107

The second scenario for which experimental plans are generated is scenario 107. The different variables a scenario consists of to point out the context of the warehouse are SKU per order, ABC-Ratio, number of SKUs, and Colli per SKU. In scenario 107, the SKU per Order is distribution 3, the ABC-ratio is level 3, the number of SKUs is 750, and the Colli per SKUs is based on distribution 3. Nedcargo chooses this scenario since it represents clients for whom they can potentially provide the warehousing in the e-commerce section of Haaften. This order characteristics can suggest a client with many different products that need to be distributed, namely 750. Based on the SKU per order, it is more likely that customers of the client place an order which has fewer different SKUs per order than Nedcargo is currently accustomed to. Next to that, due to the ABC Ratio, more products will be ordered more often because this scenario profile has a higher percentage of A-products. The probability of picking a product will be higher because of this higher share of A-product. This is also combined with the number of SKUs stored in the warehouse. The last variable is that of the colli per order. Distribution 3 shows a higher probability for each type of SKU (A, B, or C) that less colli will be picked per SKU visit than at the current state.

7.1.3. Experimental Plan of Scenario 10

The third scenario for which experimental plans are generated is scenario 107. The different variables a scenario consists of to point out the context of the warehouse are SKU per order, ABC-Ratio, number of SKUs, and Colli per SKU. In scenario 10, the SKU per Order is distribution 1, the ABC-ratio is level 1, the number of SKUs is 750, and the Colli per SKUs is based on distribution 2. Nedcargo chooses this scenario because its characteristics can represent clients with whom Nedcargo might do business. This order characteristic can refer to a client with many products and is likely to have many different products in a customer order. This is based on distribution 1 of the SKU per order. Next to that, in combination with the ABC Ratio, it can be established that fewer products are A-products, and therefore, the picker will travel to fewer locations. This is because most of the time, A-products are picked. The colli per SKU that is being picked is the same as in the current state.

7.1.4. Experimental Plan of Scenario 77

The fourth scenario for which experimental plans are generated is scenario 77. The different variables a scenario consists of to point out the context of the warehouse are SKU per order, ABC-Ratio, number of SKUs, and Colli per SKU. In scenario 77, the SKU per Order is distribution, the ABC-ratio is level 1, the number of SKUs is 500, and the Colli per SKUs is based on distribution 1. Nedcargo chooses this scenario because it could characterize a potential client in the contextual environment Haaften could operate. This scenario characterizes a client whose customer has a medium variety of product choices and mostly orders less SKU of which its A-products do not vary that much. Next to this, the amount of colli picked per SKU visit is based on distribution 1, which means that it is more likely that the customer orders a large amount of colli per SKU it orders. This means that the probability is higher per SKU visit than nowadays that a more considerable amount of colli has to be picked.

7.1.5. Experimental Plan of Scenario 92

The fifth scenario for which experimental plans are generated is scenario 92. The different variables a scenario consists of to point out the context of the warehouse are SKU per order, ABC-Ratio, number of SKUs, and Colli per SKU. In scenario 92, the SKU per Order is distribution 3, the ABC-ratio is level 2, the number of SKUs is 500, and the Colli per SKUs is based on distribution 4. Nedcargo chooses this scenario because it could represent a potential client of theirs. This contextual character of the scenario is that there is an increased chance of an order with only one or a few SKUs to pick. Whereas the number of SKUs is medium, and its distribution level is the same as nowadays in Tiel. The colli per order differs from the other scenarios in the amount of colli per SKU visit. In the sense that the chances are significantly higher than if an A-product is taken, the customer often requires fewer colli. But with the C-products, which are ordered less, the required colli are significantly more likely to be ordered in large quantities.

7.1.6. Experimental Plan of Scenario 123

The last scenario for which experimental plans are generated is scenario 123. The different variables a scenario consists of to point out the context of the warehouse are SKU per order, ABC-Ratio, number of SKUs, and Colli per SKU. In scenario 123, the SKU per Order is distribution 4, the ABC-ratio is level 2, the number of SKUs is 350, and the Colli per SKUs is based on distribution 3. Nedcargo chooses this scenario because it is plausible that these order characteristics could be the context of Haaften. Scenario 123 differs from the other scenarios regarding the SKU per order. In this scenario and thus in the experiments, the number of SKUs increases in terms of only a single SKU per order but decreases at the current levels for two or three SKUs per order. So its probability of either a small order or a larger one in terms of SKUs is increasing in this scenario.

To conclude this paragraph, Nedcargo has opted to select the most diverse package of scenarios possible. This is so that each experiment of the scenarios could result in a dummy order data set, which could occur in the Haaften warehouse's future operation. Table 1 shows the results of the generation of experiments, but to substantiate these results, we must first understand how the scenario model works. This will be explained in the next section.

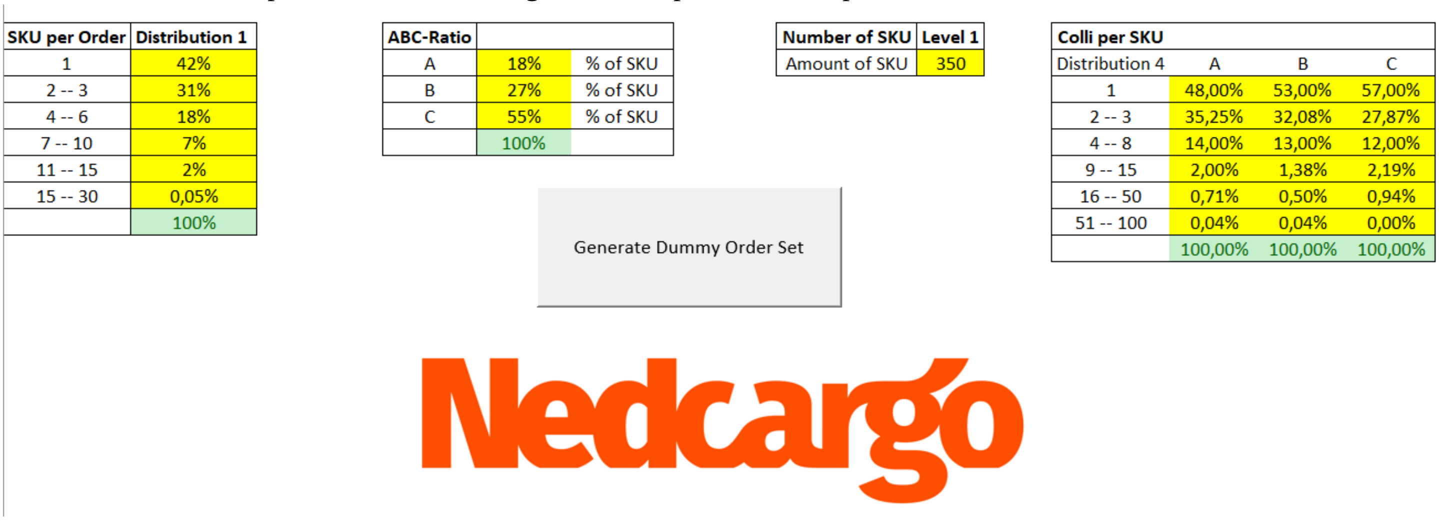
Table IV-0. Distributions and Levels per Scenario

	SKU per Order	ABC-Ratio	Number of SKU	Colli Per SKU
Scenario 50	Distribution 2	Level 2	Level 1	Distribution 2
Scenario 107	Distribution 3	Level 3	Level 3	Distribution 3
Scenario 10	Distribution 1	Level 1	Level 3	Distribution 2
Scenario 77	Distribution 3	Level 1	Level 2	Distribution 1
Scenario 92	Distribution 3	Level 2	Level 2	Distribution 4
Scenario 123	Distribution 4	Level 2	Level 1	Distribution 3

7.2 Experiment Generation Model

As mentioned, in order to generate the experiments based on the different order characteristics scenarios, a model must be created to generate a dummy order data set based on the various characteristics. The model is implemented by using Excel VBA in combination with macros and PowerPivot functions. Excel Visual Basics for Applications is a powerful built-in programming language that allows to code functions or commands in a spreadsheet. VBA is an extensible programming language made up of a core set of commands and extended on a per-application basis to work directly with objects in that application. In combination with macros, VBA makes it possible to create an experiment generation model to generate, based on the order characteristics of contextual variables, experiments. These experiments can be used as an input for the configuration models. This paragraph will explain step by step how this is achieved.

Firstly the input of the model. The input consists of the contextual variables of the scenarios. The context in which a warehouse operates can vary in order characteristics. These before mentioned variables are SKU per Order, ABC-Ratio, Number of SKUs, and Colli per SKU. These four variables are defined based on probability, and each varies in 3 or for levels/distributions. Those variables together form the input of the model. In figure 1, a snapshot of the input dashboard of the model can be seen.



SKU per Order	Distribution 1
1	42%
2 -- 3	31%
4 -- 6	18%
7 -- 10	7%
11 -- 15	2%
15 -- 30	0,05%
	100%

ABC-Ratio		
A	18%	% of SKU
B	27%	% of SKU
C	55%	% of SKU
	100%	

Number of SKU	Level 1
Amount of SKU	350

Colli per SKU			
Distribution 4	A	B	C
1	48,00%	53,00%	57,00%
2 -- 3	35,25%	32,08%	27,87%
4 -- 8	14,00%	13,00%	12,00%
9 -- 15	2,00%	1,38%	2,19%
16 -- 50	0,71%	0,50%	0,94%
51 -- 100	0,04%	0,04%	0,00%
	100,00%	100,00%	100,00%

Figure IV-1 – Dashboard of the Experiment Generation Model in VBA Excel

Figure 1 above shows all the input variables and how they can be adjusted. Each of the input variables can be adapted to the Modeller's wishes. However, in this study, we have chosen to work with different levels in order to make a convenient choice as an expert. Nevertheless, one can also choose to deviate from the levels, but we will not go into that now. After the scenario variables have been inserted in the yellow cells, the "Generate Dummy Order Data Set" button can be pressed. This generation process takes about 30 seconds with an 8GB 1,80 GHz computer. The model's input must be complemented by variables considered constant in this research. Those two variables are mentioned earlier: the number of orders for the dummy order day and the ABC inventory turnover. The number of orders is set at a constant of 300 per day. This was chosen as a constant to get the best possible assessment of the pickers' productivity. This research aims to distinguish the different contexts of warehouses, and therefore, the demand must be constant to only focus on the order characteristics. And not on the demand characteristics. However, the model can change this number of orders dynamically. The second constant variable is the ABC inventory turnover, respectively 75-20-5 percent. This means that, for instance, with the ABC ratio in figure 1, 75% of the turnover in the warehouse is caused by 18% of the products. This is given as a constant because, in warehousing logistics, this distribution has been investigated multiple times, and there is a general consensus on this ratio (Nallusamy et al., 2017).

Now that the input of the model is clear, a further look into the processing step of the model is needed. The first step in the model is to determine how many SKUs are needed in each order. This process step is carried out for 300 orders. The model determines, based on the probabilities given as an input for SKU per Order, for each order how many orderlines it possesses. This gives a list of every orderline for the dummy order day. The second step of the model is that for each orderline generated, an SKU must be assigned if the SKU that needs to be picked is an A, B, or C product. This is based on the probability indicated in the ABC-Ratio variable and with the constant of the ABC inventory turnover ratio. When this step is completed, the model must assign a specific A, B, or C product to the orderline. So that is known which specific SKU needs to be picked for that orderline. This step is the most complex one in this scenario experiment generation model.

The assignment of a specific product to an orderline is dependent on the probability that the specific type of product is chosen. First, it is therefore mandatory to know how many products of which type there are. Thus, the first step of the assignment process is to generate a list of the number of products of each type of product. In the experiment shown in figure 1, there are 350 SKUs with respectively an 18-27-55% ABC ratio. This means there are 64 A-products, 94 B-products, and 191 C-products. Naturally, this changes with other input variables. The generated list gives an output of A1 till A64, B1 till B94, and C1 till C191 products. The question then arises as to how the probability of a specific SKU being chosen is determined. For this reason, we have to go back to the data analysis of Tiel.

In table III-5, where the product characteristics of Tiel are being displayed, we can see that there is a certain probability that an SKU is chosen. In order to allocate a certain probability to the fictional SKUs in the experiments in the experiment generation model, a different look has been made into this probability of the SKUs in Tiel. The warehouse of Tiel consists of 350 SKUs. Each SKU can also be seen as either A, B, or C. If we hold on to the same ABC inventory turnover, three types of distributions can be seen in the following three figures.

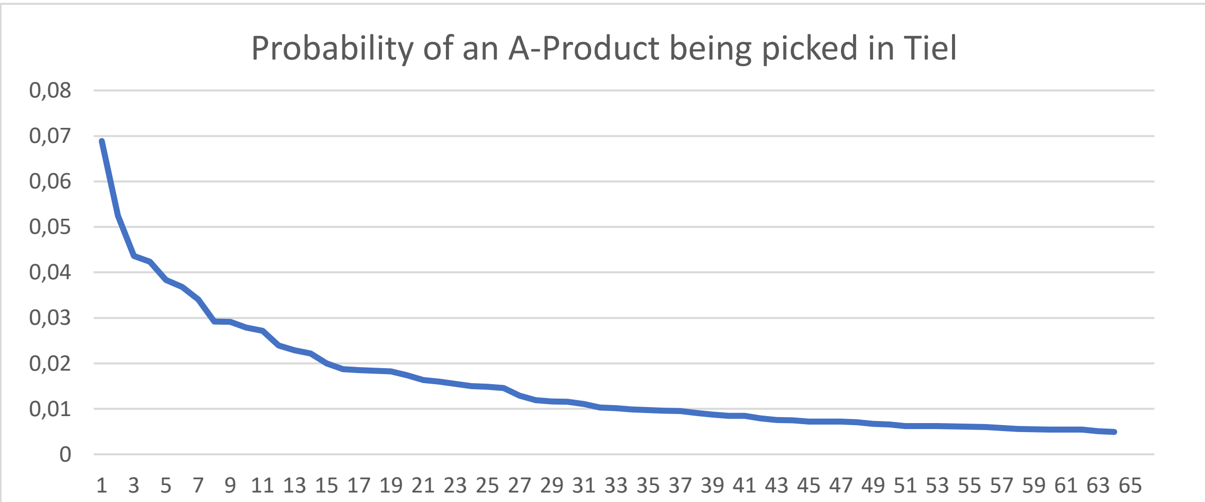


Figure IV-2 – The probability of an A-product being picked in Tiel per SKU

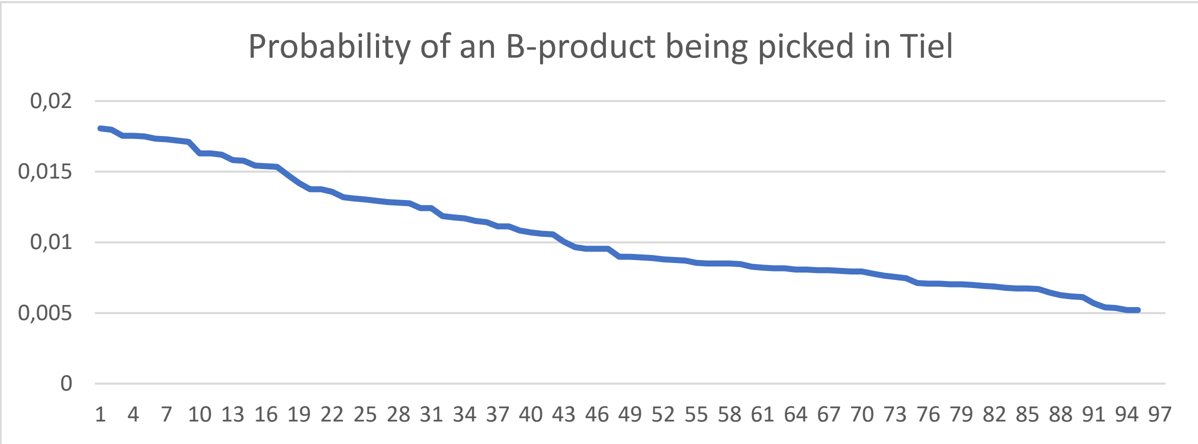


Figure IV-3 – The probability of a B-product being picked in Tiel per SKU

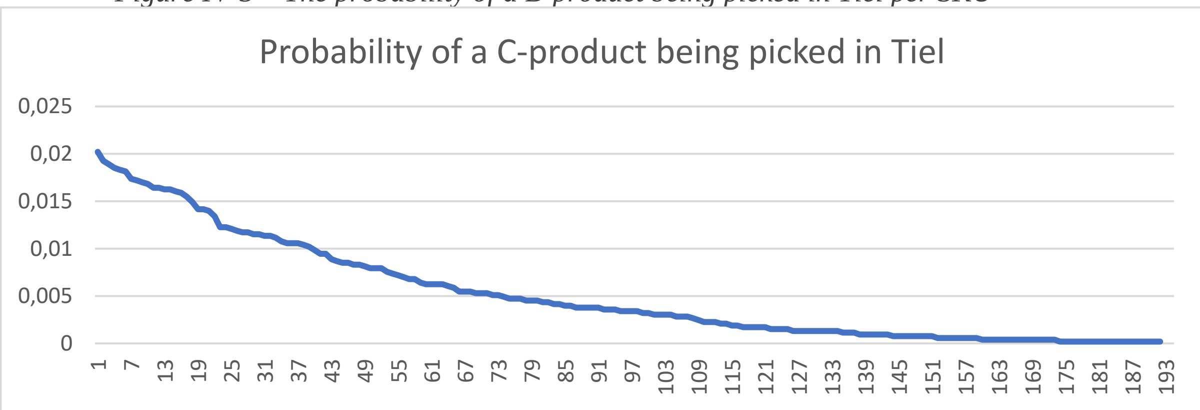


Figure IV-4 – The probability of a C-product being picked in Tiel per SKU

Each of the probabilities per type of SKU in the figures all adds up to a cumulative probability of 100%. In short, these 64 A-products provide for 75% of the inventory turnover, 94 B-products for 205 of the inventory turnover, and 191 C-products for 5% of the inventory turnover. So in each type of SKU, there is a probability that a specific SKU is chosen. Looking back at appendix A table 1 of the data analysis of Tiel, we can see that in 6,8% of the SKU visits, the fastest moving product of the warehouse is picked. In this model, we call that product A1. The SKU most likely to be picked next has its own probability and is called A2, and so on. The same is done for the B-products and C-products. But how is this probability assigned in the model?

The probability is based on a model fit to the figures above. Based on the historical data of Tiel, we will model fit this data based on an exponential decay which can be recognized. Next to that, this model fit can be scaled according to the number of needed products for each type. What is meant by exponential decay? This can be seen in the formula below.

$$y(t) = a * g^p \qquad (1)$$

$$where$$

$$y(pt) = probability\ value\ for\ SKU\ p\ of\ type\ \mathrm{t}$$

$$a = probability\ of\ most\ picked\ SKU$$

$$g = rate\ of\ decay$$

$$p = SKU\ number\ (e.g. for\ A{:}\ 1\ till\ 64)$$

The growth factor is based on the historical data in Tiel and is respectively 0,932 for A-products, 0,987 for B-products, and 0,980 for C-products. The starting value a is based on the highest probability per type of product, so those of A1, B1, and C1. Based on this formula and based on the possibility of scaling this probability in the model, the model can decide which probability is assigned for each product in the dummy data set. The fitted models for the example figures can be seen in Appendix C.

Now that the probability is known for each SKU, the model can assign a specific product to an orderline. So after it has been decided if an orderline consists of an A, B, or C product, now the model assigns a specific A, B, or C product. Therefore, the result can be that 1 order consists of 3 SKUs, e.g., A31, B44, and C107. If this is done for each orderline, the dummy order data set is almost completed. The last step that remains is to assign an amount of colli to each orderline. This is based on the product type of the SKU to visit. The colli per SKU distribution chosen in the input assigns, based on the probability of the colli per the product type, the amount of colli for each orderline. These processing steps together form the output of the model.

Now that the processing of the model is explained, we can take a look at the output the model generates. A snapshot of the first 4 orders of the output of the example in figure 5 is shown below. As can be seen, the output consists of four variables, namely the OrderID, the Product Type, the Amount of Colli, and the ProductID. As can be seen below, Order 1 only consists of 1 SKU visit and 1 Colli to be picked of ProductID A6. Order 2 consists of two orderlines, or SKU visits, of A40 and A9. This list consists of all the orderlines of 300 orders. It can be seen as a fictitious day for a warehouse of a specific client with certain order characteristics defined in the input variables. The Export OrderList button makes it possible to save the dummy order data set as an input for the configuration models discussed in the next chapter. This is to quantify and visualize the strategy, layout, storage, and performance of a potential configuration of a warehouse where the dummy order list must be handled.

OrderID	Product Type	Amount of Colli	ProductID
Order 1	A	1	A6
Order 2	A	1	A40
Order 2	A	6	A9
Order 3	A	1	A7
Order 3	B	2	B42
Order 3	A	1	A18
Order 4	B	3	B13

Export OrderList

Figure IV-5 – Snapshot of the output of the Experiment Generation Model

7.3 Verification and Validation

Validation and verification are the two steps in any simulation project to validate a model. Validation is the comparison of two outcomes. Therefore is needed to compare the representation of a conceptual model to the existing system. If the comparison is valid, it is legitimate; otherwise invalid. Verification is the process of comparing two or more results to ensure their accuracy. Therefore this process requires comparing the model's implementation and its associated data with the developer's conceptual description and specification.

Verifying the scenario experiment generation model was done by tracing the intermediate results and comparing them with the observed outcomes. Next to that, it was performed by checking the model's output using various input combinations. Finally, the last technique that was used to perform verification was by comparing the final results with the analytic results. Using the PowerPivot function of Excel gave the possibility that after an experiment was generated to check whether it was in accordance with the scenario input. For each experiment, this was performed, and no outliers or deviations were found. The Power Pivot verification tool is implemented in the models and can be found in the deliverables.

To validate the data, it needs to determine the representativeness of the output of the model. This can be achieved by using several steps. First, it is determined how close the simulation output is to the actual system output. Table 1 shows the results of all the experiments combined per scenario. This table is being analysed with the real-world data in Tiel, which is the same as scenario 50. The average orderlines per order is in Tiel 2,85, and in the model 2,78, The average colli per orderline is in Tiel 2,36 and in the experiment model 2,77, and lastly, the average colli per order which in Tiel is 7,71 and in the simulation 6,72. The five experiments that are averaged in the below table come very close to the real-life data of half a year in Tiel, and no significant changes are shown. In order to ultimately converge, more experiments should be run. But this validates that the output comes very close to real-life data.

Table IV-1. Order Characteristics per Scenario

	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Orders	300	300	300	300	300	300
Orderlines	834	747	1560	714	734	1071
Total Colli	2315	1646	4171	3251	2135	2391
Avg. Orderline/Order	2,78	2,21	5,20	2,38	2,45	3,57
Avg. Colli/Orderline	2,77	2,21	2,67	4,55	2,90	2,23
Avg. Colli/Order	7,71	5,49	13,90	10,94	7,12	7,97
Avg. SinglePicks	71,6	79,4	37,8	59,2	82,8	77,6

Another step of validation is to design a model with high validity. This can be achieved using the following steps applied in the model design process. While designing, the model must be discussed with system experts at Nedcargo. So, the model must interact with the client throughout the process, and system experts must supervise the output. All these steps have been performed in the design of the model.

7.4 Conclusion

To conclude this chapter of the scenario experiment generation model, it is needed to reflect on sub-question 6 of this research: *In which context can a future warehouse operate, and can various scenarios be envisaged in relation to the uncertainty factors that have been found?*

This sub-question can be distinguished into three parts. The first one is in which context can a future warehouse operate. As mentioned earlier, the operations of a warehouse are influenced by contextual factors and affect its performance. This being said, it is necessary to look into which contextual setting is applicable for a future warehouse of Nedcargo, in this case, Haaften III. The experts of Nedcargo were given a list of scenarios where the SKU per order, ABC-ratio of the SKUs, the amount of SKUS, and the colli per SKU are variables. The choice was given to select 6 given scenarios based on predetermined levels and distributions of the variables, which were applicable or interesting contexts to look further into. This answers that these scenarios are substantiated the potential context of a warehouse for Nedcargo. The envisaging of the scenarios was performed by designing a scenario experiment generation model. The order characteristic uncertainty factors were implemented as an input of the model in order to quantify and visualize what a potential order list would look like. This order dummy data set is the model's output and can be used to test whether specific configurations perform better and quantify the outbound operations. In table 1, the average result of 5 experiments per scenario of the model is shown. All these scenario outcomes of the model can be used to visualize a potential client, which Nedcargo can handle its distribution in an e-commerce warehouse.

Now the contingency variables are transformed into experiments by the experiment generation model. The next step is to process these experiments by different configurations of warehouses which function as the response variables. It is therefore needed to quantify, design, and visualize its warehouse performance for different configurations. This will be discussed in the next chapter.

8. Configurations Modelling

This research stresses that it is crucial to understand how various contextual factors influence the performance of a warehouse configuration, which, in the current paper, represents the combination of warehouse operations, design, and resources. Next to that, it should prove that the proposed configurations perform better (or worse) than the current state because of potential improvements found during the current state's data analysis. The proof of configuration method can therefore help improve future decision-making by realizing the quantification of configurations to demonstrate their feasibility. It can show that it has practical potential and shows if a specific throughput can be reached.

Several steps need to be taken to determine which choices must be made to configure such warehouse configurations. The first step is requirement analysis. During a requirement analysis, it is determined how and what the expectations should be of the warehouse configurations for Haaften. This is mainly adjusted through consultation with Nedcargo. They can state several wishes that the possible configurations should achieve. Next to that, the current state analysis is being used to point out specific weaknesses in the current e-commerce warehouse operations. This is all because a lot of assumptions will come from the current state, and the configurations will be tailored for Nedcargo. This means that a lot of processes and choices will be assumed. Beneficial to the outcome, it should therefore focus on the weaknesses of the current state analysis and require changes to those weaknesses. Returning to the proof of configuration concept, implementing improvements in the current system as configurations can help to make it easier for design choices for Haaften. This all will be highlighted in the requirement analysis.

In the following paragraph, multiple model assumptions will be made. Model assumptions denote the collection of clearly stated (or implicitly premised) conventions, - choices, and other specifications on which the configuration models are based. Assumptions about the data are made based on the relationship between different variables, processes, strategies, storage, layout, and resources. These assumptions are either based on the current state analysis or in consultation with the experts of Nedcargo. This is in order to make the model as complete as possible with a sufficient amount of certainty about several choices, conventions, and specifications. This will be presented as a list to the reader.

The following paragraph will explain the different configurations that are being modelled. In this research, it is chosen to model three different types of configurations of warehouses. These configurations aim to quantify and visualize the potential outcome of performance factors. Again, these configuration choices will be based on consultation with Nedcargo and the findings in the requirement analysis. The processes and operations of the outbound logistics, which form the configuration, will aim to improve the current state and give insight into how they will react to different contextual influences. This section will focus on all the different design choices, picking strategy, routing strategy, storage, and layout of the warehouse. Together they form the configuration of the warehouse.

After the configurations are determined, they are modelled. By using Excel VBA, in combination with macros and PowerPivot, three configuration models are created. These models will be explained by looking at their input, the processing steps, and output. The output of the model will form the basis for the evaluation part of this thesis. Then the results will be presented and analysed. In this section, it will be explained how the configurations are being modelled.

Next to the configurations models, the current state is also being modelled. Primarily because for verification and validation of the models, it needs to be proved that the modelled data corresponds to the real-life data and if the model matches the concept proposed in section 8.3. If the obtained results can be verified and validated, good recommendations and conclusions can be constituted. The context in which the current warehouse of Nedcargo operates is known, so it will only be experimented with using the current context. This corresponds with scenario 50.

8.1 Requirement Analysis

This paragraph will discuss how and what the expectations should be of the warehouse configurations. It should be analysed how the current state configuration could be improved based on literature findings, consultation with Nedcargo experts, personal expertise, and data analysis findings. This brings out the conditions for future state configurations to be met. The weaknesses of the current state will be discussed, and required improvements will be addressed.

The new warehouse requirements can be divided into functional and non-functional requirements. Each of those requirements will result in a baseline of requirements that the warehouse configuration must implant. The requirements should be necessary and sufficient. The difference between functional and non-functional is that functional requirements are what the end-user (client) specifically demands as basic facilities. All these functionalities need to be incorporated into the system. These are represented or stated in the form of input to the system, the operations performed, and the expected output. They are basically the requirements stated by Nedcargo, which one can see directly in the new configuration models. Non-functional requirements are mostly quality constraints that the system must satisfy and elaborates a performance characteristic of the system. It has been decided to retain many of the (non) functional of the current configuration of Tiel. This paragraph will, therefore, only deal with the new requirements. Namely, the ones Nedcargo has expressed and the new requirements which can be improved based on insights. Strategies are not included and will be elaborated on in the following paragraphs.

The functional requirements are listed below in table 2 and explained afterward.

Table IV-2. Functional Requirements of Configuration Models

Functional Requirements of the configurations	*Explanation:*
-Productivity as high as possible	-Colli per hour as high as possible.
-As few pickers as possible	-Not more pickers than needed.
-Insight beforehand how many pickers needed	-Currently, they are randomly assigned based on the number of orders.
-All orders picked in about 8 working hours	-Picking operations are based on an 8-hour work shift.
-The layout must fit its context.	-The warehouse layout must be compatible with the context it operates.
-1 SKU with 1 Collo type orders must be collected as a batch	-To decrease the packing time, 1 SKU/1 Collo orders must be collected as a batch.

One of the functional requirements of the configurations is productivity. The current state analysis showed that the productivity is an average of about 112 colli per hour. Nedcargo aims to increase this productivity in their new warehouse. This means there is a need for new strategies or policies that can raise productivity. The configurations, therefore, need to be improved in comparison with the current system in Tiel. This is all so that its productivity will increase. Expanding this requirement can also be stated that there should be as few pickers as possible in the warehouse if the productivity is higher, so fewer pickers are needed to complete all the orders. During the current state analysis, it was concluded that Nedcargo in Tiel's operations does not have prior insight into the number of pickers required. This is one of the requirements that before the operations start must be explored. This insight into the number of pickers needed can decrease expenses and, therefore, is very interesting to look into.

This is in line with another functional requirement for the configurations, and that is that all the orders must be finished in about eight working day hours. The picking operations in the warehouse can not take longer than those eight working hours. An example is that if an order day takes about 15 hours, it needs 2 pickers to complete that order list for the day. On the other hand, if the picking operations take longer, i.e., 17 hours, three pickers are needed that order day.

Another functional requirement is that the layout must be as compacted as possible. What does compact mean? As can be seen in the heat map of Tiel, the SKUs are widely stored in the warehouse, which means that the travelled distance of the picker increases per trip. In consultation with Nedcargo, based on these findings, the conclusion was drawn that the SKUs must be stored as compact as possible in new configurations. This must be seen from an aisle perspective. Use as few SKUs as possible in the least amount of aisles. Next to that, the layout must fit its context. This simply means that if 500 products need to be stored, there must be available SKU locations in the warehouse for the 500 products. Where the products are stored is a strategic choice and therefore not a requirement and will be elaborated on in the next paragraph.

The following functional requirement is that orders which consist of 1 SKU visit and 1 collo to be picked must be collected in a batch. This is mainly a strategy but is also considered a functional requirement because the packing strategy will be adapted to this strategy. A design project conducted at Nedcargo before this study concluded that the packing operations would be more efficient if this strategy were implemented. An extensive explanation of this strategy will be given in the following paragraphs.

Table IV-3. Non-Functional Requirements of Configuration Models

Non-Functional Requirements of the configurations	*Explanation:*
Conventional racking is not necessary	It can be assumed that the conventional way of racking is not necessary.
Future possibility for automation	The system should be adaptable to future automation possibilities.

As shown in the table, there are not many non-functional requirements to consider. This is since the configurations are considered in the proof of configuration theory. This means that a broad perspective is maintained for proof of these configurations. If the performance and operations are known, more non-functional requirements must be considered for the actual design process. The first non-functional requirement that Nedcargo experts mentioned was that for the new configurations, the conventional racking was not necessary. It, therefore, was possible to look at smaller SKU locations or possibly 2-floor picking. This is non-functional because it is difficult to quantify this in the model but should be considered while creating the configurations.

The following non-functional requirement is the future possibility of automation. In the long term, Nedcargo will be investigating automation in the warehouse. This means that it should not prevent this from being possible.

These functional - and non-functional requirements together must meet the quality standards set by Nedcargo for the configurations. These features are determined based on consultation, literature research, and data analysis. The next step before crafting the configurations is the assumptions that need to be made. The assumptions are crucial to scope how comprehensive the configurations must be modelled and designed. The next chapter will elaborate on the assumptions made.

8.2 Model Assumptions

In the academic environment, making assumptions is vital as the research statement of the problem when determining the new configurations of the warehouse for Haaften. For the configurations, certain operations, strategy, design, and resource choices are assumed as accurate. This is based on literature findings, data analysis insights, current state analysis, and consultation with experts. The configurations can be built step-by-step to produce working configuration models when these assumptions are known. Therefore, these model assumptions function as means for the functionality of the configuration models and must be chosen consistently and accurately. There are three types of assumptions, conceptual, mathematical, and numerical assumptions. Each category will be discussed.

8.2.1 Conceptual assumptions

This class of assumptions concerns idealizations and simplifications of the warehouse configurations that are being modelled. A table is created with each of these assumptions numbered. The table is pictured below, and a further explanation of those assumptions will be presented in the table:

Table IV-4. Conceptual assumptions of the configurations models.

Conceptual Model Assumptions	*Explanation*
1. The configuration models are based on the picker-to-goods warehouses' concept.	For the configuration models, it is chosen to look at PTG warehouses. So the pickers move to the products that need to be picked in the configuration models.
2. The pickers are human laborers.	The pickers are humans in the configuration models and act like one. The data collected from Tiel can substantiate specific picker actions.
3. Conventional rectangular layout (width and length of Haaften).	The warehouse is a rectangular space. This is reflected in the context analysis.
4. Pickers can move freely through the aisles.	Pickers can move freely through the aisles and warehouse. In the model, congestion is not accounted for. Therefore the assumption is that the picker can move freely and do not have to wait for other pickers or warehouse employees.
5. Picker ergonomics are not accounted for.	The configuration models do not account for any ergonomics of the pickers. Basically, ergonomics is the way the job is performed, and employers can change their work to better suit the needs of their employees. Because of the proof of configuration method, it is chosen not to include ergonomics in the model.
6. Product characteristics are not accounted for.	Nedcargo's current e-commerce warehouse is based on colli picks. That means that most of the items to be picked are already packaged. Those boxes to be collected are therefore considered quite similar to each other, and the same characteristics shall be maintained.
7. Packing Station (P/D point) in the bottom left of the layout.	Most warehouses have their packing station in the bottom left of the warehouse. This is also the case in Tiel. The model can dynamically change its packing station, but for the sake of this study, it is chosen that for each configuration model, the packing station will be positioned in the bottom left corner.
8. Equipment tools same as in Tiel (scanner, picker cart, etc.)	The equipment tools used in the configuration models will be the same as in Tiel. This is due to the fact that Nedcargo's pickers are known with the equipment, and there is data available about the usage. Therefore, this data knowledge can be used to quantify the processes the pickers perform.
9. No quantitative congestion restrictions accounted for.	This assumption can be considered together with assumption 4. In the configuration models, the delay due to congestion will not be accounted for.
10. Storage, picking, and handling equipment always work correctly.	This is an extension of assumption 8. The model is not accounted for any deficiency or failures of equipment. It is therefore assumed that every piece of equipment used in outbound logistics is working correctly and consistently used. So no reliability issues.
11. The inbound logistics of the warehouse are working correctly.	The inbound logistics are out of the scope of this study. Therefore in the configuration model, the receiving,

	put-away, and replenishment processes are considered as functioning correctly and should not cause any deficit in the outbound logistics processes.
12. There is a safety stock on the 2nd level racks.	This is an inbound strategy choice of Nedcargo. This means that there is always enough stock because the pickers can replenish from the safety stock, which is located at the 2nd level of the racks where the SKUs are stored.

8.2.3 Mathematical assumptions

This class of assumptions concerns assumptions around the mathematical representation of the configurations that are being modelled. These are implicit or explicit choices about distributions and dependencies. This is also the choice of parameter fitting, which is done with the Experiment Model explained in section 7.2. A table is created with each of these assumptions numbered. The table is pictured below, and further explanation of those assumptions will be presented in the table

Table IV-5. Mathematical assumptions of the configurations models.

Mathematical Model Assumptions	*Explanation*
1. Fixed time per colli has a uniform distribution.	A more extensive explanation will be given in the next chapter, which explains the configurations. But it means that there is a particular distribution based on the data analysis of the current state that will be held in the configurations models. By the fixed time is meant the time each SKU visit takes. So for every stop for an SKU, each pick is in an order. Think of the stop time, scan time, search time, etc.
2. Variable time per colli has a uniform distribution.	A more extensive explanation will be given in the next chapter. There will be assumed that a specific distribution is maintained for the variable time of an SKU visit. This distribution is based on the data analysis of the current state in Tiel. The variable time means the time each colli needs per SKU visit. Think of the picking time of one collo and the extra time needed if multiple colli needs to be picked at an SKU location.
3. Idle Time of Picking tour has a uniform distribution	A more extensive explanation will be given in the next chapter. There will be assumed that particular distribution of time is assumed or the idle time between picking tours. This distribution of idle time is based on the data analysis of the current state of Tiel. By idle time is meant the time that the complete orders are returned, the picker cart is disconnected, and preparation is made to pick up new orders.
4. The speed of the human picker on the reach truck is constant	The speed of the reach truck is known and is in the model taken as a constant. Because the accelerating, constant speed, and decelerating are explored together in the data analysis, it is chosen to set the speed of the reach truck as a constant. More about this in the explanation and quantification of the configurations.
5. ABC-Analysis turnover is based on, respectively, a 75% - 20% - 5% distribution.	As mentioned in chapter 7.2, the ABC analysis turnover is based on a 75/20/5 distribution. This means that every SKU considered an A product provides for 75% of the volume turnover, respectively 20% volume turnover for B-products and 5% for C-products. This is implemented in the models together with the ABC ratio of the contextual factor of the scenarios. It is chosen based on the data analysis of Tiel, in which this

	volume turnover distribution was found. This is also widely considered plausible in warehousing literature.
6. If there is a cross-section aisle, this will be at 60% of the warehouse's length.	Nedcargo is familiar with a cross-section aisle. It is currently used in multiple active warehouses of them. A cross-aisle section is a horizontal lane through a vertical conventional racking layout. This assumption states that every cross-section aisle in the configuration model is located at 60% of the active length of the warehouse. This assumption is made because it is also used in the current states.

8.2.2 Numerical assumptions

This class of assumptions concerns assumptions around the explicit selection of numerical values of the configurations that are being modelled. It represents quantitative choices that are there to be made in order to create a sufficient configuration model. Therefore certain assumptions are chosen as given in consultation with Nedcargo. A table is created with each of these assumptions numbered. The table is pictured below, and further explanation of those assumptions will be presented in the table

Table IV-6. Numerical assumptions of the configurations models.

Numerical Model Assumptions	*Explanation*
1. 300 orders per day.	The amount of orders that need to be handled in each experiment is set at 300 orders. It is chosen to keep a constant demand to see whether the productivity is dependent on the order characteristics and not on-demand characteristics. This is an essential assumption in this study. The models are nevertheless dynamic. Thus, future research can increase or decrease the number of orders.
2. Three SKUs per location.	A location is meant as a storage place for SKUs. E.g., in Tiel, it is possible to store four different SKUs in one location. For the reason that Nedcargo requires their warehouse to be more compact. It is chosen to store three different SKUs at each location. Therefore the width of the locations can be smaller.
3. The 12 SKUs locations closest to the P/D point are reserved for the 12 most visited SKUs	In the model, these SKUs will be referred to as AA-products. In the current state data analysis, it is seen that a small number, i.e., 12, of products are picked much more often than the other products. Just as explained in the Experiment Generation model chapter, an exponential decay formula can be used to describe its SKU visit characteristics. Because it is unknown where the product must be placed in which context, it is therefore assumed that the 12 "AA" products are stored the closest to the P/D point.
4. A batch consists of 4 orders.	The batching strategy is a component of the configurations that can be improved the most, as seen in literature, the data analysis, and personal belief. However, an assumption must be made as to how many orders a batch contains. In Tiel, they batch with an FCFS-strategy, and the batches exist out of 4 orders. It has been decided to keep this batch size also at 4 orders so that the picker productivity can

	be copied. This is because now the pickers do not have to get used to the new batch size.
5. The notation of the data will be the same as the WMS of Tiel.	These assumptions are based on the numerical expression of the model. The assumption is made to record the notation of the data as similar as possible to Nedcargo's current WMS. This is so that the data can be understood more quickly and easily.

Now that the three categories of assumptions are presented and explained. In addition to the Experiment Generation model, which explains how the contextual factors of order characteristics can generate a dummy order day, the requirements of the model are covered. We can start looking at the configurations. The input, the requirements, and the assumptions of the model are known. The following paragraph will elaborate on the different configurations and which strategy, layout, storage, and routing choices are made.

8.3 Configuration 1

In the following paragraphs, each configuration of a warehouse of Haaften will be elaborated on. The previous chapters focused, among other things, on warehouse literature and the current state analysis. Based on these insights, different configurational choices for the warehouse are being made. This is in combination with the requirements and assumptions raised by this study. These configurations can be seen as possible configurations for the new e-commerce warehouse of Haaften. As indicated, the context of the order characteristics of Haaften is currently unknown, and therefore different context scenarios must be investigated. These scenarios are chosen by Nedcargo and converted into experiments with the Experiment Generation model, presented in chapter 7. These experiments can be considered a dummy order data set, which will act as the input for the configuration models. So this contingency input, with the response variables of the configuration model, must eventually lead to the performance of the different configurations. This so-called contingency approach should enable this study to prove that specific configurations perform better or differently in a given context.

This section is structured as follows: for configuration 1, its choice of layout, storage, picking strategy, and equipment will be elaborated. There are a total of three configurations, and each is a bit different from the other. All the operations, resources, and design choices have been made based on literature insights and improvements for the current state based on data analysis and in consultation with experts.

8.3.1 Picking Strategy

Firstly, we take a look at the picking strategy. The focus of configuration 1 is mainly on improving the picking strategy. In Tiel, we noticed that an FCFS (first come, first serve) batching strategy is followed and is stated to be inefficient. Both insights from Tiel and the found literature will determine the new batching strategy.

This study considers three types of picking strategies: the so-called "SinglePick" strategy, the star aisle batch strategy, the First Come, First Serve strategy, and the SinglePick combined with the star aisle batch strategy. These strategies will be explained except for the FCFS strategy, which is already explained in the current state chapter.

8.3.1.1. The SinglePick Strategy

What is striking from the data analysis is that the majority of orders contain 1 SKU pick a moment from which 1 package is picked. In the 2021 data of Tiel, this equals 16% of the total orders, which can be seen in table III-6 and III-7. This type of order characteristic, consisting of just a few order lines with low collo quantities, are the biggest challenge for e-commerce retailers. Traditional picker-to-goods warehouses such as Tiel are often ill-suited for these prerequisites (Boysen et al., 2019). A possible different batch picking strategy will be explained, which can possibly help to address these types of order characteristics mentioned beforehand, namely the SinglePick strategy.

In the current process in Tiel, this is still carried out based on one trip for the picker per four orders. So even if the picker only has to pick one collo from one SKU, that will be 1 of the 4 trips out of a tour. Although a trip consists of four orders, in practice, 4 colli could be picked up intended for 4 orders. It may also be interesting for Nedcargo to see whether a different way of thinking could influence the entire pick and pack process.

Suppose now that the choice is made to pick all 1 SKU with 1 collo order in a batch. Order batching means that orders are grouped into batches and picked in a single tour to save on travel time.

This means that, on average, 36 orders per day in Tiel can be picked up in as few trips as possible, preferably 1 trip. This is possible because the packer does not need to look at which customer needs which product, but rather which product belongs to which customer. This is because the packer knows, with this type of order characteristic, that all the packages on the particular load carrier are equal to the number of shipping boxes it needs to be in. This will also reduce human error. This will create a shift from picking based on customer-to-product toward product-to-customer picking. An additional hypothesis could therefore be that the number of trips made by the picker will go down as a large number of orders can now be picked up in bulk. This strategy will be quantified in the models and shown the effect on the performance measures. So every SinglePick order (1 SKU with 1 collo) will be collected as a batch and will only consist of one tour instead of considering these orders as a separate trip, which the pickers currently do in Tiel. In appendix D, figure 1, a simplified way of thinking is illustrated in the SinglePick Strategy.

8.3.1.2 The Star Aisle Batch Strategy

Before we begin explaining this strategy, it is essential to mention that another author's paper inspired it. Aboelfotoh et al. (2019) paper called "Order Batching Optimization for Warehouses with Cluster-Picking." The paper focuses on optimizing the static order batching problem with multiple pickers. Before explaining the strategy and conclusions of this paper, It is important to mention that we have been in contact with Aboelfotoh et al. to ask for permission to investigate her findings further by using the algorithm proposed in her research. The algorithm is modelled in our way but based on her explanation of the model in the paper.

The star-aisle batching strategy is a simplified aisle-by-aisle heuristic. The heuristic considered various parameters such as item location, order details, detailed layout of pick area, and the maximum number of orders allowed per batch. The heuristic is based on six steps which are shown below.

Step 1: Define star aisle k
Step 2: Generate star aisle vector X^*
Step 3: Generate order aisle vector X^i for each order
Step 4: Choose the first order for this assignment based on the minimum sum of squared distance S_i of order i
Step 5: Update the star aisle vector X^*
Step 6: Group next order
For each order i, calculate its sum of the squared distance S_i to star aisles and assign the order with the least S_i.
Is the number of orders grouped greater than the maximum number of orders that van de assigned in one batch assignment?
Then go to Step 1
Else, go to Step 5

$$i = order\ index$$
$$k = batch\ index$$
$$j = aisle\ index$$

$$n = number\ of\ orders$$
$$a = number\ of\ aisles$$
$$B = Batch\ Size$$
$$N_a = Number\ of\ aisles\ visited$$
$$A_{last} = last\ visited\ aisle$$

This is all we need to know to understand the algorithm proposed by Aboelfotoh et al. (2019) and is adjusted to be configured for Nedcargo data as well. We will start by explaining the algorithm step-by-step.

The algorithm starts by distinguishing the most frequently visited aisle by all orders and calls it $star\ aisle\ k$. In the case of a tie, the heuristic chooses the smallest aisle number. During step 2, the star aisle vector $X^* = [x_1^*, x_2^* \ldots x_a^*]$ for each order is determined and x_j^*=1, if order i visits (star) aisle j. So if the j is equal to k, and 0 otherwise. Step 3 determines the order aisle vector for each order index i. $X^i = [x_1^i, x_2^i \ldots x_a^i]$ x_j^i = 1, if order i visits aisle j, and 0 otherwise. Step 4 determines the sum of squared distance S_i between each order i and the star aisles using the following equation. When for each order, this sum of squared distance is found in the order with the least amount of S_i is denoted as order h and is the first order assigned to the first batch. For clarification, a numerical explanation is given of the below formula with the input of table 7.

$$S_i = \sum_{j=1}^{a} \sum_{j*=1}^{a} (j - j^*)^2 \qquad \forall x_j^i = 1 \ \ \forall x_j^* = 1 \ \ (2)$$

Table IV-7. Order information for the example problem.

Order	1	2	3	4	5	6	7	8	9	10	11	12
Aisles	1,2,5	2	2,3,5	1,2	3,5	5,6	6	3,6	1,2,4	2,4	5,6	4,5

Numerical example: Table 7 shows that order 3 requires packages from aisle numbers 2, 3, and 5. Aisle 2 is the most frequently visited aisle; therefore, aisle 2 is defined as the star aisle. This translates for order 3 to $x_2^3, x_3^3, x_5^3 = 1$ and $x_2^* = 1$. Applying the sum of the squared distance equation from above, this corresponds to $(2-2)^2 + (3-2)^2 + (5-2)^2$ and resulting in a total sum of square distance S_3 of 10.

Next, the star aisle vector $X^*$is updated in step 5 by checking the following conditions for all the x_j^* elements in the vector, if x_j^* = 0 and $x_j^h \neq 0$, then change x_j to equal 1, otherwise x_j^* remains the same. Finally, in step 6, it is determined which is the following order to group, again based on the sum of the square formula. Likewise, the order with the minimum S_i is chosen in the following order to group and is denoted as h. If the number of orders grouped in the current batch has reached the maximum capacity of the batch size, then return to step 1. Otherwise, return to step 5 and update the star aisle vector $X^* = [x_1^*, x_2^* \ldots x_a^*]$.

To clarify what the heuristic calculates for each step, we can present an example. Table 8 shows the implementation of the star aisle batch strategy on the example problem given in table 7.

Table IV-8. Order information for the example problem.

	Order i	1	2	3	4	5	6	7	8	9	10	11	12
1st order	**j**	1,2,5	**2**	2,3,5	1,2	3,5	5,6	6	3,6	1,2,6	2,4	5,6	4,5
	$(\boldsymbol{j-2})^{\mathbf{2}}$	1,0,9	**0**	0,1,9	1,0	1,9	9,16	16	1,16	1,0,16	0,4	9,16	4,9
	$\boldsymbol{S_i}$	10	**0**	10	1	10	25	16	17	17	4	25	13
	Order i	1	-	3	4	5	6	7	8	9	10	11	12
2nd order	**j**	1,2,5	-	2,3,5	**1,2**	3,5	5,6	6	3,6	1,2,6	2,4	5,6	4,5
	$(\boldsymbol{j-2})^{\mathbf{2}}$	1,0,9	-	0,1,9	**1,0**	1,9	9,16	16	1,16	1,0,16	0,4	9,16	4,9
	$\boldsymbol{S_i}$	10	-	10	**1**	10	25	16	17	17	4	25	13
	Order i	1	-	3	-	5	6	7	8	9	10	11	12
3rd order	**j**	1,2,5	-	2,3,5	-	3,5	5,6	6	3,6	1,2,6	**2,4**	5,6	4,5
	$(\boldsymbol{j-2})^{\mathbf{2}}$	1,0,9	-	0,1,9	-	1,9	9,16	16	1,16	1,0,16	**0,4**	9,16	4,9
	$(\boldsymbol{j-1})^{\mathbf{2}}$	0,1,16	-	1,4,16	-	4,16	16,25	25	4,25	0,1,25	**1,9**	16,15	9,16
	$\boldsymbol{S_i}$	27	-	31	-	30	66	41	46	47	**14**	56	38
	Order i	1	-	3	-	5	6	7	8	9	-	11	12
4th order	**j**	1,2,5	-	2,3,5	-	**3,5**	5,6	6	3,6	1,2,6	-	5,6	4,5
	$(\boldsymbol{j-2})^{\mathbf{2}}$	1,0,9	-	0,1,9	-	**1,9**	9,16	16	1,16	1,0,16	-	9,16	4,9
	$(\boldsymbol{j-4})^{\mathbf{2}}$	9,4,1	-	4,1,1	-	**1,1**	1,4	4	1,4	9,4,4	-	1,4	0,1
	$\boldsymbol{S_i}$	24	-	16	-	**12**	30	20	22	34	-	30	14

The heuristic in table 8 starts with defining the most frequently visited aisle of all the orders, which is in the example aisle 2. Then, the order to star aisle sum of squared distance is calculated for all aisles j required by all orders for star aisle 2. Therefore, order 2 is the first order to be assigned to the first batch, based on a minimum sum of squared distance S_2 of 0. Order 2 only consists of aisle 2, so the same sum of squared distance formula is held. Order 4 is assigned next to the current batch, using the same procedure as the 1st order assignment. Since order 4 requires aisles 2 and 1, the star aisles are updated accordingly to step 5 in order to include aisles 1 and 2. Order 10 is then assigned to the next batch, using the same procedure as the previous orders with S_{10} =0+4+1+9=10. As a result, the star aisle is still 2 but based on the previous order 10, aisle 4 is added. Finally, order 5 is assigned to complete the batch. Since the maximum orders per batch are reached for the current batch. The process starts again with the remaining orders at step 1 to define a new star aisle.

The table below shows the final batching results using the star aisle batch heuristic strategy. The number of aisles visited gives an insight into the number of aisles to be visited and the

Table IV-9. Order information, for example, problem.

Assignment	Batch 1				Batch 2				Batch 3			
Order	2	4	10	5	6	7	11	12	9	3	8	1
Aisles	2	1,2	2,4	3,5	5,6	6	5,6	4,5	1,2,6	2,3,5	3,6	1,2,5
Aisle Visited	1,2,3,4,5				4,5,6				1,2,3,5,6			
N_a	5				3				5			
A_{last}	5				6				6			

Aboelfotoh et al. (2019) compared three different picking strategies. A mixed-integer programming method, the star aisle heuristic, and the First Come, First Serve strategy. They concluded that the FCFS is a fast and straightforward approach, but for every order size, it results in a significantly higher traveling distance which consequently increases the picking time in the warehouse. The following conclusion was that if more than 50 orders were in the data set, the MIP method did not produce a lower total travel distance than the star aisle heuristic. Even after a computation time, that was way more than the star aisle strategy.

On the other hand, the star aisle heuristic computation time stays low and for more than 50 orders gives less total distance than the other methods. Therefore, this strategy is beneficial because this study consists of 300 orders and has 30 experiments to run. In which each experiment has 10 iterations. The computation time has to be fast, and the order size is of a size that performs better than optimization models. For this reason, the star aisle batch heuristic could be a good fit for the configuration of Haaften. Therefore it is chosen for configuration 1 to implement the star aisle batch strategy into the model.

8.3.1.3 The Star Aisle Batch - combined with the SinglePicks Strategy

Since the SinglePick strategy has not been quantified in literature, it is more interesting to see how it will perform if combined with the star aisle batch instead of the FCFS strategy. This is based on the findings in the literature that heuristics or optimization models outperform FCFS. Therefore for this study, it is chosen to also combine the two in configuration 1. This means that first, the SinglePick orders are batched and after the remaining orders are batched following the star aisle heuristic. This can be seen as a new picking strategy and, therefore, will be compared with both the star aisle strategy and the FCFS strategy in different warehouse contexts. To see whether it has any effect on the performance of the warehouse. Both its quantification and exploration have not yet been seen in warehousing literature.

8.3.1 Routing Strategy

The routing strategy is a strategy by which the route through the warehouse is determined. The route is the path of the picker in which you pass all items of an order. The orders obviously influence the route it has to pick and determine the length. Just as in the current warehouse of Tiel, the shortest route strategy is maintained for configuration 1. The shortest path solution finds the shortest path between two nodes in the warehouse, with the nodes representing the SKUs that have to be visited. The shortest route algorithm is valuable since it can be used at each SKU to determine the shortest distance between that location and the rest of the order’s location. This is reasonably practical. The starting point of the order is always at the P/D point, which is located in the bottom left of the warehouse. It moves to the nearest aisle, from which SKUs need to be picked in the batch. Important to note that all the SKUs of an aisle are first visited before moving to the next aisle. When the last SKU of the aisle is visited from a particular batch, it then chooses the closest aisle and SKU to be picked next. This route is then offered to the picker, and he will follow it. The cross-aisle can be seen as a decision variable if the picker travels via the cross-aisle or not. Cross aisles provide greater flexibility in the routing of order pickers, thus providing shorter order picking travel distances (Vaughan, 1999). There is a cross-aisle section at 60% of the warehouse's active length in this configuration. If the pickers end at an SKU whose route is shorter when traveling through the cross-aisle, the routing strategy will then decide that he will traverse the cross-aisle. How the strategy is precisely modelled will be explained in the next chapter.

8.3.2 Warehouse Layout

The table below shows the characteristics of the warehouse layout of configuration 1.

Table IV-10. Warehouse layout information of configuration 1

Warehouse Length	62,1	*Meter*
Warehouse Width	48	*Meter*
SKU per Location	3	*SKUs*
Cross Aisle Section	Yes	
Pick Location Length	2,7	*Meter*
Pick Location Width	2,5	*Meter*
Aisle Width	3	*Meter*
Pick Locations per Aisle	44	*Locations*
AA-Locations	4*3=12	*SKUs*

As can be seen, is the warehouse's length and width 62,1 meters and 48 meters. The warehouse length is based on the pick locations per aisle, namely 23 locations on each side, every 2,7 meters in length. This results in a length of 62,1 meters of the warehouse. The width is based on the maximum amount of SKUs that the experiments have, so 750 SKUs. If all these SKUs need to be stored in the warehouse, a total of 6 aisles are required. Therefore, this is the configuration's maximum amount of aisles, which gives a width of 48 meters—more about the storage strategy of the configuration in the next paragraph. Configuration 1 does have a cross-aisle located at 60% of its warehouse's length. The pick location has a width (or depth) of 2,5m and a length (or width if you stand in front of it) of 2,7m. This is chosen because it can easily store three euro pallets next to each other and one (even two) behind. The aisle width has a width of 3 meters. A reach truck has to operate in this configuration, and this can use a narrow aisle. The minimum width that an aisle can have when using a reach truck is 9 feet, so approximately 3 meters is allowed. In appendix D, figure 2, the minimum aisle width per forklift type and according to rack layout is shown. Lastly, are the number of pick locations, which are stored with three SKU each, in the warehouse. This is the same amount as in Tiel, so 44 locations per aisle. The so-called AA locations, reserved for the 12 most visited SKUs, are nearest to the P/D point. These are the characteristics of the layout of configuration 1 that will be modelled.

8.3.3 Storage

The storage strategy is how you determine where to store the SKUs/products. As mentioned in the previous paragraph, there is room for 44*3=132 SKUs per aisle. The current state data analysis showed in the heat map in appendix A, figures 11 and 12, that the SKUs were stored quite randomly and widely spread over the active aisles. One of the requirements of the new configurations is that the warehouse must be as compact as possible, which means that this spread of products over multiple aisles is not preferred. First, it is crucial to choose the configuration strategy to store its SKUs. Figure 6 shows the ABC-class-based storage strategy from Yu & Koster (2010).

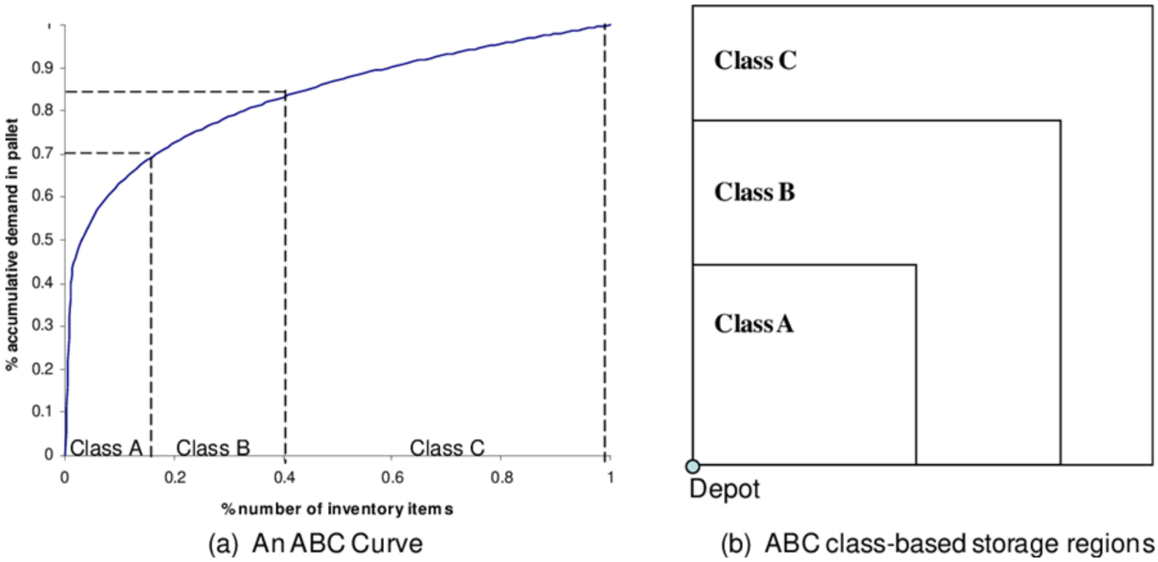


Figure IV-6 – ABC-Class-Based analysis and ancillary storage strategy

This is the strategy that will be adopted in the configurations. The storage strategy means that it will be stored in the warehouse based on the class that a product is in. This is called an ABC-class-based storage strategy. So, if a specific SKU is an A-product, it has to be stored nearest to the depot. This is due to the reason that it has to be picked more often. Thus, this strategy will decrease the traveling distance of the pickers. The ABC ratio and the number of SKUs affect the storage assignment in the model, which are contingency variables. These variables differ per experiment, and that is why the model must be dynamic. This will be further explained in the configuration models section.

That leaves the question, how is each specific product assigned to an SKU location? Beforehand, it is known through the experiments how many products are A, B, and C. Based on that information, the storage assignment can be formed so that all the A products must be stored in the nearest SKU locations from the P/D point. The same goes for B-products in the second closest SKU locations and C-products in the third closest. Each of the locations has a location ID, and each of the SKUs is to be stored as an ID. The model then randomly assigns each SKU ID to a location ID, resulting in three SKUs having the same location ID. This is done for all A, B, and C products, except for the AA products. These 12 SKUs are always randomly assigned to the 4 nearest SKUs from the P/D point. After this, it can be generated how and where the SKUs are stored for each context. The model chapter will explain how this is implemented in the model.

To conclude, the storage assignment is based on an ABC-class-based assignment. Which stores the most visited SKUs the nearest to the depot. Based on their characteristics, the SKUs are assigned randomly to a location in the configuration. This is done in a manner that the stored products are as compact as possible. So there are no widely spread locations in the warehouse as we saw on the heat map at Tiel. It, therefore, always generates the least amount of aisles needed for the number of SKUs to be stored. How this is modelled will be explained in the Configuration Models chapter.

8.3.4 Equipment and Picking Speed

Equipment in the warehouse operations is primarily crucial for the picking speed. Most of the picking activities are performed by human action. But many of those actions are supported by the equipment. Think of scanning the colli and SKUs through a scanner, the pickers who move through the warehouse using the picker cart. This all influences the total time in the system. It is chosen for configuration 1 to use the same equipment as in Tiel. This is due to the data already gathered, which allows us to quantify each action that a picker has to conduct. The model has several actions that need to be quantified to justify the picker's speed. This by using the data from Tiel. We will each discuss them.

First is the speed of the picker cart. By analysing the data from Tiel and with the consultation of the warehouse manager of Tiel, the speed of the picker cart is set at a constant of 5,7 km/h or 1,58 m/s. This means that the picker will always travel at a constant speed on its cart in the model, so there is no accelerating or decelerating. Since this emerged from the data analysis, actually, the acceleration and deceleration are already included in this speed. Now that the speed is known of the picker cart, the distance can be measured through the route that is needed to collect the batch. The model can calculate how long the driving time along the route will be, including the trip back to the P/D point from the last pick of the batch.

Next is the picking speed, which processes can be found in the IDEF-0 discussed in the current state. It is stated that the picking speed consists of a fixed time and a variable time. Fixed time means the pickers have to make at every stop irrespective of the amount of colli to be picked. Think about getting off the picker cart, searching time, the scan time of the SKU location, and preparing the picking. This is quantified using table III-14 of the data analysis, and it was decided to distribute this using a continuous uniform distribution. The fixed time in the model is a value between 15 and 30 seconds. This is based on an average of 23 seconds and a mode of 16. The variable time per SKU visit is based on the amount of colli that needs to be picked. If there are more colli to be picked, the picking time increases. Nedcargo researched to quantify the extra time needed per extra colli to be picked. They stated that it could also be seen as a continuous uniform distribution. Their findings showed that for each colli to be picked, the picker takes about 4 to 9 seconds per colli. The fixed time plus the variable time gives the picking time per orderline (SKU visit).

The last time measurement is idle time. This is also gathered from the data analysis of Tiel. The idle time is the time between each picking tour. Several things can occur in idle time. The actions that each time occur are disconnecting the picker cart at the packing station and the preparations for the new picking tour. This may include, for example printing the new order list and attaching new picker carts. What also is implemented in the idle time can be a break. Think of a toilet break or lunch break for the picker. This can be the case because the idle time comes from the data of Tiel, which is real-life data.

The idle time data of two picking tours can be significantly higher than other tours because of, e.g., a lunch break. That is why the average has been in table III-15 in the data analysis with a slight deviation based on the mode. This results in an idle time in the model of a time value between 150 and 400 seconds.

To conclude, each picking tour takes a certain amount of time. This time is based on the equipment available to the picker. Configuration 1 is chosen to use the same equipment as in Tiel. Therefore the data of the time measurements in Tiel can be used as quantification for the time measurements in the model. To complete one picking tour and start with the next tour, the time that is needed is based on the fixed time per orderline, the variable time per colli per orderline, the driving time of the route, and the idle time before the next picking tour starts. In the model explanation, it will be shown how this is modelled in the configuration model.

8.4 Configuration 2

As indicated earlier, the configurations are very similar to each other. This study has made a choice only to tweak them a little bit. Configuration 1 has made some significant changes from the current state, which are substantiated by literature and data analysis to improve its current operations. Configuration 2 copies all of these changes and adds an extra element to this, namely, in the storage assignment.

Each day is different at a warehouse. This is due to the reason that every day it receives new orders with different characteristics. This is what we call the context of the warehouse. Is there a way how we can benefit from this? In configuration 2, a new strategy is implemented: the “Dynamic SKU Locations.” The dynamic SKU locations are locations in which, at the beginning of each experiment is analysed if there are SKUs that day that have (1) a high demand that given day or (2) two SKUs that are affiliated with each other that day. If so, would it benefit to bring these SKUs closer to the depot? This means that a product far away from the depot will be placed closer to the dynamic SKU location. Will that decrease the travel time and therefore increase productivity?

The Dynamic SKU locations are 2 locations that are next to the AA locations. So there is a place for 6 SKUs each day. Before the start of the experiments, it is analysed if there is an SKU that needs to be visited multiple times that day that is not placed near the packing depot. It can then be moved by an inbound employee to the dynamic SKU location so that the picker decreases its picking distance since it is now closer to the P/D point. Next to that, a second analysis is made before the picking starts. To see whether two SKUs are affiliated with each other. An affinity analysis checks if SKUs are likely to pair in an order. If two SKUs are often picked in an order together, as seen in the Tiel analysis with the milk powder and cacao powder. Then the warehouse manager can decide before the operations start to move those SKUs to the exact location at the dynamic SKU locations. This is in order to also decrease the travel time in the warehouse for the picker.

The strategy of configuration 2 is a hypothesis and has not been seen or quantified in the literature. Therefore it is a hypothesis that the travel time will decrease because of the less travelled distance for the picker. And if the context of the warehouse can influence the functioning of the strategy. This has to be concluded in the result chapter, where the performance will be discussed. How this is modelled in the configuration model will be explained in paragraph 8.6.

8.5 Configuration 3

Configuration 3 also adopts almost everything configuration 1 has and only differs in one type of strategy. Namely, the routing strategy. In configurations 1 and 2, the routing strategy was based on the shortest route algorithm. In configuration 3, this is based on the s-shape routing strategy. The s-shape routing strategy leads to a route in which the aisles that need to be visited for completing the batch are traversed totally. Aisles, where nothing needs to be picked, are skipped. It is called an S-shape strategy because the aisles are visited in shape of an S. The picker, therefore, enters the aisle on one side and leaves the aisle from the other side. This strategy is commonly used in a warehouse because it is easy to understand for the picker, and it decreases the change of congestion (De Koster, 1998). Since congestion is one of the qualitative performance measures in this study. Configuration 3 will focus on the s-shape routing strategy and how it will affect the performance in a certain context. Nedcargo can decide if they find it beneficial to switch to the s-shape strategy if they see that the other configurations lead to congestion. Then they have the insights into the model into what a potential switch of routing means for their performance. In this configuration is chosen not to go with a cross-aisle section. Next to that, the width of the aisles will become slightly smaller. This is for the reason that there is less chance of congestion, and the pickers traverse only one way in the aisles. The below table shows the layout characteristics of configuration 3.

Table IV-11. Warehouse layout information of configuration 3

Warehouse Length	62,1	*Meter*
Warehouse Width	44,4	*Meter*
SKU per Location	3	*SKUs*
Cross Aisle Section	No	
Pick Location Length	2,7	*Meter*
Pick Location Width	2,5	*Meter*
Aisle Width	2,4	*Meter*
Pick Locations per Aisle	44	*Locations*
AA-Locations	4*3=12	*SKUs*

How can we calculate the distance using the s-shape strategy? Each batch includes multiple SKU pick locations. Every SKU has to be visited once and could be located in multiple aisles. The distance travelled consists of the distance within the visited aisles and the distance between the visited aisles. The layout is based on the fact that every aisle that is in the model has an active SKU in it, so it is not possible to make it any more compact. Figure 7 gives an example of a warehouse with an s-shape routing strategy.

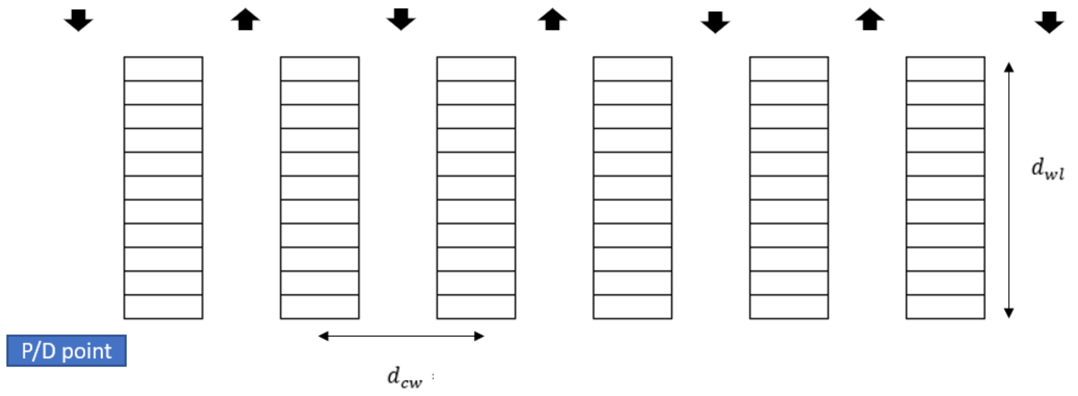


Figure IV-7 – Example of Warehouse Layout where S-routing strategy is maintained

In order to calculate the in-aisle distance of the batch, the number of aisles that should be traversed in the batch or N^b_{aisles} is multiplied by the aisle length. Every picking route starts and ends at the P/D point, and it is not allowed to traverse an odd number of aisles (aisle 1 goes up, 2 goes down, 3 goes up, etc.).

Therefore the number of aisles is rounded up to the nearest even number by dividing it by two, taking the ceiling, and multiplying it back by two. This formula looks like this:

$$In - aisle\ distance = 2 \cdot \left(\left\lceil \frac{N^{b}_{aisles}}{2} \right\rceil \cdot d_{wl} \right) \quad (3)$$

$$Where:$$

$$d_{wl} = Lenght\ of\ the\ warehouse$$

$$N^{b}_{aisles} = number\ of\ aisles\ visited\ in\ batch\ b \qquad b\ \epsilon\ B$$

The distance between aisles, or to cross the aisles, is needed to switch from the one aisle to the next aisle. This distance is dependent on the width of the aisles and the depth of the SKU locations, and this is notated as d_{cw}. Those two can be different based on the pallets that are stored. This distance between aisles can be decomposed into two parts: the distance between the depot and the start of the farthest (last) aisle to be picked and the distance back from the end of the last visited aisle. It is assumed that these distances are symmetric, which means that from x to y is the same as from y to x. Thus, afterward, the formula must be multiplied by two. The following formula is needed to calculate the distance between the aisles.

$$Between - Aisle\ Distance = 2 * d_{cw} * A_{last} \qquad (4)$$

$$Where:$$

$$d_{cw} = cross\ lenght\ between\ 2\ aisles\ (or\ distance\ between)$$

$$A^{b}_{last} = Last\ aisle\ to\ be\ visited\ in\ batch\ b \qquad b\ \epsilon\ B$$

Combining the two previous formulas, thus the distance covered within the aisles and the distance covered between the aisles gives:

$$d_b = 2 \left(\left\lceil \frac{N^{b}_{aisles}}{2} \right\rceil \cdot d_{wl} + d_{cw} * A_{last} \right) \quad (5)$$

$$Where:$$

$$d_b = distance\ covered\ in\ batch\ b \qquad b\ \epsilon\ B$$

It is assumed that the horizontal and vertical velocity of the picker is constant and that within an aisle, the distance from one rack to another rack is 0. This is commonly assumed in warehouse literature when the width of an aisle is narrow, which is here the case (Roodbergen & Vis, 2006).

Configuration 3 replaces the shortest routing strategy with an S-shape routing strategy without a cross-aisle section. This can be beneficial in preventing congestion because pickers can now only traverse an aisle in one direction. Nedcargo wanted to investigate what a smaller width of the aisles in combination with the S-shape strategy has on the performance in a specific context. How this will be modelled will be explained in the next paragraph.

8.6 Configuration Models

In the previous paragraphs, the three configurations were explained, and their choices in picking strategy, routing strategy, layout, equipment, and storage were elaborated on. Now that these configuration choices are known, to reach the objective of this study, the configurations must be modelled. The contingency approach is based on three variables: contingency variables, response variables, and performance variables (Neuenberg, 2010). The contingency variables can be found in the Experiment Generation Model. The response variables are meant to be found in the configuration model, which, respectively, its output must be the performance variables. These performance variables must then show that the context in which a warehouse operates influences its operation. In that manner, Nedcargo can have insights into their decisions for their new warehouse in Haaften.

In this chapter, we will discuss how the model works. What is the input, processing, and output of the configuration model? This model is created by using Visual Basics for Applications (VBA) for Microsoft Excel (MS Excel 2019). This is a programming language tailored to act as a macro language found in most spreadsheets. Macros permit the Modeller to automate repetitive tasks by programming user keystrokes. It gives the Modeller also the option to incorporate a spreadsheet-specific macro language for writing more complex applications. The potential of the configuration model is that it can function as a spreadsheet simulation via VBA as a decision-making tool.

Primarily, the model of configuration 1 will be elaborated on. As explained in the previous paragraphs, configurations 2 and 3 are very similar to configuration 1 except for minor tweaks in different strategies. Therefore the models will be elaborated generic, and afterward, the additional steps of configuration models 2 and 3 shall be described.

First of all, the figure below shows the dashboard of the model. As can be seen, the dashboard model consists of four steps before the performance results are obtained. We will cover all these steps gradually so that the model's functioning becomes clear. Occasionally, references will be made to explaining the strategies in the previous sections.

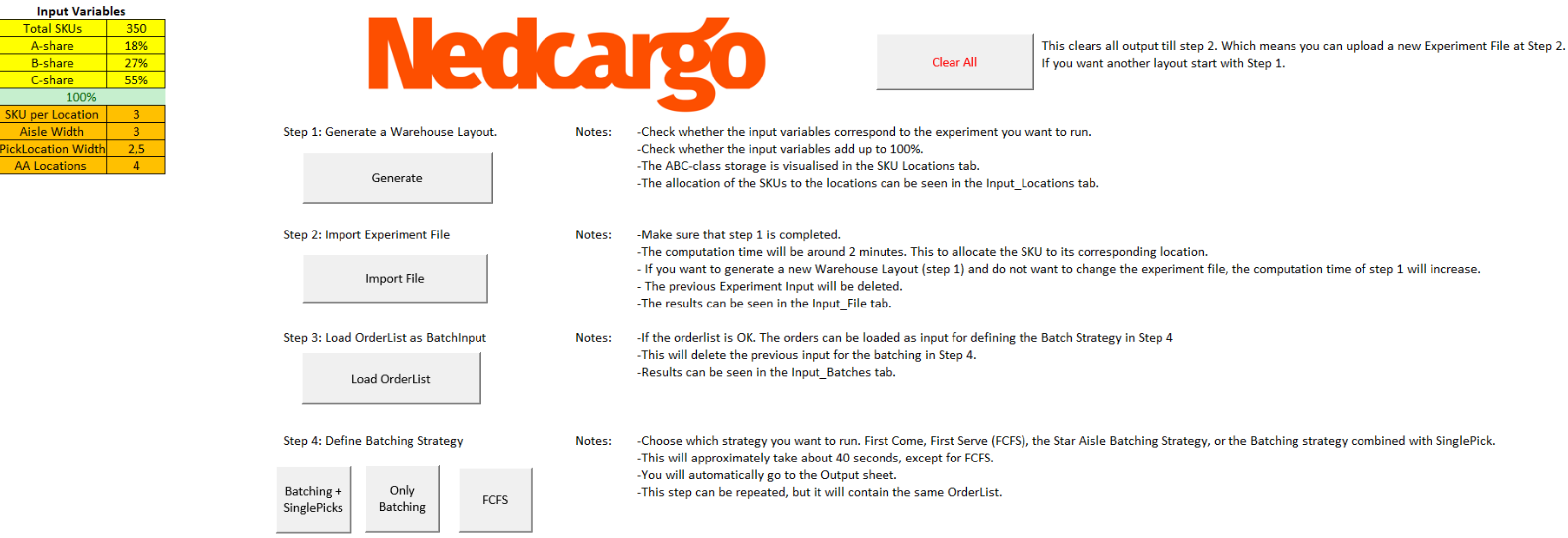


Figure IV-8 – Dashboard of Configuration Model 1 in VBA Excel

The dashboard has multiple steps, tables, and buttons that need further explanation. In the upper left corner, the input variables are shown. These input variables are part of the layout and storage characteristics of the warehouse, which need to be simulated. There are two types of input variables: those in the yellow cells and those in the orange cells. The yellow variables are two order characteristics variables, and the ones in orange are warehouse layout variables. This study focuses on the uncertainty of order characteristics. Therefore, they should be changed per experiment. This gives insight into the effect of that uncertainty on the performance. Nevertheless, it is possible in the model to change the warehouse layout characteristics in the orange cells. But as it is not the objective of this study, they are displayed in orange. If Nedcargo also wants to experiment with different layout characteristics, the model can dynamically change.

Now that the input variables have been explained. Step 1 can be performed. This step generates a warehouse layout based on the input variables that have been inserted. Some conditions must be taken into account before generating a layout. The first condition is that the input variables must correspond with the order characteristics of the experiment that you want to run. Each experiment has incorporated the variables, total SKUs, and ABC-Ratio. These input variables must correspond with the levels chosen to generate an experiment for a scenario. So if Nedcargo wants to generate a layout for 350 SKUs with an ABC ratio of 18/27/55, these dashboard settings are corresponding. Next to that, it needs to check whether the ABC-Ratio adds to 100%, which can be seen under the yellow cells. If those conditions are met, we can generate a warehouse layout. This dynamically changes the warehouse layout and assigns which location to store which SKU type. Therefore the layout generation and the storage strategy (partly) are performed in this step. The results for two different input variables are shown in the figure below.

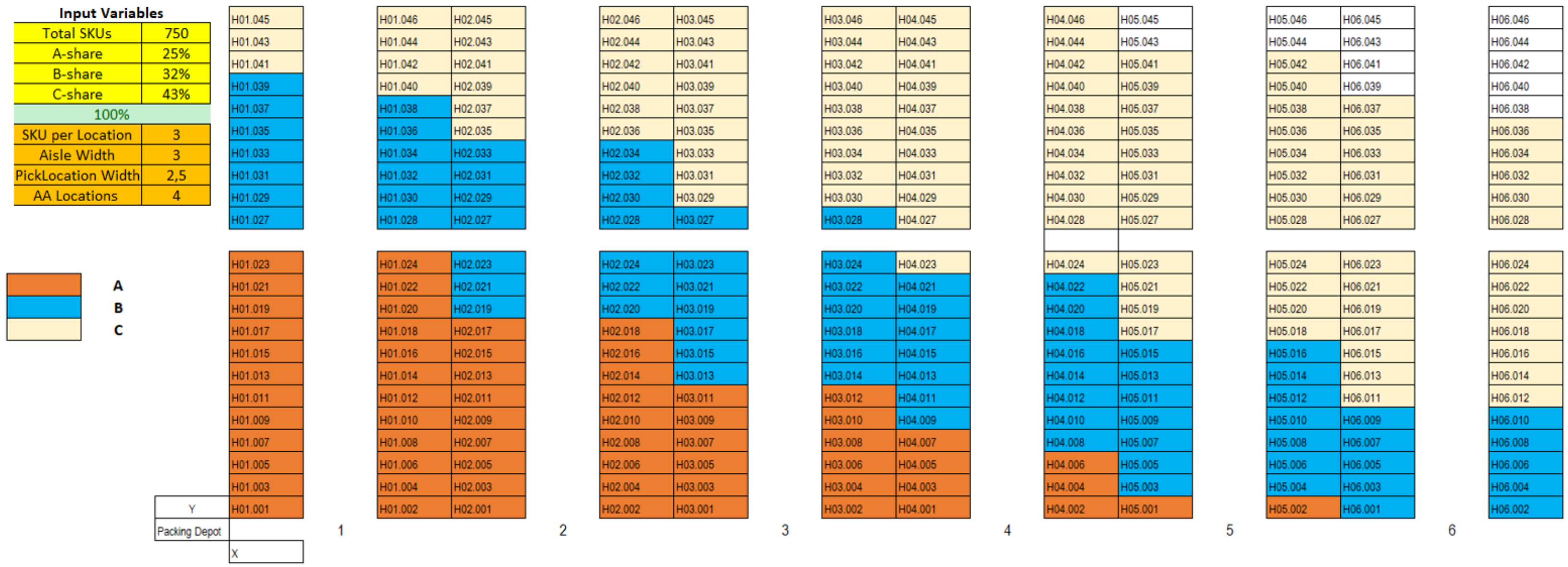


Figure IV-10 – Overview of model's layout and storage allocation output for the input shown in the yellow coloured table

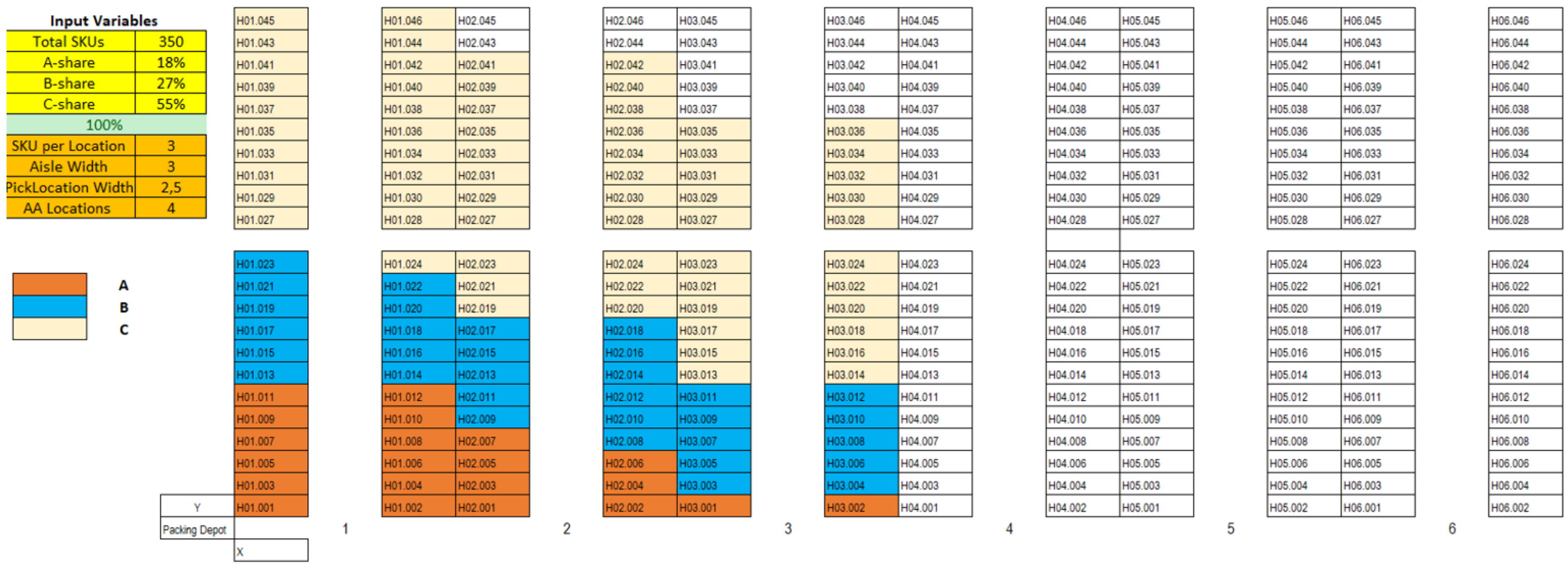


Figure IV-11 – Overview of model's layout and storage allocation output for the input shown in the yellow coloured table

The figures above show two different outcomes for a warehouse layout with different order characteristics. This example can represent an experiment that is simulated in the model. As can be seen, the locations can be either for A, B, or C SKUs. Based on the ABC-class-based storage strategy, the locations which are the closest to the packing depot or P/D point are reserved for the A-products shown in red. The second closest locations for the B-products are shown in blue and respectively beige for C-products, which are the farthest away from the P/D point. The generation of this layout is dependent on the total SKUs to be handled and how these SKUs are defined as A, B, or C.

Now the warehouse is generated for the experiment; each SKU must be allocated to a specific location. The SKUs are each randomly assigned to a location. This is dependent on the number of SKUs and the distribution of the type of SKUs that need to be handled in the warehouse. As is seen in the Experiment Generation Model, each SKU has a Product ID. In the dashboard example, the active Product IDs are A1…A64, B1…B94, and C1…C191. The model assigns each active SKU to a location, except for the AA products assigned to the closest 4 locations to the depot. In the table below, an example of the output is given.

Table IV-12. Example of allocation of SKUs to Locations

Location ID	SKU 1	SKU 2	SKU 3
H01.001	A2	A11	A3
H01.002	A7	A9	A5
H01.010	A41	A37	A28
H02.006	A30	A48	A14
H01.020	B19	B2	B80
H03.011	B92	B24	B37
H01.036	C24	C168	C58
H02.035	C169	C81	C3

Now that step 1 is clear; we move to step 2. First, the dummy order data set of an experiment, which is the output of the Experiment Generation Model, is imported into the model. Then the model assigns each Product-ID from the dummy order list to its corresponding location in the warehouse. This approximately takes 2 minutes of computation time. What is then created is an order list for that specific experiment. This order list can then be loaded as “batch input.” Batch input means that the generated order list is accepted as the input for defining the batching strategy. If so, the load order list button can be pressed, and steps 2 and 3 are completed.

The model has a dummy order list of an experiment that needs to be picked in the generated warehouse. The last step is to define which picking strategy is used to pick those orders. The Modeller can choose between the FCFS strategy, the only batching, which is the Star Aisle Batch strategy, and the Star Aisle Batch strategy combined with the SinglePick Strategy (see step 4, figure 8). All three strategies are described in previous paragraphs. All three are available in order to compare the three strategies in terms of performance. The FCFS strategy is simple. In this strategy, the orders are batched based on when they arrive. This means that orders 1,2,3,4 are collected as batch 1, orders 5,6,7,8 in batch 2, etc. The Star Aisle Batching strategy follows the algorithm proposed in paragraph 8.3.2.1. This strategy batches the orders based on the aisles that need to be visited. The SinglePick strategy, in combination with the Star Aisle Batch Strategy, is batched in two steps. First, it looks at the order list, consisting of 1 SKU and 1 Collo. These orders are assigned to the SPBatch and are collected as the last pick tour of the day, and there is no capacity constraint. These can be picked as bulk because the packers can pack per customer instead of per order, which significantly minimizes the packing time. An example of the batching strategy is shown in the table below.

Table IV-13. Example of Batching output for each strategy in the model.

FCFS	ORDER_ID	*BATCHS*	ORDER_ID	*BATCHS+SP*	ORDER_ID
Batch 1	1,2,3,4	Batch 1	4,8,24,92	Batch 1	5,82,122,212
Batch 2	5,6,7,8	Batch 2	15,29,159,176	Batch 2	8,20,101,192
Batch 3	9,10,11,12	Batch 3	78,122,200,211	SPBatch	1,6,4,90,91,82,102,156,211,219,277

Now the model has batched all the orders based on the selected strategy in step 4. The only two actions the model has to perform are assigning and determining the route per batch for the picker and the total travel distance this route takes. And the time measurements of each action of the picker, with the fixed time, variable time, and idle time described in the previous paragraph. The route in configuration 1 is based on the shortest route algorithm, and know that every SKU that needs to be visited is known per batch. The shortest route algorithm can provide a route for each batch. It also calculates the distance that needs to be travelled for the picker, and by dividing it by the velocity of the picker cart, the model can give the total drive time of the route. Next to the drive time is the fixed time per SKU visit, the variable time per colli pick, and the idle time between batches. The fixed and variable time is calculated for each orderline that the model produces, and the idle time is calculated after the batch. So the drivetime plus the fixed and variable time per orderline and the idle time combined gives the total time of the batch. For the reason that the fixed, variable, and idle times are randomly continuously distributed, each experiment needs 10 iterations. This means that each result of the experiment differs in picking time. The average of those iterations gives the performance of the model.

Now that the processing variables are discussed, we can look at the model's output. The model's output is based on the quantitative key performance indicator discussed in paragraph 6.4. These are **the picking time, the productivity, the number of pickers, the total distance, and the average batching time**. The model is capable of quantifying each of the proposed KPIs as the output. For each experiment, it is possible to generate, strategize and clarify the quantified performance of a warehouse. In figure 11 below, a snapshot is seen of the output of the configuration model. The analysis of the results of the different context experiments will be discussed in the next chapter.

Total Picking Time (s)	48636
Total Picking Time (min)	810,6
Total Picking Time (h)	13,51
Total Colli	2227
Total Colli/hour pick	164,84
Total Pickers	2
PickTime(h)/Picker	6,8
Avg. Distance Batch (m)	108,3
Total Distance (m)	6495,3
Avg. Batching Time	811

Figure IV-12 – Snapshot of the output table of Configuration Models

8.6.1 Configuration model 2

The model of configuration 2 largely resembles the model of configuration 1, except that now the storage strategy is different. As stated, in configuration 2, there are two locations, namely H01.005 and H01.006, which are now "dynamic" SKU locations. This means that before the allocation of the SKU and batching of the orders is carried out, the dummy order list (experiment) is analysed. The order list is analysed and checked whether (1) there is an SKU that is located far from the depot, which is picked often that day, and (2) if there are 2 SKUs that are affiliated, which means that there a 2 SKUs which are often paired in an order. If that is the case, it can be chosen to move these SKUs before the allocation and batching of the orders are placed in the dynamic SKU locations. In the below figure is seen how this is implemented in the model. This analysis is performed after step 2.

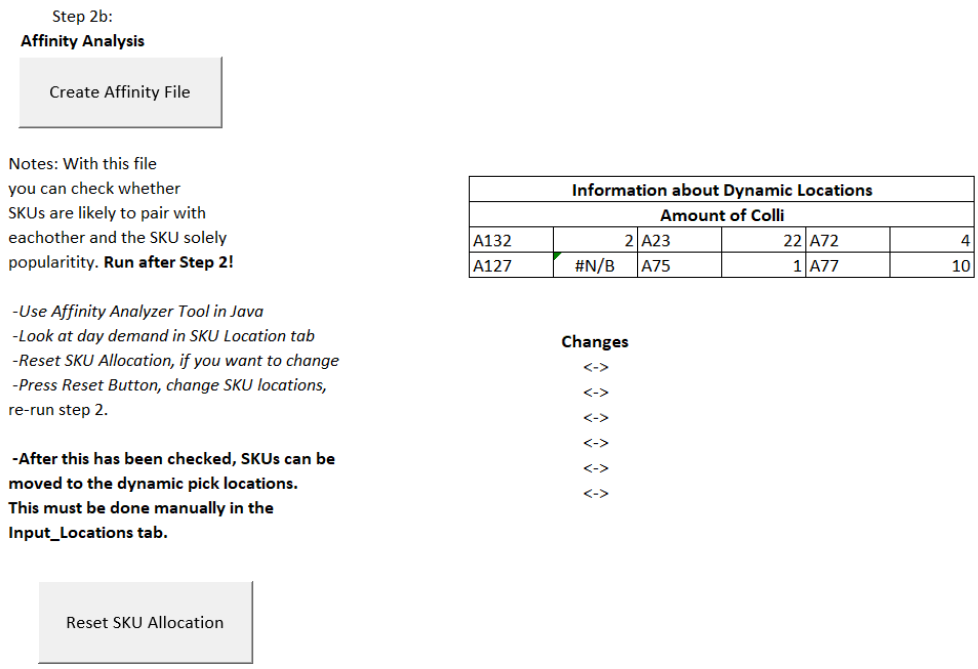


Figure IV-12 – Snapshot of Dynamic SKU Location Input of Configuration Model 2 in VBA Excel

The above figure shows the actions that need to be taken in order to analyse if certain SKUs can be beneficial to move to the dynamic SKU location. Firstly, we will take a look at the affinity analysis. After step 2, the dummy order list of the experiment is imported into the model. Step 2b is to create an affinity file, which can check whether certain SKUs are likely to pair with each other in that experiment file. This affinity analysis is performed by using the affinity analyser of John J. Bartholdi III found on warehouse-science.com. The copyright to this computer program is held by John Bartholdi, who reserves all rights thereunto appertaining (2007). The affinity analyser checks whether a pair of SKUs in an order list is likely to be picked in the same order. Then you may be able to reduce travel in the warehouse by storing the two SKUs in the dynamic SKU location. When the generated affinity file is imported into the tool, it gives the affinity of each SKU pair. If the analysis shows that this is the case, these SKUs can then be replaced with one of the SKUs currently placed in the dynamic location.

Secondly, the amount of colli that needs to be picked is checked. If the demand of the experiment day is high for an SKU that is far away from the depot, it can be chosen to move that SKU to the dynamic SKU location. This is done with PowerPivots in the configuration model. After this has been checked, the (optional) SKUs can be moved to the dynamic SKU location by swapping the SKU location of the SKUs that are already in the dynamic SKUs. Then step 3 and step 4 can be run, and the performance of the warehouse will be shown in the output file.

8.6.2 Configuration 3 model

Configuration 3 is almost the same as configuration, and only the routing strategy is the S-shape strategy. This means that the cross-aisle is removed, and the aisles are slightly smaller since the pickers can only traverse the aisle in one direction. This should lead to less probability of congestion within the aisles. The model is almost the same as the model of configuration 1; only the travelled distance is based on the formula that is explained in paragraph 8.5.

8.6.3 Sensitivity Analysis

A sensitivity analysis is used to show how the uncertainty in the output of a simulation model can be divided and allocated to different sources of uncertainty in its input. The distributed variables in this model are the one of the picking time. Namely, the fixed time, the variable time, and the idle time. The sensitivity was already tested by making 10 iterations per experiment. In this manner, a convergence was reached. The sensitivity indices converge when their value stabilizes. This is not an extensive sensitivity analysis, but this (mostly picking time) data was validated and verified based on the current state analysis. For further studies, it is recommended to extend the sensitivity analysis.

8.7 Conclusion

This extensive chapter elaborated on the requirements, assumptions, configurations, and the models of the configurations. With the contingency approach in mind, we state that the configuration models function as the processing variables of the research. The Experiment Generation model's input function as the contingency variables and the output of the configuration models as the performance variables will be analysed in the next chapter. This all to prove that configurations perform differently given the context they have to operate in so that Nedcargo can have a decision-making tool for choices at the new warehouse in Haaften.

To summarize this chapter, first, the requirements were discussed. They were divided into functional and non-functional requirements, which were composed in consultation with Nedcargo, insights from the data analysis of Tiel, and prior findings from warehousing literature. Out of this analysis, several requirements were formed, which can be seen in tables 2 and 3. They are all related to warehouses' design, strategies, layout, and equipment, of which configurations are a generic term. Next, before confident configuration choices could be made, the model assumptions were formulated. These assumptions were divided into three different categories: conceptual assumptions, mathematical assumptions, and numerical assumptions. These assumptions are necessary because it is not necessary/beneficial for the outcome study to model every process in the warehouse. Therefore, these assumptions are made to construct a viable model that focuses on aspects that are considered necessary in this research.

Then the three configurations were explained. Each choice regarding picking strategy, layout, routing, storage, equipment, and the picking speed were proposed and substantiated by either literature, data analysis of Tiel, and/or with expert's view. First configuration 1, which focus lays on improving the picking strategy. In Tiel, we noticed that an FCFS (first come, first serve) strategy is followed and is stated to be inefficient. Both insights from Tiel and from literature determined the new strategy. This resulted in the Star Aisle Batch strategy in combination with the SinglePick strategy. Which are, respectively, a picking strategy that examines at which aisles need to be visited and batches similar orders, and which batches all the single SKU with single collo to be picked. Next to that, configuration 1's routing strategy is that of the shortest path algorithm. It stores its SKUs using an ABC-class-based storage strategy, uses a more compact layout than Tiel, and uses the same equipment as in Tiel. Secondly, Configuration 2 is a slightly modified version of configuration 1 where the storage strategy is different. Therefore the focus of configuration 2 is on the dynamic improvement of the warehouse storage strategy. This is done by adding flexible SKU locations near the packing depot. Then, by analysing the orders beforehand on affinity and/or demand, these SKU locations can be stored with different SKUs each day. This is all to reduce the traveling distance of the picker. Lastly, configuration 3 changes the layout by removing the cross-aisle, using slightly smaller aisles, and by using a different routing strategy. The routing strategy that is used is the S-shape strategy, which states that each aisle can only be traversed in one way by the picker. This is in order to decrease the possibility of congestion.

All this information allows us to answer the following sub-research question:

Which new configurations are applicable for an e-commerce warehouse, and which requirements and assumptions must be made?

The three configurations are applicable for an e-commerce warehouse that Nedcargo potentially can apply for the new warehouse in Haaften. Based on the requirements that are stated in combination with the assumptions, we can conclude that these configurations are applicable to Nedcargo's objectives for Haaften III.

That brings us to the next sub-question that can be answered and validates the method proposed in chapter 6.

What method can model the proposed context scenarios and configurations of an e-commerce warehouse?

The configurations are straightforward, applicable, and modelled using Visual Basics for Applications (VBA) for Microsoft Excel (MS Excel 2019). The proposed context variables are modelled using the Experiment Generation Model and its output functions as the input for the configuration models. Namely, the dummy order list of the given context scenario, which each configuration model processes. The model's output gives the warehouse's performance in the experiment. These performance indicators are based on the proposed indicators of the picking time, the productivity, the number of pickers, the total distance, and the average batching time. This model could be seen as a conceptual configuration of Haaften.

Now that the experiment generation model and configuration models are explained. Can the proposed experiments be simulated? First, each experiment is being generated, after which each configuration model will process each experiment. This gives the performance of each picking strategy per configuration per experiment. These results will be discussed in the next chapter and will contribute to the proof of configuration to eventually answer the main research question.

V. Evaluate

9. Results and Analysis

We start by re-asking the sub-question we want to answer using the obtained results to introduce the results. These two sub-questions are the last three questions that need to be answered before this research can be concluded by answering the main research questions. The questions that need to be answered in the analysis of the results are:

9. *How do these new configurations perform compared to the current state?*

10. What is the influence of the different context scenarios on the performance measures of different warehouse configurations?

11. How can the results be interpreted and used for decision-making in the future for Haaften III?

9.1 Comparing New Configurations with Current State

Firstly, we start by answering the ninth sub-research question. We compare the proposed configurations with the current state, which is also modelled. This gives us insight into whether the findings and choices for configuration changes from the data analysis, consultation with experts, and literature findings, are plausible. These insights were applied to substantiate certain modifications in the current state configurations. This resulted in three new configuration concepts, which were being translated into a simulation model. Therefore, these configuration models must be compared in the same context as Tiel is currently operating, thus with the current state model. The current state order characteristics are the same as in scenario 50. The specific order characteristics of Tiel can therefore be found back in appendix X.

The current state model was verified and validated in chapter 5.7. This brings us to the fact that the model could represent real-world performance. In order to see whether the new configurations have any effect, we have to simulate them within the same experiments. In Appendix E, tables 10, 11, and 12, the results are shown of that simulation. Each batching strategy for the configurations is compared with the current performance of the Tiel warehouse, where currently the FCFS strategy is being used. The below graphs shows visualizes these results per strategy.

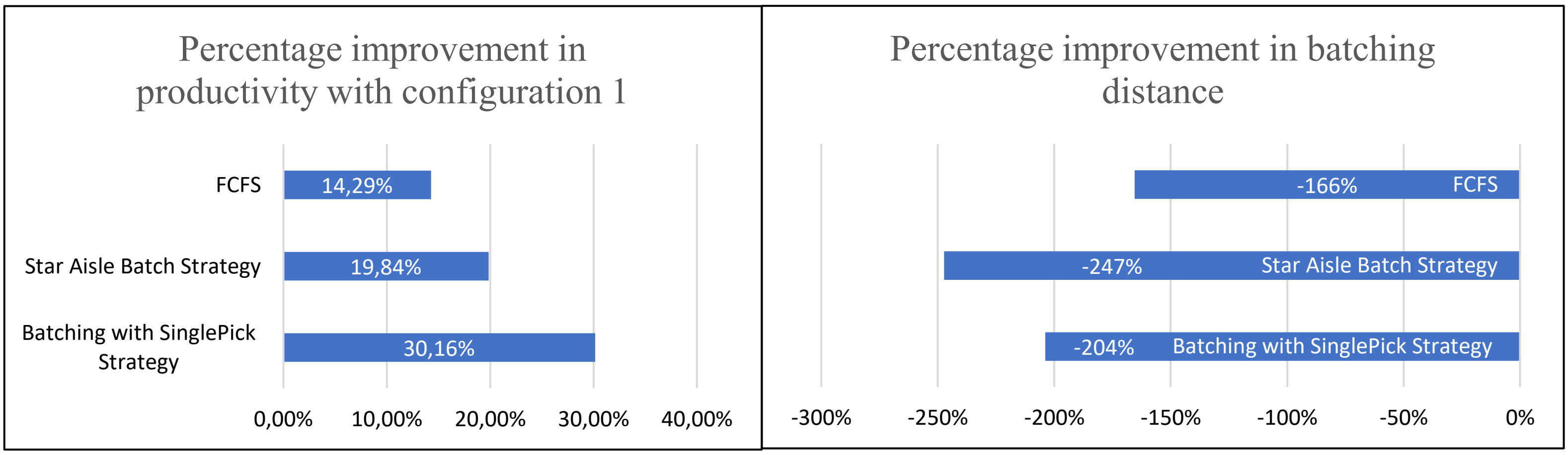


Figure V-1 – Improvement in productivity and in batching distance per strategy in configuration 1, compared to Tiel's configuration

These are the most important results that can be analysed by comparing the current state with the new configurations. It should be noted that several extra analyses could be made but that these graphs are sufficient for answering sub-question nine. As can be seen in the results tables in the appendix, which configuration has the most improvements in performance compared with the current state? It can be noticed that this is configuration 1. Therefore we visualize its improvement compared with the current state in the graphs above. As seen in both graphs, the improvement per strategies is measured. This percentage improvement is analysed for the productivity, which is based on the picking time per colli, and the batching distance, which is the average meters of a picking tour.

The first thing that strikes immediately is that even with an FCFS strategy, the productivity in configuration 1 is more than 14% higher than that of the current state performance in Tiel. If we do not look at the picking strategy, the only thing that was changed is that in configuration 1, a more compact layout was implemented. There were only as many aisles as storage locations for SKUs needed. Next to that, the locations now store 3 SKUs instead of 4. These improvements in storage and layout strategy give an immediate improvement of almost 15%. How can this significant improvement be justified? Therefore we need to look at the percentage improvement of the batching distance. Namely, a more compact layout is used for the warehouse in the same order characteristics context, resulting in less distance travelled per batch for the picker. This resulted in an improvement of 166% due to its compactness. Instead of the 8 active aisles in Tiel, configuration 1 only uses 3 aisles which explains this reduction. This reduction in travel distance accounts for an improvement of almost 15% in the picking productivity.

How does the star aisle batching strategy and the star aisle strategy combined with the SinglePick strategy influence the productivity of the current state? Due to the fact that in this context, only 3 aisles are being used, the star aisle batching strategy can probably easily batch these orders, judged by the proposed algorithm. Nevertheless, it is seen that it improves productivity by 5% compared to the FCFS in configuration 1 and by almost 20% compared to the current state in Tiel. The productivity increase of the star aisle – with SinglePick batching strategy increases the productivity by over 30%. Even within the configuration 1 model, adding the SinglePick strategy to the Star Aisle batch strategy will increase productivity by 10%. However, the star aisle batching strategy decreases the average batching distance the most. Combining it with the SinglePick strategy increases the average batching distance by over 14% (see appendix E table 1) but increases productivity by over 10%. This shows that for the current context of the Tiel warehouse configuration, model 1 with the SinglePick and star aisle batching strategy is the best new option for Nedcargo. So if configuration 1 with the *BatchSP* strategy is implemented in the Tiel warehouse, it will increase its productivity by 30%.

This significant increase in productivity and the decrease in the average batching distance also affect the total number of pickers needed to complete the orders. As can be seen in table 1 in appendix E, with the current state configuration of Tiel, to complete the orders of the experiment data set, a total of 3 pickers are needed. In configuration 1, with the most efficient strategy, only 2 pickers are required to complete all the batches within 8 hours of picking. In addition to this finding, the configuration model now optimizes the number of pickers needed, which is not the real-world case in Tiel. In Tiel, the number of pickers assigned to complete the orders is entirely random. So if we take the average number of pickers of 4, as seen in the data analysis of the current state. Nedcargo (at least) can save two pickers using configuration 1 and the proposed strategy. This can even be implemented as soon as possible in the configurations of Tiel. That brings us to answering the sub-question nine:

How do these new configurations perform compared to the current state in the current context?

The answer to this is that if we implement the new configuration 1, which is the best of the three configurations performance-wise, in combination with the star aisle batch strategy and SinglePick strategy in the current context of Tiel. It will improve productivity by over 30%, saving costs due to fewer pickers needed.

9.2 Results and Analysis of Scenarios Experiments

Secondly, the tenth sub-research question will be addressed. The influence of the context scenarios on the performance measures for each of the three proposed configurations needs to be studied. In order to answer this question, we need to look back at which scenarios were proposed. Nedcargo's experts have chosen scenarios 50, 107, 10, 77, 92, and 123 as the contingency order characteristics scenarios. For each of these context scenarios, 5 experiments were being generated by the Experiment Generation Model. In Appendix E, in table 4 till 9, the order characteristics output of the experiments are being shown per scenario. Each of those experiments' outputs, namely the dummy order data set, is processed by the configurations models 1,2, and 3. In the table below, we can see each experiment's average output, which shows the specific order characteristics or so-called context of each scenario.

Table V-1. Order Characteristics per Scenario

	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Orders	300	300	300	300	300	300
Orderlines	834	747	1560	714	734	1071
Total Colli	2315	1646	4171	3251	2135	2391
Avg. Orderline/Order	2,78	2,21	5,20	2,38	2,45	3,57
Avg. Colli/Orderline	2,77	2,21	2,67	4,55	2,90	2,23
Avg. Colli/Order	7,71	5,49	13,90	10,94	7,12	7,97
Avg. SinglePicks	71,6	79,4	37,8	59,2	82,8	77,6

Each scenario generates five experiments, which will be simulated into 3 configurations with every 10 iterations for each picking strategy. This means that a total of $5 * 3 * 3 * 10 = 450$ KPI as output has been simulated in all of the configuration models. This is performed on an 8GB 1,80 GHz computer, which took four working days. All the results of each experiment can be seen in appendix E, tables 13 till 48. The average results of all experiments per scenario can be seen as well in appendix E, tables 49 till 138. The final results are summarized for each configuration in tables 10, 11, and 12. These 3 tables give us the average results of all the experiments for each configuration, per scenario, per strategy, and its performance indicators. In this paragraph, we will analyse the findings that can be seen from the results of appendix E tables 10, 11, and 12. There are only two variables that we can compare between the context scenarios, the productivity per scenario and the average batching distance. These are generic performance measures, and based on these performance indicators, we can see whether the context of the warehouse impacts the performance of the configurations differently. Next, we also look within the context variables to see if the strategies have a different impact on productivity, total picking time, or the total distance.

The next paragraphs aim to answer the following sub-question: *What is the influence of the different context scenarios on the performance measures of different warehouse configurations?.* Each paragraph will analyse the different proposed performance measures of the configuration model's output. And see if the context scenarios, in different configurations and picking strategies, affect it.

9.2.1. Productivity

Firstly, we start by analysing the productivity performance per scenario. There is a distinction between the three types of picking strategies in the configuration models. In order to investigate which strategy performs the best for both the scenario it is in and the configuration, the model processes the experiments for each of the picking strategies proposed. Those strategies are the *Star Aisle Batching strategy combined with the SinglePick Strategy*, *the Star Aisle Batching strategy*, and *The First Come, First Serve strategy*. The experiments are processed for each of the three configurations and each of the scenarios, and the outputs are given in the table below.

Table V-2. KPI's of Configuration 1 with batching strategy and singlepicks in the multiple scenarios

Batch+SP	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Configuration 1						
Avg. Colli/Hour	163	124	178	208	160	156
Configuration 2						
Avg. Colli/Hour	163	124	178	207	159	157
Configuration 3						
Avg. Colli/Hour	158	121	174	185	155	152
Batching Strategy						
Configuration 1						
Avg. Colli/Hour	149	111	173	195	143	143
Configuration 2						
Avg. Colli/Hour	149	111	173	194	143	143
Configuration 3						
Avg. Colli/Hour	142	107	169	184	137	138
FCFS						
Configuration 1						
Avg. Colli/Hour	142	104	167	187	135	136
Configuration 2						
Avg. Colli/Hour	143	104	167	187	135	136
Configuration 3						
Avg. Colli/Hour	133	96	158	174	126	128

The first thing to notice in the above table is that the Star Aisle Batching strategy combined with the SinglePick Strategy is the best in terms of productivity in every scenario. In each scenario, productivity decreases if the Star aisle batching strategy or FCFS strategy is used. This is the first conclusion this research can present. Namely, the productivity in each configuration is the highest with the *Star Aisle Batch strategy combined with the SinglePick* strategy compared to the other two strategies. Later on, we will show the exact loss in productivity when the Batch+SP strategy is not adopted. In order to show that the contextual setting each influences this differently.

Next, we will only focus on the Batch+SP strategy and then the performance between the context scenarios to see if the difference between performance is deductible. The productivity is the highest in scenario 77 and the lowest in scenario 107, respectively, 208 and 124 colli per hour. We can divide the productivity of these context scenarios into four groups: the very high productivity (scn. 77), the high productivity (scn. 10), and the average productivity (scn. 50, 92, and 123), and the low productivity (scn.107).

How can we explain this by looking at the order characteristics of the scenarios? How and which of these order characteristics (contingency) variables influence the productivity in the warehouse and therefore perform better in a different context?

To explain why scenario 77 has higher productivity than the other scenarios can be explained by looking at two order characteristics: the amount of colli to be picked and the number of orderlines per order. How higher the amount of colli in combination with not so many orderlines per order is beneficial for the picker's productivity. It means that the picker has to visit not that many SKU locations, making it easier for the batching algorithm to batch orders that are primarily positioned in the same aisle. Next to that, it is beneficial for the productivity to have fewer A-products as in ratio in combination with more colli for A-products. 75% of the time, the picker picks A-products that are located much closer to the depot. This scenario is based on a context in which there can be a client in which customers order a lot of the same products and, more occasionally, in more significant amounts. This results in the picker often visiting the same SKU in a day, so their productivity is higher than in another context. The model results confirm this, and this can be retrieved from table 1 with the order characteristics per scenario.

Scenarios 10 and 77 have in common that they both have an ABC-Ratio of level 1. As said, this means that there are fewer A-products in the warehouse. This means that the inventory turnover is primarily dependent on only 10% of the total SKUs (namely A-products). This has a high impact on the productivity of the pickers because for the logical reason that they have to travel less through the warehouse and often visit the same SKUs. Therefore, more orders will consist mainly of the same SKUs, namely the A-products. This also makes the star aisle batching algorithm more efficient.

Scenario 107 has the lowest productivity, and how can that be explained? The scenario has 750 SKUs and an ABC ratio where 25% of these products are considered A-products. Also is seen that there are fewer colli per order and a small number of orderlines per order. This means that the picker has to travel to many different SKUs and picks a small amount of colli. This is difficult to batch as efficiently as the other scenario, and therefore, it has the lowest productivity of all the scenarios. Next to that, it is the only scenario with an ABC-Ratio of level 3. So not only do the pickers have to travel to multiple SKUs, but they also have the increased chance that they are widely spread over the warehouse.

Concluded, the ABC ratio, the orderlines/order, and the amount of colli to be picked are very influential for the productivity of your warehouse. Suppose the ABC ratio is one that there are not that many A-products, combined with a lot of colli/order and a low orderlines/order. This means that multiple orders primarily consist of the same SKU with a higher chance of multiple colli picks. The picker, therefore, has not had to travel to many different locations and can collect multiple colli per SKU visit, which increases productivity. Next, we have to take a look at the productivity within each configuration per scenario and how each configuration responds in each scenario if a decrease/increase in productivity is different per given context scenario.

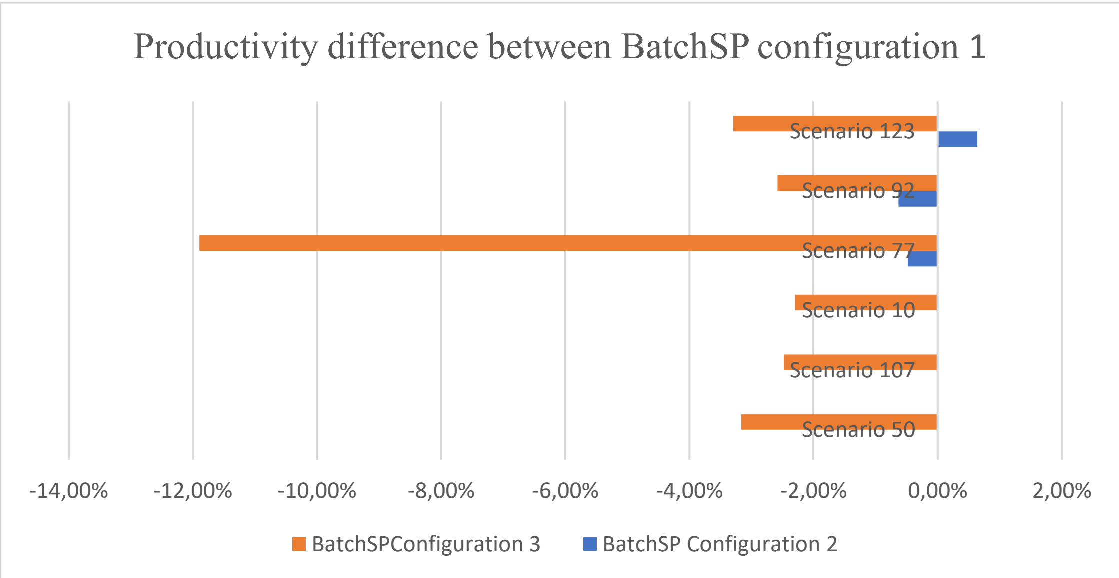


Figure V-2 – Percentual productivity change if switched to a different configuration using the Star Aisle Batching combined with Singlepick Strategy

The figure above shows what the percentual decrease is in productivity compared to configuration 1 with the *BatchSP Strategy*. In three of the six scenarios configuration 1 has the same productivity as configuration 2. In scenarios 77 and 92, the configuration has a minor decrease in productivity. Only in scenario 123 does configuration 2 perform slightly better in terms of productivity than configuration 1. Configuration 3 has in each scenario lower productivity. This differs per scenario and ranges from more than 2% to almost 12%. Scenario 77 does certainly not perform better when using configuration 3. This also confirms the idea that each context has a different impact on the performance of a configuration.

Now that we have presented the results and analysis of the productivity between scenarios, we have to analyse what happens within the scenarios between the different configurations. The research question asks about the impact of different context scenarios on the different proposed configurations and if these impacts differ per scenario. So, within the scenarios, is the effect weaker and the other more robust in terms of productivity per configuration and strategy? This is seen in the following graph:

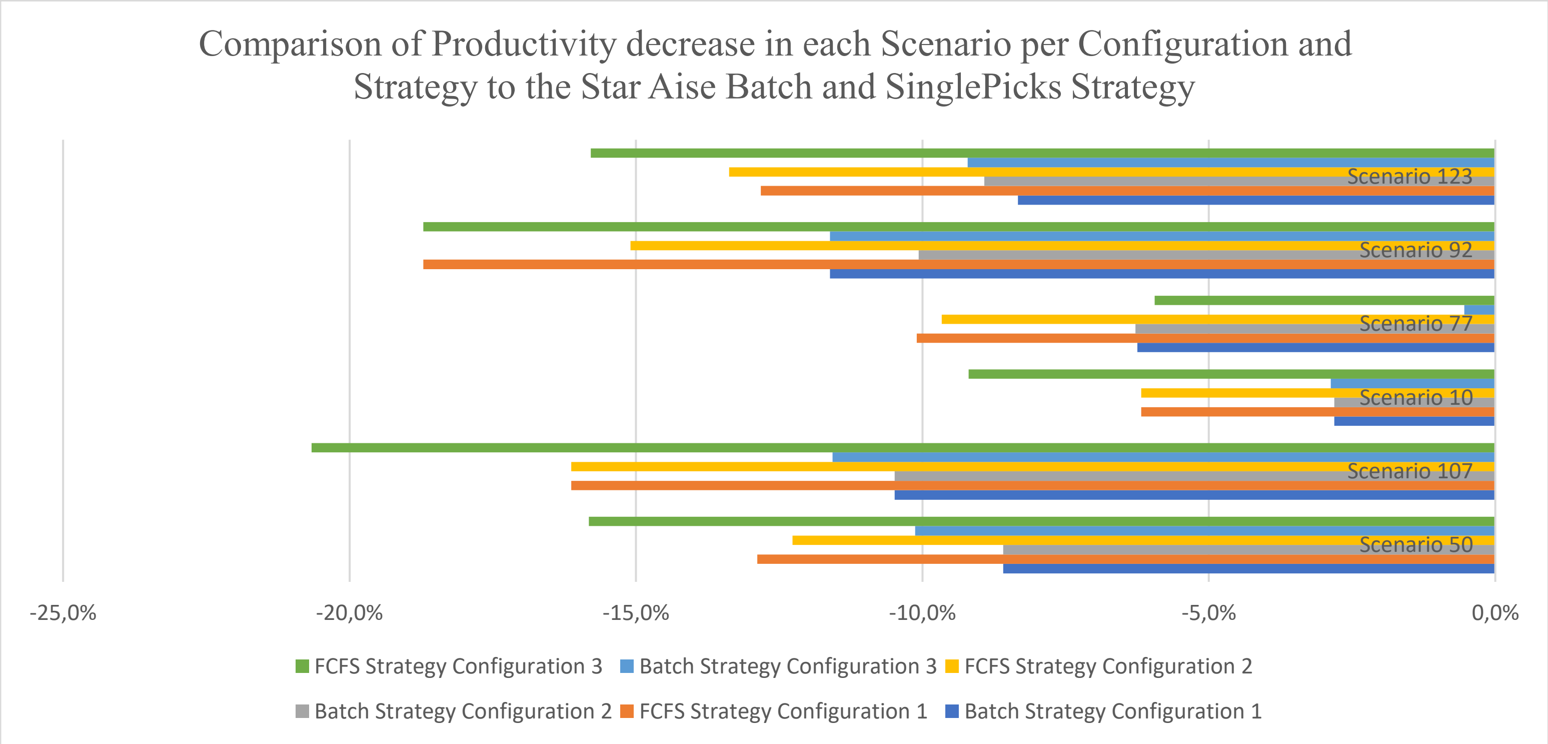


Figure V-3 – Productivity decreases per scenario when switched from the highest productivity combination (picking strategy and configuration) to another combination.

The above graph shows that each scenario reacts differently to a change of configuration in combination with the involved strategy. This means that the different context in which a configuration is placed in combination with the strategy impacts its productivity. In this way, we can state that the experiments show that different configurations perform differently in specific scenarios. For example, in scenario 10, if not chosen for configuration 1 or the Batch+SP strategy, it does not impact productivity as much as scenario 107. In scenario 107, if not chosen for configuration 1 with the Batch+SP strategy, it will decrease the productivity in the best case by more than 10% already. Therefore the context in which a warehouse operates is essential to see whether some configurations perform better or worse. This must therefore be investigated before starting to design. This can help in the pre-design phase of a warehouse design. To see how specific configurations will perform and react to confident configurational choices. Nedcargo can do this using the proposed method with each experiment and configuration of their liking.

9.2.2 Total Picking Time

The total picking time is the time that is needed to finish all the orders. In this paragraph, we will compare within each configuration and between the scenarios what the influence of the context scenarios is on the picking time.

As can be seen in appendix E tables 10, 11 and 12, the picking time is the smallest in configuration 1 in scenarios 77 and 92, and scenarios 50,107, 10, and 123 have the lowest picking time for configuration 2. These differences in picking time between configurations 1 and 2 are all less than 0,3 percent and therefore almost neglectable. The below figure shows the impact of a different configuration for each scenario on the picking time.

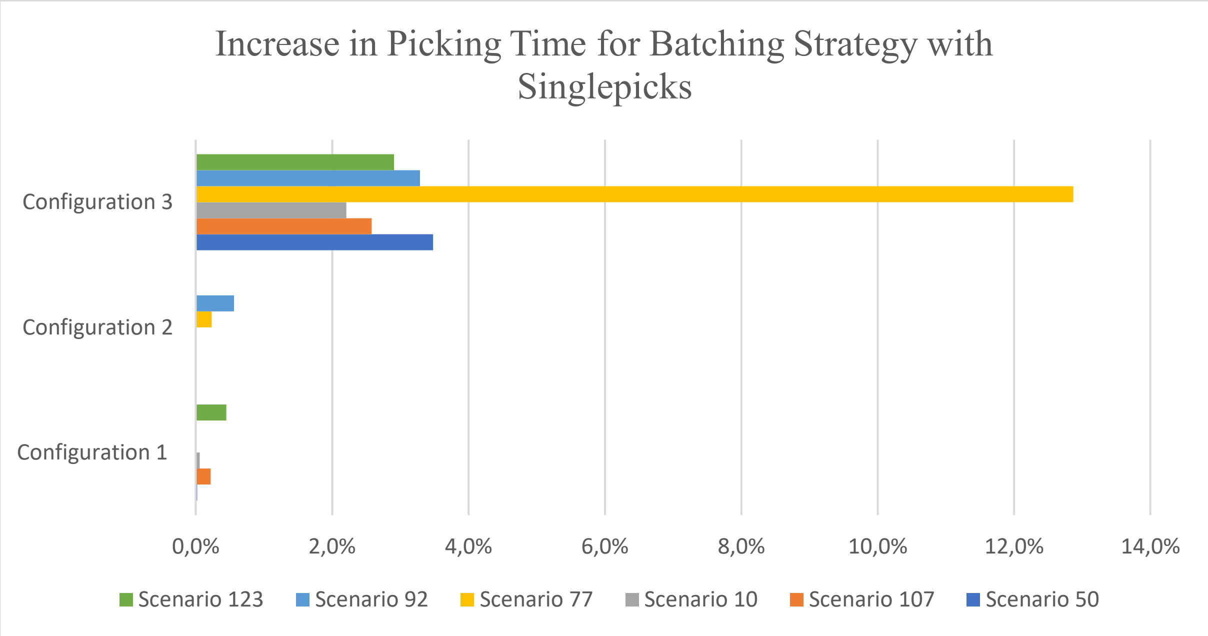


Figure V-4 – Increase in picking time per scenario when switched to other configuration

As can be seen in figure 4, in terms of picking time, the difference between configurations 1 and 2 is almost neglectable. It is also slowly becoming apparent that configuration 2 does not significantly impact productivity and, as a result, the total picking time of the warehouse. Also can be concluded from the graph that scenario 77 does perform a lot worse when using the configuration 3 models. The rest of the context scenarios differ slightly but also have a slight decrease in total picking time when the model of configuration 3 is used.

The total picking time is almost the same percentual decrease in productivity. This is because the total picking time is mainly based on the productivity the pickers achieve in the warehouse. The reason for showing the total picking time is that it is easier to see the exact difference between the configurations. The total picking time is also essential to see how much time is needed for that type of client. This makes it easier for Nedcargo to predict their (labor) costs. The total picking time also shows that it can be concluded that configuration 2 has no significant effect on the picking time compared to configuration 1. Therefore there is proof of configuration that configuration 2 does not perform better or worse than configuration 1 while using the *BatchSP strategy*. This is because the *star aisle batching* algorithm already considers that orders are picked from the same aisle. Therefore the dynamic shuffling of SKUs has no impact compared to configuration 1.

In the following graph, we compare the percentage increase in picking time in each scenario per configuration and picking strategy within the scenario. They are being compared with the most efficient configuration and strategy per configuration. This line is missing per batching strategy in the figure and is for every configuration: the Batch+SP strategy. In appendix E, tables 10, 11, and 12, the effect of each strategy on the picking time is seen per configuration. The below figure combines those three tables.

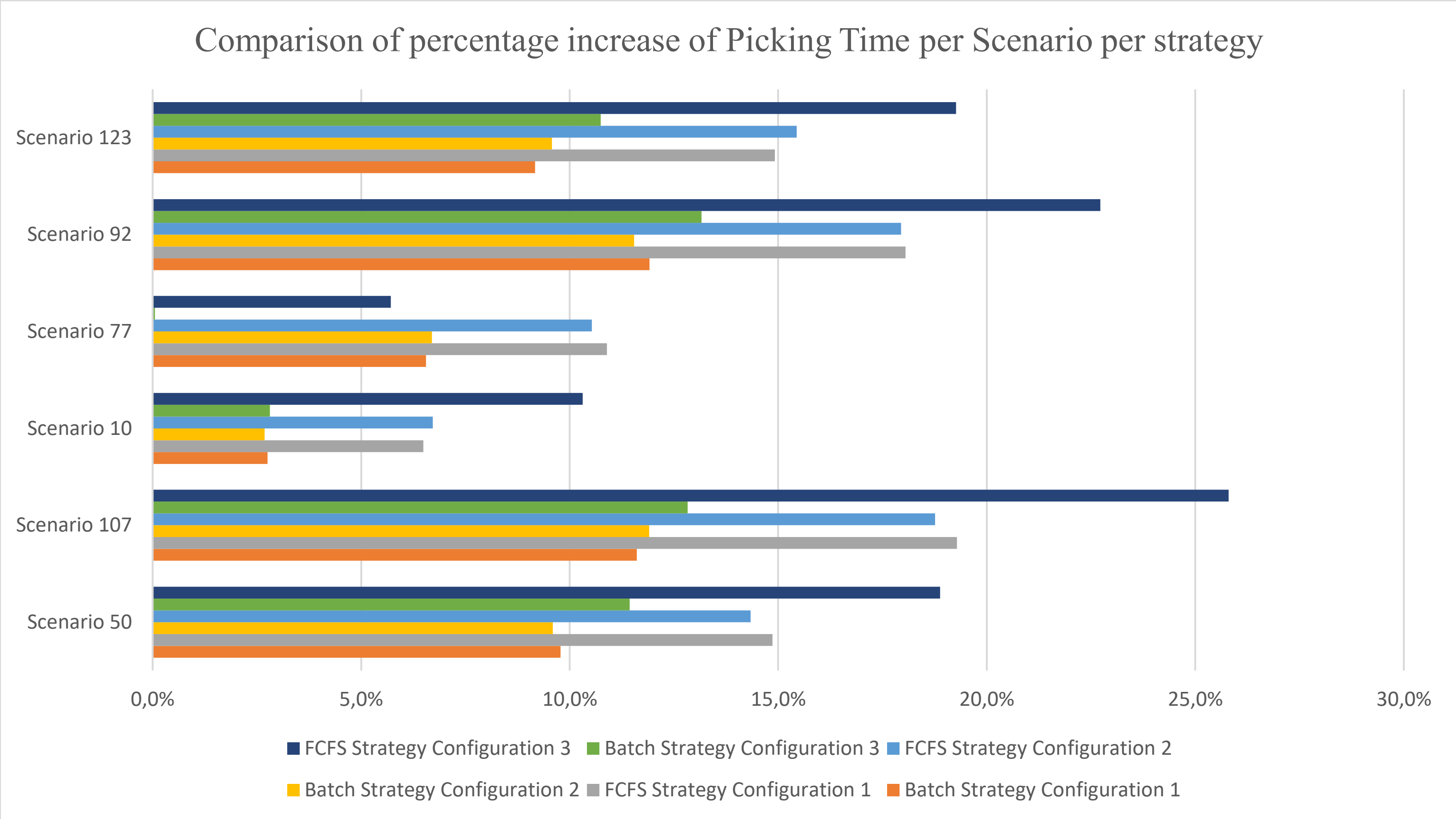


Figure V-5 – Picking time increase per scenario when switched from the highest productivity combination (picking strategy and configuration) to another combination.

It is seen that almost in every scenario, each configuration responds differently to a change in a strategy. This means that the contingency variables, which in the study are the order characteristics, have on each configuration different effects. In some scenarios like 107 and 92, the picking time is susceptible to configuration and/or strategy changes. On the other hand, if we look at scenarios 10 and 77, they are not that sensitive to a change in configuration and/or strategy.

9.2.3 The Total Travelled Distance

Another performance indicator that this research looks into is the total travelled distance. The following table displays the results of the experiments on average batching distance, and the total distance travelled in the warehouse.

Table V-3. The Avg. Batching distance and total distance per strategy in Configuration 1

Configuration 1	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Batch+SP						
Average Batching Distance	113	186	200	103	131	126
Total Distance	6647	10486	13401	6355	7283	7184
Batching Only						
Average Batching Distance	99	157	186	92	109	107
Total Distance	7267	11460	13822	6790	7975	7798
FCFS						
Average Batching Distance	126	206	231	123	145	139
Total Distance	9479	15476	17352	9206	10880	10406

The first noticeable thing is that the average batching distance is the smallest in each scenario when the *star aisle batching* strategy is being used. Although the total distance in the *Batch+SP* strategy is for each scenario the smallest compared to the other two strategies. This has a simple explanation, namely the *batching only,* and *FCFS* strategies consist of 75 batches, i.e., 300 orders with 4 orders per batch (300/4=75). In the *Batch+SP* strategy, the quantity of batches depends on the number of SinglePick orders. Since all the SinglePick orders are handled in one batch, this quantity of orders is different in each experiment. These Singlepick orders are placed into one batch, and the remaining orders are batched following the *star aisle batch* strategy. Therefore, the SinglePick batch is increasing the average batching distance, and it appears that this batch has a longer picking route. It may also be that it becomes more difficult to efficiently *star aisle batch* strategize with fewer orders to batch with. Next to that, the results show that the FCFS distance is the highest for each scenario. Which, logically, was also to be expected.

What the results reveal that is happening is that even though the average batching distance increases with the *Batch+SP* strategy, the total distance will be lower in each scenario. This is for the reason that in the *Batch+SP* strategy, fewer batches need to be picked because the SinglePick orders are being collected in one batch. This increases the average batching distance (1) because the SinglePick batch has a lengthier route and (2). After all, fewer orders are available to batch with, which makes it more challenging to be efficient with the *star aisle batching* strategy.

The difference between the total travelled distance of the configurations with the Batch+SP strategy is shown in the following graph. Figure 6 shows the increase in total distance per configuration and per scenario in the *SinglePick* strategy. As can be seen in the results table, in some of the scenarios, configuration 2 has slightly decreased the total distance in the scenario, as shown in figure 6, are scenarios 50, 107, and 123. In this scenario, the distance travelled by the pickers is approximately 3% less than if configuration 1 is used. As was expected in each scenario, the total distance travelled significantly increases when using the S-shape routing strategy proposed in configuration 1. This routing strategy does not allow the pickers to traverse the aisles in both ways and no longer has a cross-aisle. This will increase the total distance that needs to be covered to complete all the orders. Later on in this chapter, we will come back to what impact this may have on congestion and how Nedcargo can cope with this knowledge.

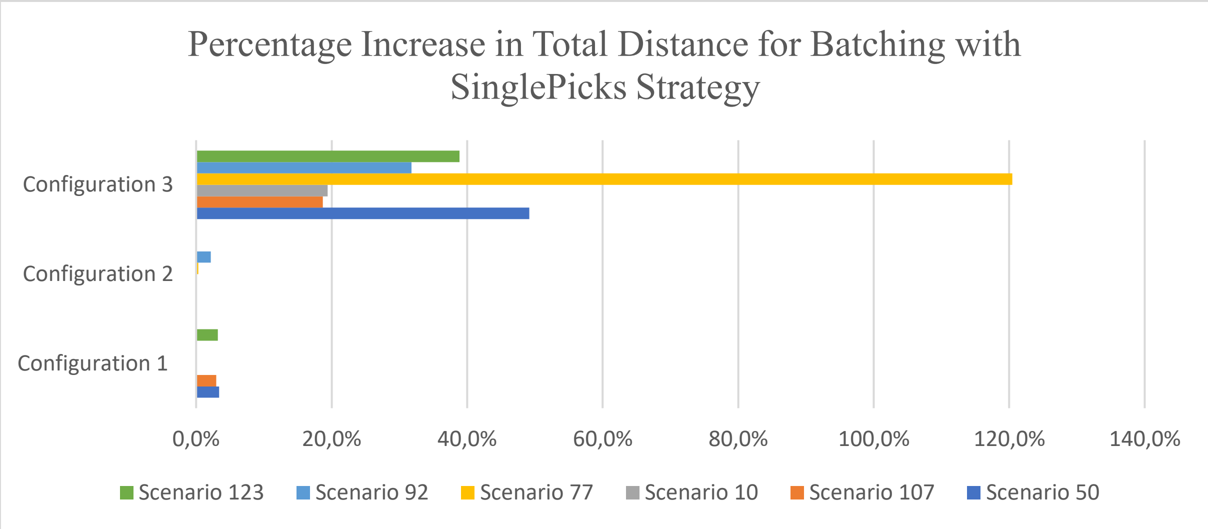


Figure V-6 – Increase in total distance per scenario when switched to other configuration

Table 6 shows all the strategies per configurations combined per scenario in appendix E. It shows the increase in the total distance when another strategy and/or configuration is used per scenario.

9.2.4 The Average Batching Time

The average batching time is a result of the productivity and the amount of colli that needs to be picked. As shown in appendix E tables 10, 11, and 12., in each configuration, the total batching time is the lowest when the *star aisle batching* strategy is being used. This can be explained by the findings of the last paragraph, namely that the average batching distance that needs to be travelled is the lowest when using the *star batch strategy*. Which consequently decreases the average batching time. What stands out is that in each scenario and configuration, the average batching time is the highest for the *Batch+SP* strategy. This is reflected in the below table, where it is seen that for configuration 1 in each scenario, the average batching time is the highest for the *Batch+SP* strategy. The table shows the percentage decrease in batching time per scenario.

Table V-4. The Avg. Batching Time and total distance per strategy in Configuration 1

Configuration 1	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Batch+SP						
Average Batching Time (s)	869	850	1257	914	862	963
Batching Only						
Average Batching Time (s)	763 (-12%)	732 (-14%)	1167 (-7%)	815 (-11%)	737 (-15%)	823 (-15%)
FCFS						
Average Batching Time (s)	781 (-10%)	763 (-10%)	1196 (-5%)	832 (-9%)	756 (-12%)	844 (-12%)

How can this be explained? The average batching time is higher, but as highlighted in the previous paragraph, the picking time is the lowest for the *Batch+SP* strategy in each scenario and configuration. Table 1 shows for every scenario the average amount of Singlepicks per experiment. This average number of Singlepicks equals the amount of colli that needs to be picked in the SinglePick batch. For example, in scenario 50, where the average number of SinglePicks in all experiments is approximately 72. This means that 72 orders are collected as one batch and are not included in the *star aisle batching* algorithm. This results in there being 17 batches less to be picked, i.e., 57 batches (for the remaining 228 orders) and 1 SPBatch. Consequently, as can be seen in the results, this increases the scenario's picking time by 10% and 12%. On the other hand, the productivity increases with the *Batch+SP*, as seen in table 4. Based on these findings, it can be concluded that despite the increasing average batching time and distance travelled when using the *Batch+SP* strategy due to the SPbatch, which takes more time and distance. Nevertheless, fewer batches need to be picked. So, this fastens the needed time to complete all the orders.

9.2.5 Congestion and Automation

Next to the quantitative performance indicators modelled as the output of the configurations models, there are qualitative performance indicators that must be compared between the different and within configurations. We will discuss the two qualitative indicators, the possibility of congestion and the possibility of automation, per configuration. In each of those configurations, there are pros and cons for each of the two.

Firstly, configuration 1 in terms of congestion and automation in each scenario. The scenarios where there are multiple active aisles due to the number of SKUs. So, in scenarios 107 and 10, where there are the most SKUs (750) in the warehouse, it is the probability less likely that there is congestion in the warehouse. Therefore, configuration 3, which is proposed to decrease the chance of congestion with the S-shape routing strategy, is not really necessary since pickers are less likely to be in the same aisle. On the other hand, scenarios 50 and 123, which experiments consist of only 350 SKUs stored in three aisles. It can be beneficial because the pickers are most of the time in the same aisle to investigate configuration 3 in this context. So, if Nedcargo wants to avoid the potential of congestion in these scenarios, it can be chosen to switch to configuration 3. But as can be seen in the productivity chapter, this decreases in both scenarios by almost 15%. Therefore, the models provide a good insight into the pros and cons of switching configurations in different scenarios, and Nedcargo will have to weigh up itself. Regarding the possibility of automation in configuration 1, their model does not give a swift answer to that question. It is therefore recommended to further look into this requirement and indicator.

Secondly, configuration 2 differs from the previous configurations in that it applies the principle of dynamic SKU location. In terms of congestion, it can be considered the same as configuration 1, based on the similarity of the results. But in terms of the possibility of automation, Nedcargo can look at the possibility of automating the process of replenishing the dynamic SKU location. This is a much less complex process to automate because it only needs the replenishment of six SKUs. Nevertheless, the costs of this automation must be recovered from the increase in productivity. And as the model results have shown, the increase in productivity of configuration 2 is almost neglectable compared to configuration 1.

Lastly, configuration 3 uses the S-Shape routing strategy. This strategy decreases the chance of congestion. Nedcargo has to arrogate in which scenarios it is likely to have congestion. As stated before, this can happen when not a lot of active aisles are used. This increases the chance of congestion. This model results can be used to see whether a change in configuration influences the performance of the warehouse. As shown in figure 5, scenario 77 and scenario 10 are not as sensitive to changes in strategy and configuration as the other scenarios. This proves that the context does influence the performance of particular configurations. This model can therefore give insight if Nedcargo should change its configuration to decrease the chance of congestion. This is an omission of multiple indicators which must be tested in practice.

9.3 Haaften III

Now that almost all the sub-questions have been answered, and before we move to answer the main research question. There remains one sub-question that needs to be answered. Namely, *How can the results be interpreted and used for decision-making in the future for Haaften III?*

The problem statement showed that Nedcargo is opting to build a new warehouse in Haaften, where e-commerce warehousing operations are included. The current warehouse configuration of e-commerce warehousing is for Nedcargo, located in Tiel. The context of the Tiel warehouse is known, but for Haaften, the context in which the warehouse will operate is still unknown. Therefore the uncertainty of a specific contextual factor of order characteristics must be pointed out and investigated.

Whether a specific context influences the performance of a particular configuration, which configuration performs better or worse?

The order characteristics are being modelled using a Model Generation model. This model allows Nedcargo to experiment with different client order characteristics. Nedcargo chooses 6 scenarios out of the 144 proposed contextual scenarios to investigate in this research. The model is transforming these scenarios into experiments. Each experiment represents a dummy order day that must be processed by different warehouse configurations, which gives insights into its performance per scenario. The configuration models perform this processing of the contextual variables. These models are based on three types of different configurations.

We discussed the above method results in the previous paragraphs for each different picking strategy per configuration. How can these results contribute to future decision-making for Haaften III? Nedcargo has chosen scenarios that their experts think are plausible as future client order characteristics. Therefore it can be the potential context of Haaften III. By using this model, the uncertainty regarding the order characteristics is eliminated. This is due to insight into the contextual variables of a client, which results in a dummy order set. These dummy order sets could represent a real-life order list that must be handled in the future warehouse of Haaften. The output of the Experiment Generation Model can therefore be used to partly resolve the uncertainty of a possible context in which Haaften III is placed. This model must therefore be used as means to give clients and Nedcargo itself insights into the potential order list that its clients' customers demand. Each model output, the dummy order data sets, can be processed by different warehouse configurations. The warehouse configuration that Nedcargo is accustomed to is that of Tiel. But can there be improvements in that configurations based on data analysis, expert consultation, and literature? Based on this, three new configurations were presented and modelled.

Let us look at the results of the configuration models. It can be stated that Configuration 1 is the most optimal configuration investigated in terms of productivity and therefore decreases the total picking time. Next to that, it can be concluded that the *Star Aisle Batching Strategy,* combined with the *SinglePick Strategy,* has the highest performance in each scenario. Therefore, it needs this strategy to be included in potential decision-making for the configuration choice of Haaften. Another improvement is the compact layout of the configurations. Compared with the current state model, if a compact ABC-class-based storage layout is proposed, the productivity will increase by 15%. Another result that can benefit the future decision-making of Haaften is that the output of the models gives an insight into the number of pickers needed. This can decrease labor costs. It is unnecessary to use more pickers than needed to complete an order list for a specific day.

The two proposed models can help Nedcargo investigate in (1) the specific context Haaften will operate. The Experiment Generation Model can help Nedcargo give insight into the uncertainty factor of order characteristics by defining how a potential client is characterised. This model can create experiments that can test configurations in terms of performance. And (2) the proposed configuration models. The models include three types of configurations where improvements to the current state are processed based on literature, expert insights, and data analysis. Proofs that certain choices, for example, the compact layout, ABC-class based storage, and the Star aisle batch strategy with Single Pick, improve the performance of the warehouse. Nedcargo must therefore use this model to investigate, improve and quantify potential configurations for Haaften III. This can be seen as a pre-design phase for Haaften III.

10. Conclusions and Implications

In this chapter, the findings from the research are concluded. First, all the key findings of the research will be discussed, after which the main research question will be answered. Thereupon recommendations will be made for Nedcargo, and we will reflect on the objective of the study.

10.1 Key Findings and Main Research Question

The order characteristics' contingency variables generated experiments using the experiment generation model, in which the configurations models were being processed and gave the final results as the proposed performance indicators. This is all to answer the following question:

What is the impact of context uncertainty of order characteristics on the different outbound configurations of an order-picking warehouse?

This is in order to have flexible decision-making in the future warehouse configuration of Haaften III.

The first important conclusion that can be made is that the configurations model has been shown. What if the new requirements of a potential configuration option are being implemented in the models? The current state can be improved. It was examined how each of the configuration models would perform in a scenario with the same order characteristics of Tiel. This was compared with running the same experiments through the current state model. The results showed that respectively configuration 1, with the FCFS, Star Aisle Batching, and Batch+SP, resulted in an improvement in productivity of 15, 20, and 30% compared to the current state. Next to that, a significant decrease is measured in the total distance travelled by the pickers. This also allows for completing the orders with fewer pickers, namely 2 fewer pickers on average. Therefore can be concluded that if only the warehouse's layout were more compact, an increase of 15% in productivity would be reached, and if this is combined with the *Star Aisle Batching with SinglePicks,* the productivity will increase by 30% in Tiel.

Next to this, this study aimed to investigate if the context of the warehouse has an impact on its performance in different configurations. There were a total of six scenarios chosen by Nedcargo, and three new configurations were being modelled. The experiments were simulated in each configuration model, and their performance was compared. This comparison could be checked within the configuration models and between the scenarios. We will start by discussing the conclusions that can be made from the performance of each of the scenario experiments.

First, the results showed that the productivity for each configuration and picking strategy differs from each other. In specific scenarios, productivity is much higher or lower than in others. The context, therefore, influences the performance between scenarios. This is also the case with the other performance indicators, such as travelled distance, picking time, and average batching time. How can be explained which contingency factors are causing that the increase in productivity? The results showed that the ABC-Ratio contingency variable has a significant impact on the productivity of the chosen configurations. Respectively, high productivity is reached if the warehouse consists of a lower percentage of A-type SKUs and lower productivity if the warehouse has a high percentage of A-type SKUs. This can be concluded by comparing the high and low productivity scenarios with their corresponding contingency variables. Next to that, a context scenario where the amount of colli is high and the orderlines per order are low will result in higher performance. This is since the picker can grab more colli during an SKU visit, which decreases the travel distance and thus increases the performance. For example, scenario 77, which has all of the above order characteristics, has the highest performance of all context scenarios. On the other hand, scenario 107, which does not characterize the above findings, has the worst performance measures.

Next to that, it can be seen that in each scenario, the change between configuration and picking strategy has another effect. In some scenarios, such as 10 and 77, another picking strategy or configuration does not have an as significant impact as, e.g., 107 and 92. In those scenarios, the percentage decrease in productivity is much higher when not the best configuration and picking strategy option is implemented. This is an important insight because the order characteristics influence how well it functions per configuration and picking strategy. But looking at the performance, which configuration and picking strategy perform the best? To answer this question, we need to look within each scenario.

This research proposed a new batching strategy that was not yet been seen or quantified before in warehousing literature. The ones that were known are the First Come, First Serve (FCFS) strategy that is currently implemented in Nedcargo's current warehouse in Tiel. The SinglePick strategy was proposed during a previously conducted design project at Nedcargo. States that each of the single SKU and single colli orders should be collected in one batch. And the Star Aisle Batching strategy is derived from the literature that batches the orders based on the aisles that need to be visited. The new strategy proposed is a combination between the SinglePick strategy and the Star Aisle Batching strategy. The results showed that for each configuration, this strategy has the best performance in terms of productivity and picking time within each scenario. Which means that this strategy fits each scenario and configuration best and outperforms the other two strategies modelled.

The proposed three configurations were based on the requirements and assumptions that were urged. Each of the configurations was simulated within each scenario, and its performance was measured. A series of conclusions can be drawn from these results. First, it is seen in the performance that in each scenario, configuration 1 performs the best in terms of productivity together with configuration 2. Configuration 3, where the S-shape routing strategy is implemented, has lower productivity, reducing 2 to 11 percent. This is also affected by the context scenario it operates in. It can be concluded that configurations 1 and 2 in each scenario have higher productivity than configuration 3, but there is no significant increase between configurations 1 and 2. Configuration 2 uses another storage strategy that implements the idea of dynamic SKU locations, where SKUs can be moved based on SKU affinity and SKU demand. The model results in prove that configuration 2 does not significantly improve the performance of the warehouse if compared with configuration 1, from which it slightly differs in layout and storage. This proof in performance concludes that configuration 2 is not worth further investigation.

The proof of configuration concept that is being withheld in this research aims to demonstrate the feasibility of the chosen configurations. The results prove that configuration 1 performs better in terms of productivity for each of the scenarios than configuration 3 for each picking strategy and that configuration 2 has no significant effect on the performance irrespective of the context. Therefore the contingency approach proved that specific configurations perform differently in each context, and their performance is affected. On the other hand, configuration 3 has less chance of congestion due to the routing strategy. Pickers can only traverse the aisle in one direction. This should also be kept in mind if, in practice, i.e., configuration 1 causes a lot of congestion. Nedcargo now has insight into the impact per scenario when it is switched to configuration 3.

So, if we look back at the main research questions, the following can be concluded. The context in which an order-picking warehouse operates, based on the order characteristics uncertainty, has a significant impact on the performance of different configurations. Each configuration performs differently considering its context scenario. This is shown using the contingency approach. The contingency variables represent the uncertainty of the order characteristics, the response variables, which are the three configurations and picking strategies modelled, and the performance variables, which are the output of these models. Now that this has been stated, how can this be used for the purpose of flexible decision-making for Nedcargo? In order to make the right choices in the right contextual setting for Haaften III.

Based on the findings, Nedcargo has an insight into how a configuration would react in a particular context of order characteristics. The order characteristics of the future state for Haaften are uncertain, and therefore Nedcargo can use the findings of this study to be prepared. The experiments show that it is essential to test different configurations on their performance before you start designing. The results of this thesis function as a proof of configuration, which is that configuration performs better or worse in a specific context. Nedcargo must use these models as a tool to improve its decision-making.

10.2 Discussion

The simulation models developed have some limitations due to their assumptions and simplified representation of some processes. Therefore, the results and findings should be discussed by looking at confident choices that are being made in the research process. Further research could tackle these points, and thus this will also be indicated.

Firstly, the experiment generation model uses only four contingency variables. In real life, more order characteristics can be added to the model. Next to that, it can also be chosen also to take the demand characteristics into account to see what the impact of the demand is on the functioning of the configurations. This research is chosen to only focus on the order characteristics. Nevertheless, there are more contextual factors that can influence the configurations. Structural equation Modelling could implicitly look at all of those contextual factors for the functioning of a warehouse. Next to that, it could be investigated whether the demand characteristics could be implemented as stochastic variables. Stochastic variables are time-dependent and could therefore generate each order day with a different demand based on the stochastic distribution. Further research is obliged to investigate this.

The picking time is chosen to be continuously uniform distributed in the configuration models. This is due to the data that was collected and analysed. This is acceptable, but it is recommended that Nedcargo and future researchers further look into the data gathering of the picking activities. This optimizes the configuration models. Iterations were required to obtain sufficiently close to zero residuals to reach iterative convergence in the models. In the future, this could be more efficient if more data about the picking activities are being gathered.

The configuration models all used the same layout per experiment within the scenarios. It can also be investigated what the effect would be if another layout were used per experiment. This could therefore be compared with the current results. The current models can quickly obtain these results, but for the sake of the research, it was chosen to keep the storage of the SKUs in the layout the same. Next to that, more analyses could be made based on the gathered results from the experiments. In this study, only the analyses relevant to answering the main research question and its corresponding sub-research questions were elaborated. It could be discussed if more analyses could be made to substantiate the aim of the research.

10.3 Scientific Relevance

Scientific research, such as this thesis, is performed to fill up a gap in knowledge by performing research on a particular topic. It can also be conducted to give insights into vaguely or unknown topics. This study aims to fill some research gaps and also to investigate new topics. The listed four points stress the scientific relevance of this paper based on the method or findings.

- The *SinglePick* strategy is a picking strategy that has not yet been quantified in the literature. It is described as a strategy option but not quantified what its specific impact on the productivity it causes. Also, the literature stated that warehouse strategies are non-generalizable and are very case specific. Therefore each quantification could benefit Nedcargo because it reflects their operation.
- The *Star Aisle Batching Strategy* combined with the *SinglePick* strategy is a new strategy proposed. The combination of the two has not been seen in literature before. This strategy outperforms the other two strategies in each of the experiments. Hence, it is exciting to carry

out further research on this strategy. This, of course, is context-dependent, which has also been concluded in this research.

- Quantification of the contingency approach has only been seen once in literature (Sadowski et al., 2021). The research approach of this thesis, in combination with the proof of configuration aim, is a new approach that could benefit the stage before the design process of a new warehouse starts. This approach could prove that confident configurational choices would improve or deteriorate performance in a particular context. This can be executed preliminary to the design phase of a warehouse.
- "*Develop scales to more precisely measure different contextual factors and configuration elements for warehouses.".* This is a literature gap by Kembro (2020), that is filled with the experiment generation and configuration models. These models give an insight into the scales of contextual factors, although only those of the order characteristics. The configurational elements were modelled as response variables. A Modelling approach that integrates multiple components of warehouse configurations as response variables. This is not yet been developed in previously conducted research. Next to that, multiple components were implemented in the model. While in other warehouse modelling studies, mostly one or few specific component(s) were investigated.

10.4 Deliverables

The models that are proposed in this thesis can function as a decision-making tool for Nedcargo. For their new warehouse in Haaften, it is advised to further look into the proposed strategy, design, storage, resources, and layout choices. Most of all, the *BatchSP* strategy, which results in the highest productivity, should be considered for implementation. The batching output could be modelled with the current WMS so that even Tiel could benefit from the productivity gain for its picking operation. Configuration 1 is seen as the best configuration, in terms of quantitative performance, that is modelled in this study. Therefore, it is recommended to include the components suggested there during the design process. Adjustments could always be made to the configuration model and its results quantified.

Next to that, Nedcargo can use the Experiment Generation Model to recreate a specific client and the configuration model to see how this client will affect their potential warehouse performance. The Experiment Generation model can be used to recreate a fictitious order list for a specific client. If the client knows their order characteristics, their orders could be generated as experiments. This gives both the client and Nedcargo insight into the potential orders that must be handled. This can be presented to the client as the future state of their order profile.

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Appendices

Appendix A: Current State Analysis

Integration definition for function (IDEF) is a lean method that provides a structured overview of process flows (Lightsey, 2001). It is a diagram containing rectangles and arrows. The rectangles indicate a process step or function where some activity is performed. On the left side, incoming arrows provide the input for that activity, whilst the arrows coming out on the right side provide the output. Arrows coming in from the top depict control, and arrows from the bottom indicate materials or employees needed to perform that process step. IDEF is particularly useful because it is possible to zoom in on one of the subprocesses even further quickly. To fully understand and depict the warehouse process related to B2B type e-commerce orders, an IDEF diagram is drawn in which several of the subprocesses will be further dived into.

As said, an IDEF0 diagram is a functional Modelling method that can help with Modelling the decisions, actions, and activities of an organization or system. An IDEF0 diagram is built up with an activity block with an input on the left side and an output on the right side. Controls are depicted by arrows that come from the top, whereas required resources are shown by arrows that come in from the bottom. This can be visualized in the following figure:

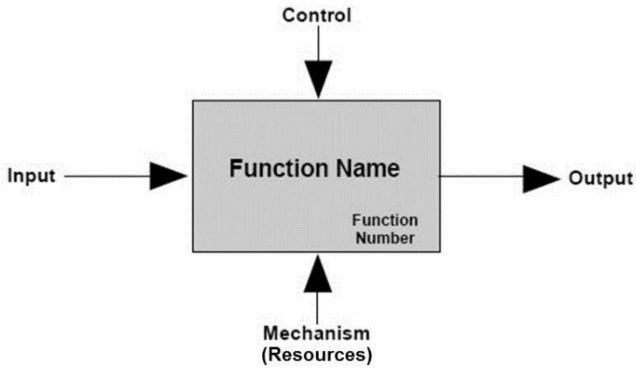

Figure A-1 – IDEF-0 Conceptually

IDEF-0 diagrams consist of several levels in which each level dives deeper into a certain sub-process. In this report, an IDEF0 diagram was made to provide insights into the processes considering warehousing activities of Nedcargo related to B2B e-commerce type orders. It starts with level A-0, which depicts all the controls and materials that are required for all of the warehouse operations. It also shows that the flow considered is scoped to an inbound load carrier in a truck and an outbound sealed load carrier in a truck.

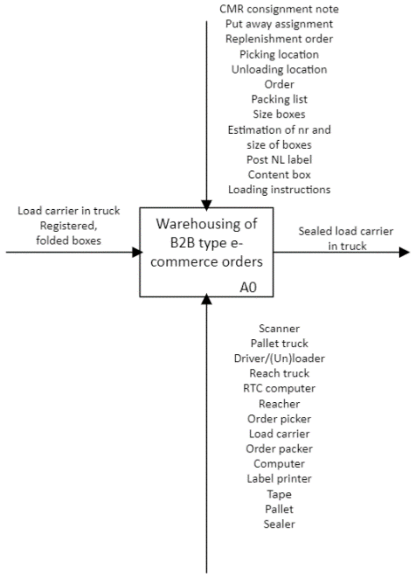

Figure A-2 – A-0 Level IDEF-0

As can be seen from the figure above, a lot of control mechanisms and materials are required to fulfill the warehousing of B2B type e-commerce orders.

If we go into these processes a little bit deeper in the second level, the A-1 level, the flow is depicted a little bit more logically. There are 6 subprocesses defined in this diagram, ranging from A1 to A6. These processes are unloading, storing, picking, packing, sealing, and loading.

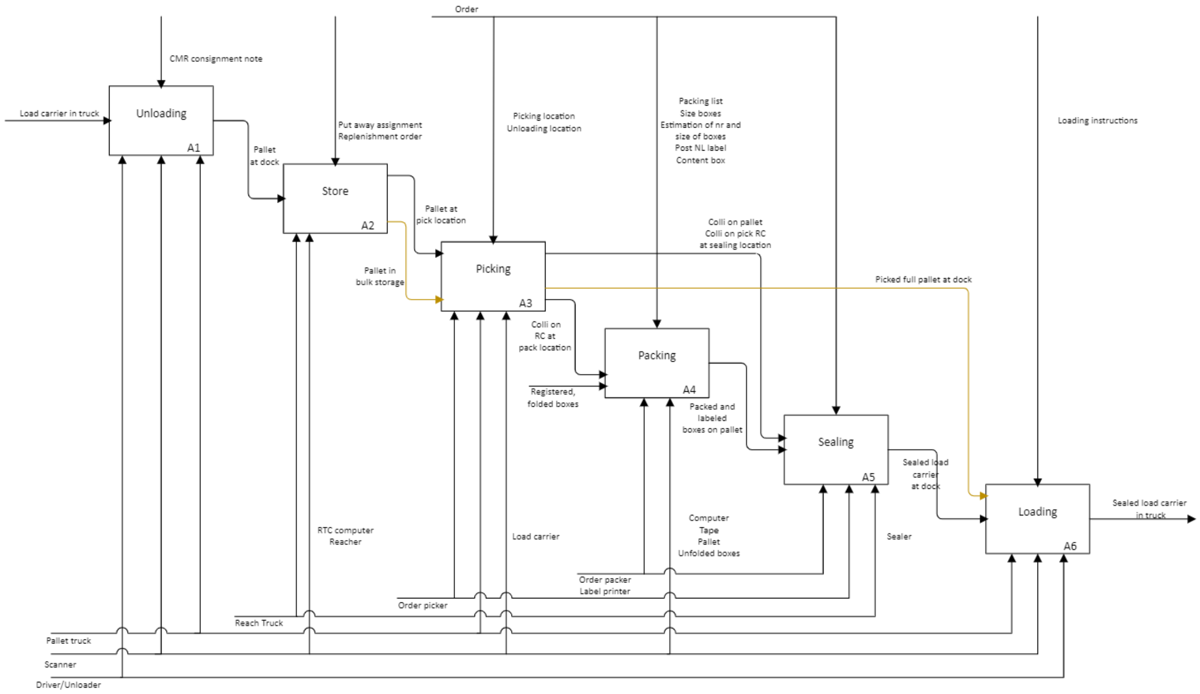

Figure A-3 – A-1 Level IDEF-0

As stated before, this diagram describes the processes a little bit more specifically. It can be seen that it all starts with the unloading of a truck, in which the driver or an unloader uses a scanner and a pallet truck to unload, and he needs a CMR consignment note in order to do so. With this control, the number of goods carried can be checked, as well as confirmed. After the pallets have been unloaded, the pallets have to be stored. The storage of goods entails the put-away process as well as the replenishment of the pick location. When the storing process is zoomed in on, the following processes can be defined:

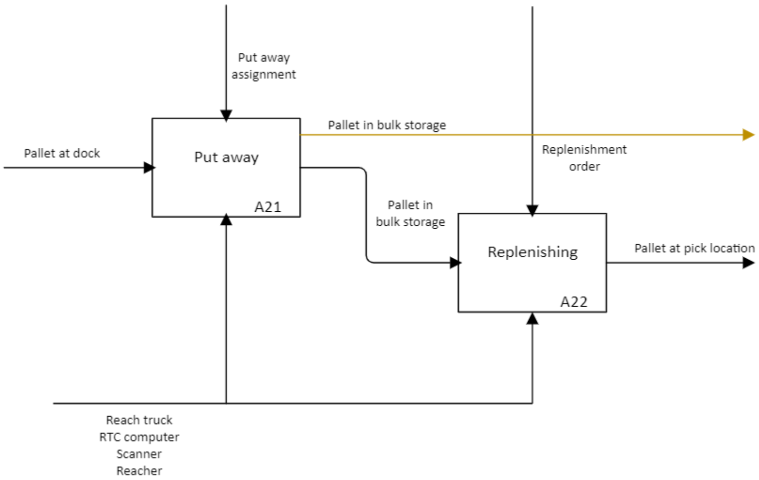

Figure A-4 – A-2 Level IDEF-0

The main takeaway from this diagram is that there can occur two situations: after being put away, the pallet in bulk storage goes directly towards the picking process, or the pallet goes from bulk storage through the replenishing process towards a picking location. These two flows depict the input for the picking process, which can be found in figure 4.

As stated before, the to-be-picked goods can either be a full pallet in bulk or a pallet at a picking location, where colli can be picked from that location. The process is built up with several steps that have to be taken. Firstly, a load carrier has to be picked up. After this, the order picker drives the pallet truck to the pick location. The location has to be scanned, after which goods can be picked and consequently registered.

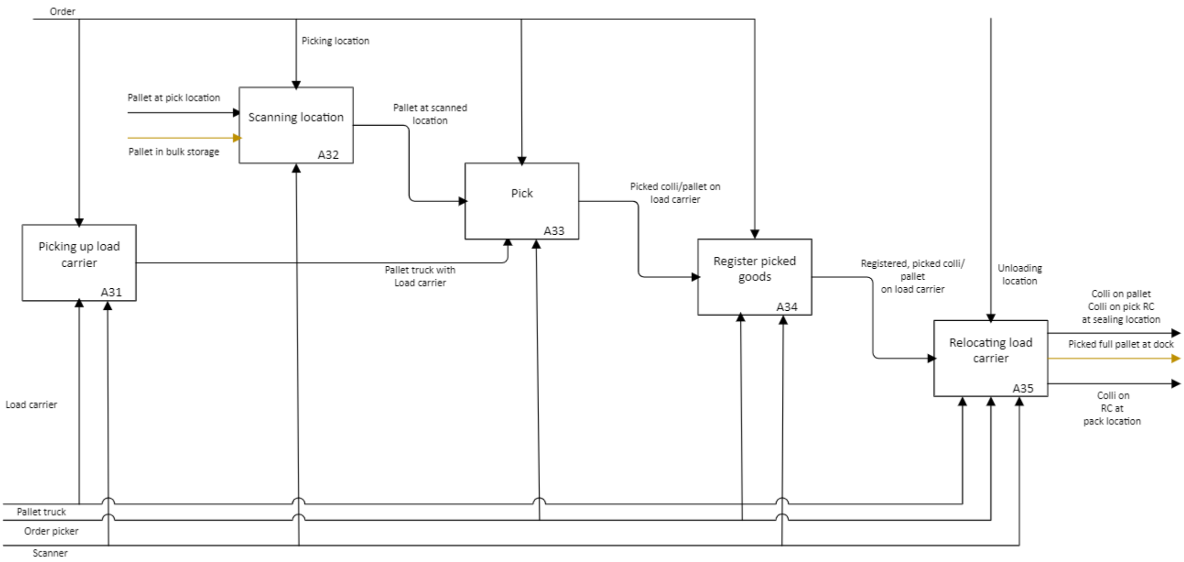

Figure A-5 – A-3 Level IDEF-0

Finally, the load carrier, which can be colli on a full pallet, on a 'pick roll container' or colli on a roll container with dividers, is headed for the packing process. These last orders are for outbound goods transported by PostNL, whereas the first two load carriers are transported by van Vliet.

It's vital to notice that there are three types of outputs from this flow, all of which flow toward a different next activity. The full pallets are still sealed from the inbound process and go directly towards the dock. The colli on pallet/pick RC go towards the sealing location, and lastly, the colli on RC with the dividers go to the packing location. The packing process consequently can be depicted by the following figure:

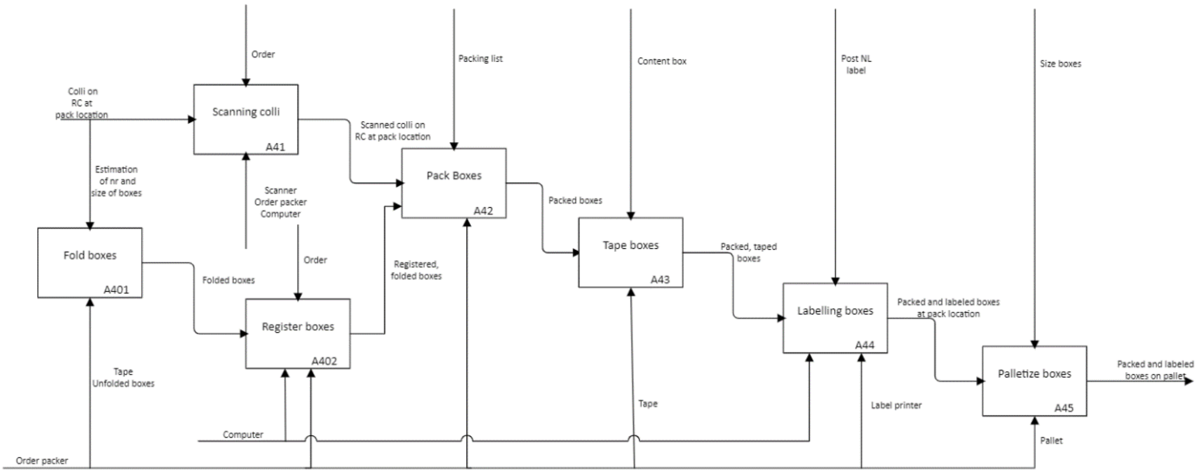

Figure A-6 – A-4 Level IDEF-0

There are two different flows that are important: the folding and registering of boxes, in which the colli eventually have to be packed, and the packing process itself in which the colli are scanned, packed, labeled, and eventually palletized. The end product is packed and labeled boxes on pallets which are consequently made ready for sealing. It is essential to see that both of these processes are executed by the same order packer. She, as stated before in the Gemba walk, has to make an estimate of the number of boxes that are needed to pack all the colli in an order. She then has to fold those boxes and pack them.

After the colli are packed, all of the load carriers are ready to be sealed, as can be seen from the first A-1 level diagram, after which they are loaded into outbound trucks. This shortly described how the warehouse operations are filled in at Nedcargo with e-commerce B2B type orders.

In order to see how the process flows are moving between different parties, in our case, employees, a swimlane diagram is created. A swimlane diagram is based on the analogy of lanes in a pool, and it places process steps within horizontal "swimlanes" of a particular department, workgroup, or employee (Office Timeline, 2020). The lines between different lanes represent communication between these lanes. The swimlane diagram can serve as an indicator of waste, redundancy, and inefficiency in a process.

The swimlane diagrams made in this study focus on the release, picking, and packing of orders. One diagram is made: one of the picking and packing processes of the small Post NL orders (see figure 8). The swimlane diagram includes all subprocesses from the release of orders to be picked by the team leader of the warehouse towards the final positioning of the load carrier with the picked (and packed) orders on the assigned dock.

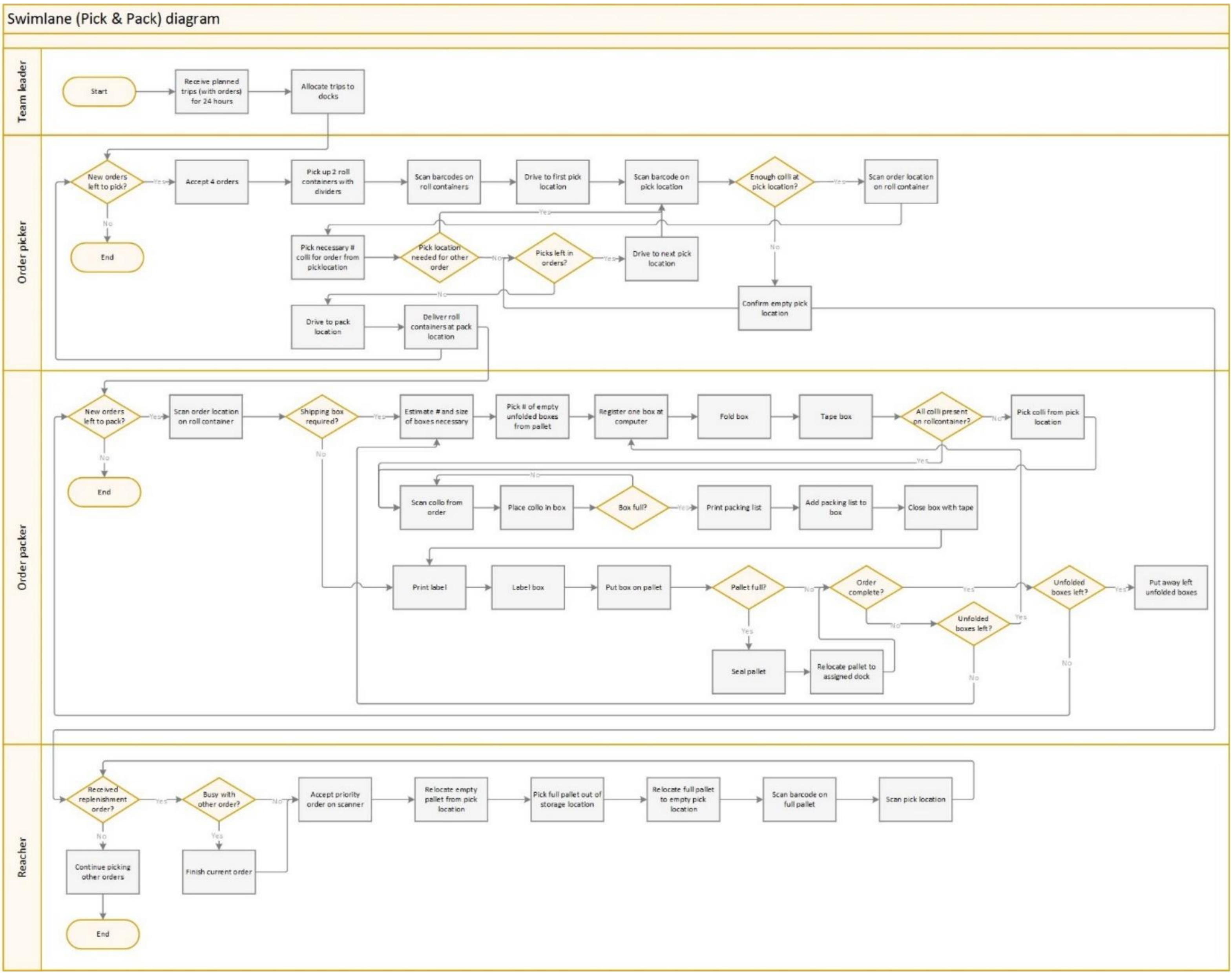

Figure A-7 – Swimlane Pick and Pack Diagram

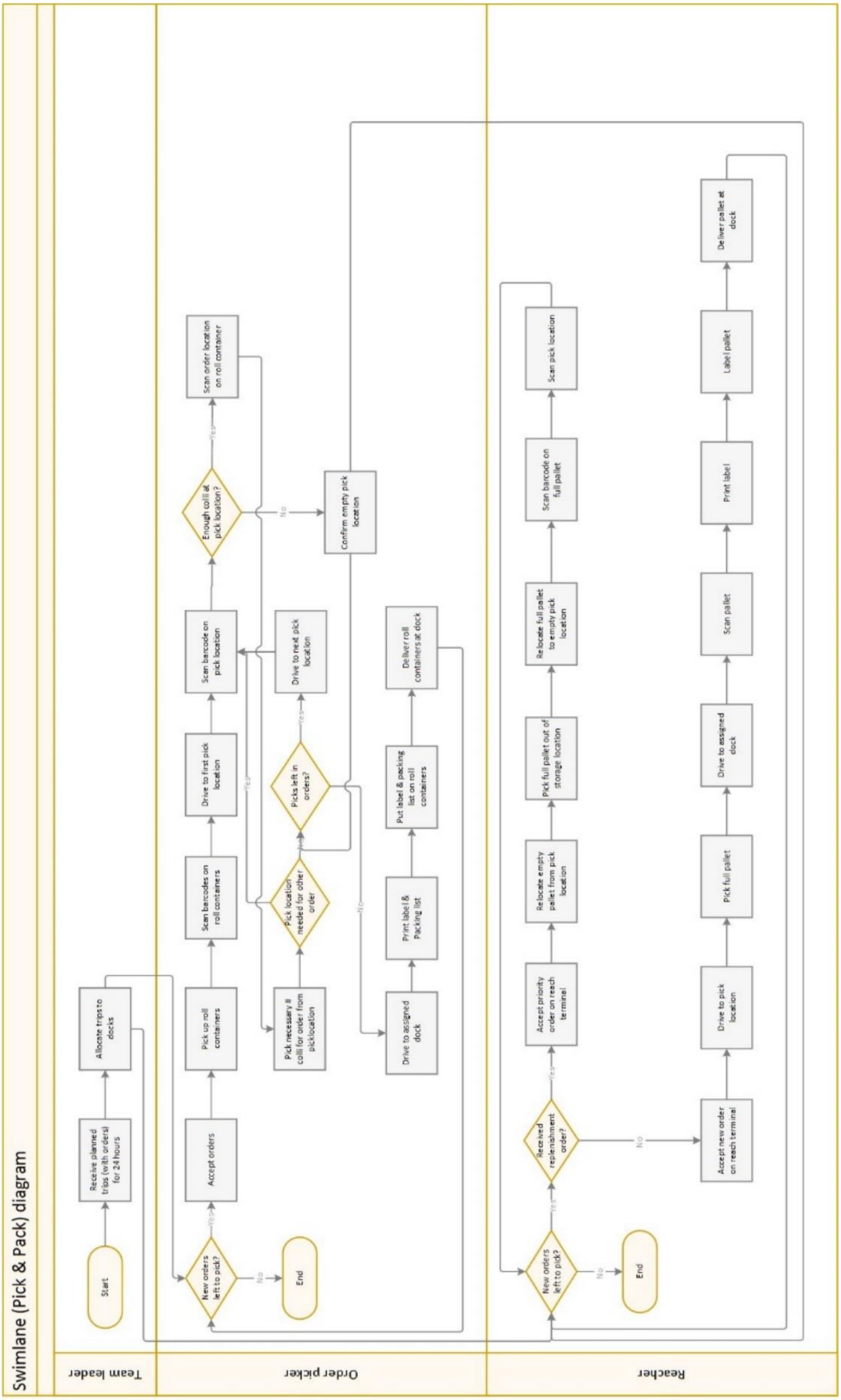

Figure A-8 – Swimlane Pick and Pack diagram, Replenishment

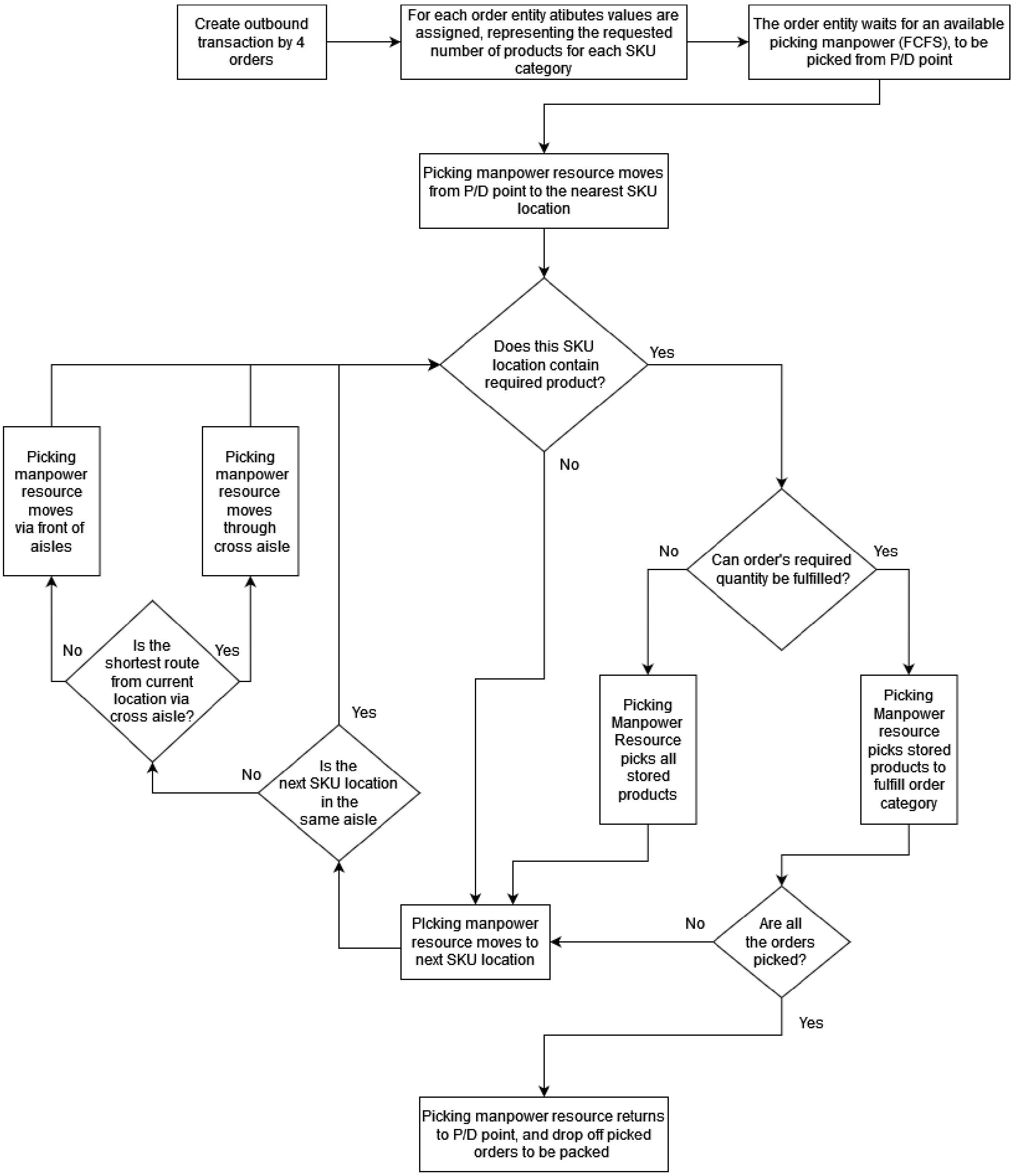

Figure A-10 – Logistics Flow Decision Chart per Picking Tour

Table A-1. Characteristics of fast-movers of total SKU Picked

Product Name	Ranking SKU	SKU Picks	% SKU	Ranking Colli	Amount of Colli	% Colli
DE MELKPOEDER ZAK	1	5356	6,81	4	7375	3,23
DE CACAO FANT BLUE	2	4081	3,93	11	5165	2,26
DE ESP DRST100%ARA	3	3390	3,26	2	8054	3,53
DE ESPR MED ROAST	4	3294	3,17	1	8654	3,79
DE CAFE MILC LIQ	5	2980	2,87	5	6973	3,05
DE WOODEN STIRRERS	6	2859	2,75	6	6765	2,96
DE SUIKERSTICKS	7	2646	2,54	12	5030	2,20
DE P. CUP BLCK	8	2269	2,18	13	4040	1,77
PICKW GR TEA LEM PRO	9	2264	2,18	3	7423	3,25
PICKW FOR FRT PROF	10	2167	2,08	10	5644	2,47

Table A-2. Characteristics of fast-movers of total Colli picked

Product Name	Ranking Colli	Amount of Colli	% Colli	Ranking SKU	SKU Picks	% SKU
DE ESPR MED ROAST	1	8654	3,79	4	3294	3,17
DE ESP DRST100%ARA	2	8054	3,53	3	3390	3,26
PICKW GR TEA LEM PRO	3	7423	3,25	9	2264	2,18
DE MELKPOEDER ZAK	4	7375	3,23	1	5356	6,81
DE CAFE MILC LIQ	5	6973	3,05	5	2980	2,87
DE WOODEN STIRRERS	6	6765	2,96	6	2859	2,75
PICKW ROOIB ORIG	7	6375	2,80	11	2114	2,03
LOR PROMESSO MILC	8	5913	2,79	18	1428	1,37
PICKW ENGLISH PROF	9	5644	2,59	12	1862	1,79
PICKW FOR FRT PROF	10	5165	2,47	10	2167	2,08

Table A-3. Picker Performance on Busiest Day

23-06-2021		*Total Colli:*	*1761*		
		Day Performance:	*101,27 Colli/h*	*Avg. Picking Time:*	*8720*
PickerID	Performance	Amount of Colli	Picking Time (sec)	Amount of Batches	
BELJRF	182,14	51	1008	1	
DOBARF	58,41	35	2157	1	
FIGSRF	32,06	10	1123	1	
JURARF	103,53	619	21523	16	
JURPRF	100,47	419	15013	8	
NICTRF	109,89	398	13039	15	
STYARF	114,85	229	7178	10	

Table A-4. Picker Performance on Average Day in Colli

18-03-2021		*Total Colli:*	*1006*		
		Day Performance:	*92,97 Colli/h*	*Avg. Picking Time:*	*6585*
PickerID	Performance	Amount of Colli	Picking Time (sec)	Amount of Batches	
BELJRF	86,31	58	2419	6	
FIGSRF	139,96	18	463	1	
KAWPRF	96,81	629	23390	25	
OSCBRF	128,40	82	2299	2	
RUIGRF	61,77	83	4837	3	
VERGRF	80,25	136	6101	8	

Table A-5. Picker Performance on Average Performance Day

08-07-2021		*Total Colli:*	*925*		
		Day Performance:	*111,99 Colli/h*	*Avg. Picking Time:*	*9588*
PickerID	Performance	Amount of Colli	Picking Time (sec)	Amount of Batches	
KLESRF	147,37	409	19506	28	
WIEMRF	95,23	516	19027	20	

Table A-6 ABC-analysis of Colli picked per product in Tiel

	A-Products	*B-Products*	*C-Products*
Total Products	60	80	244
Share of Products	17,09%	27,07%	55,84%
Share of Colli Picks	75,52%	19,60%	4,88%

Table A-7. Colli picked share for A-products total Colli

Colli Picked	1	2-3	4-8	9-15	16-50	50-250
Total Picks	34983	26432	11243	1577	592	36
Share	46,73%	35,31%	15,02%	2,11%	0,79%	0,05%

Table A-8. Colli picked share for B-products total Colli

Colli Picked	1	2-3	4-8	9-15	16-50	50-250
Total Picks	12256	7232	2690	311	114	1
Share	54,22%	31,99%	11,90%	1,38%	0,50%	0,00%

Table A-9. Colli picked share for C-products total Colli

Colli Picked	1	2-3	4-8	9-15	16-50	50-250
Total Picks	4184	1655	562	84	17	0
Share	64,35%	25,45%	8,64%	1,29%	0,26%	0,00%

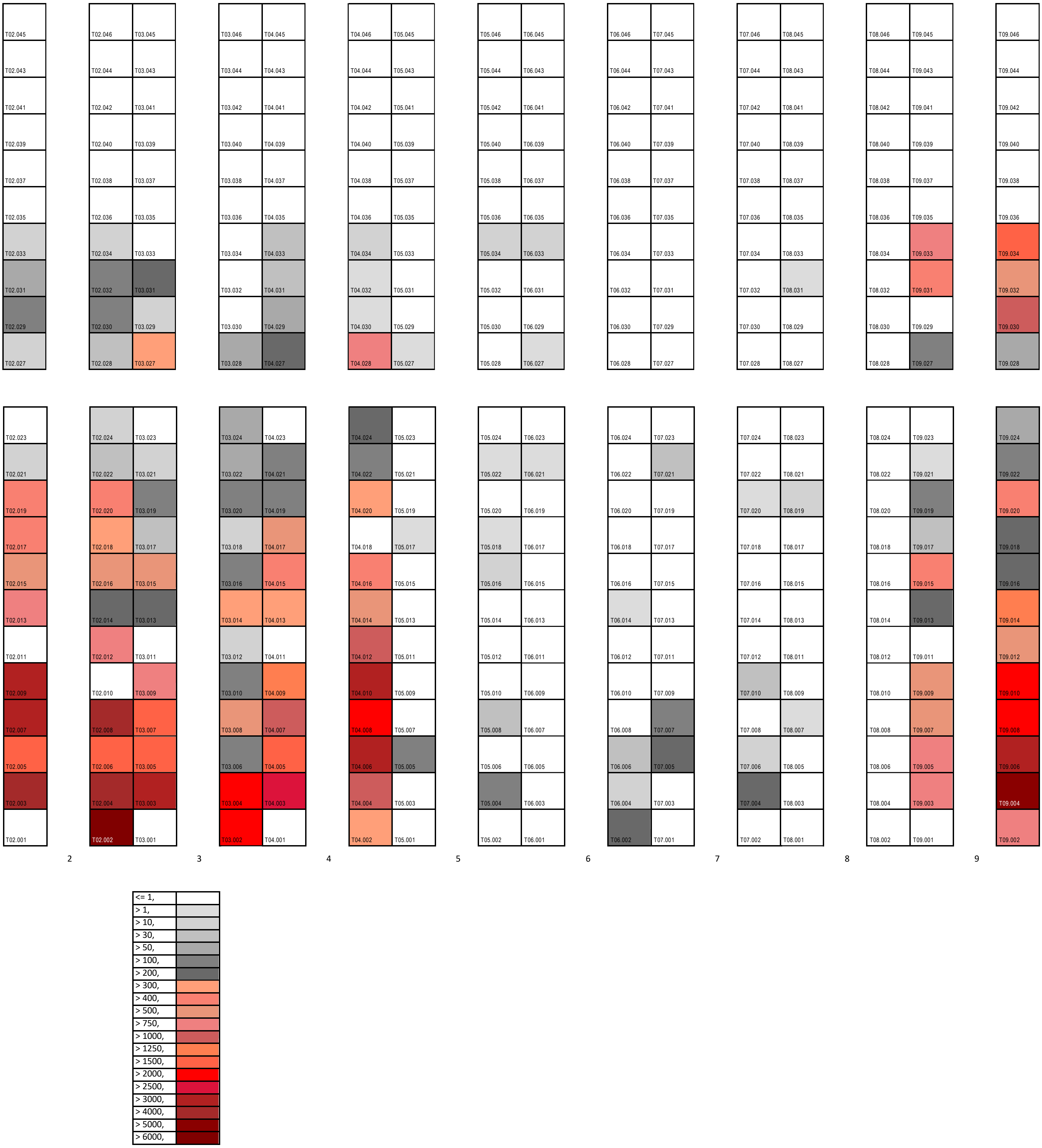

Figure A-11 – Heat Map of SKU picks in Tiel

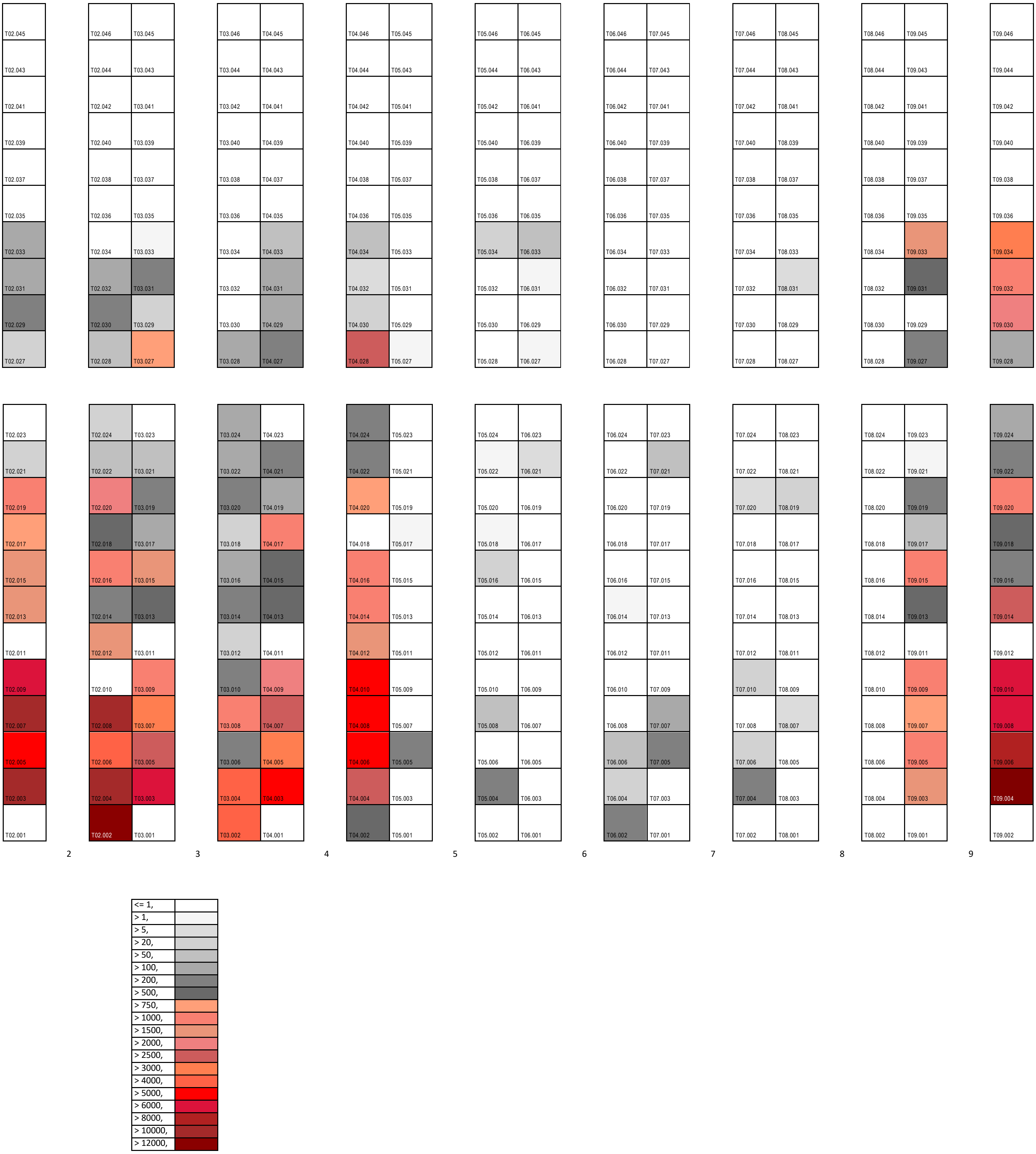

Figure A-12 – Heat Map of Colli Picked in Tiel

Appendix B: Scenarios

	SKU per Order	*ABC-Ratio*	*Number of SKU*	*Colli per SKU*
Scenario 1	Level 1	Level 1	Level 1	Level 1
Scenario 2	Level 1	Level 1	Level 1	Level 2
Scenario 3	Level 1	Level 1	Level 1	Level 3
Scenario 4	Level 1	Level 1	Level 1	Level 4
Scenario 5	Level 1	Level 1	Level 2	Level 1
Scenario 6	Level 1	Level 1	Level 2	Level 2
Scenario 7	Level 1	Level 1	Level 2	Level 3
Scenario 8	Level 1	Level 1	Level 2	Level 4
Scenario 9	Level 1	Level 1	Level 3	Level 1
Scenario 10	Level 1	Level 1	Level 3	Level 2
Scenario 11	Level 1	Level 1	Level 3	Level 3
Scenario 12	Level 1	Level 1	Level 3	Level 4
Scenario 13	Level 1	Level 2	Level 1	Level 1
Scenario 14	Level 1	Level 2	Level 1	Level 2
Scenario 15	Level 1	Level 2	Level 1	Level 3
Scenario 16	Level 1	Level 2	Level 1	Level 4
Scenario 17	Level 1	Level 2	Level 2	Level 1
Scenario 18	Level 1	Level 2	Level 2	Level 2
Scenario 19	Level 1	Level 2	Level 2	Level 3
Scenario 20	Level 1	Level 2	Level 2	Level 4
Scenario 21	Level 1	Level 2	Level 3	Level 1
Scenario 22	Level 1	Level 2	Level 3	Level 2
Scenario 23	Level 1	Level 2	Level 3	Level 3
Scenario 24	Level 1	Level 2	Level 3	Level 4
Scenario 25	Level 1	Level 3	Level 1	Level 1
Scenario 26	Level 1	Level 3	Level 1	Level 2
Scenario 27	Level 1	Level 3	Level 1	Level 3
Scenario 28	Level 1	Level 3	Level 1	Level 4
Scenario 29	Level 1	Level 3	Level 2	Level 1
Scenario 30	Level 1	Level 3	Level 2	Level 2
Scenario 31	Level 1	Level 3	Level 2	Level 3
Scenario 32	Level 1	Level 3	Level 2	Level 4
Scenario 33	Level 1	Level 3	Level 3	Level 1
Scenario 34	Level 1	Level 3	Level 3	Level 2
Scenario 35	Level 1	Level 3	Level 3	Level 3
Scenario 36	Level 1	Level 3	Level 3	Level 4
Scenario 37	Level 2	Level 1	Level 1	Level 1
Scenario 38	Level 2	Level 1	Level 1	Level 2
Scenario 39	Level 2	Level 1	Level 1	Level 3
Scenario 40	Level 2	Level 1	Level 1	Level 4
Scenario 41	Level 2	Level 1	Level 2	Level 1
Scenario 42	Level 2	Level 1	Level 2	Level 2
Scenario 43	Level 2	Level 1	Level 2	Level 3
Scenario 44	Level 2	Level 1	Level 2	Level 4
Scenario 45	Level 2	Level 1	Level 3	Level 1
Scenario 46	Level 2	Level 1	Level 3	Level 2
Scenario 47	Level 2	Level 1	Level 3	Level 3

Scenario 48	Level 2	Level 1	Level 3	Level 4
Scenario 49	Level 2	Level 2	Level 1	Level 1
Scenario 50	Level 2	Level 2	Level 1	Level 2
Scenario 51	Level 2	Level 2	Level 1	Level 3
Scenario 52	Level 2	Level 2	Level 1	Level 4
Scenario 53	Level 2	Level 2	Level 2	Level 1
Scenario 54	Level 2	Level 2	Level 2	Level 2
Scenario 55	Level 2	Level 2	Level 2	Level 3
Scenario 56	Level 2	Level 2	Level 2	Level 4
Scenario 57	Level 2	Level 2	Level 3	Level 1
Scenario 58	Level 2	Level 2	Level 3	Level 2
Scenario 59	Level 2	Level 2	Level 3	Level 3
Scenario 60	Level 2	Level 2	Level 3	Level 4
Scenario 61	Level 2	Level 3	Level 1	Level 1
Scenario 62	Level 2	Level 3	Level 1	Level 2
Scenario 63	Level 2	Level 3	Level 1	Level 3
Scenario 64	Level 2	Level 3	Level 1	Level 4
Scenario 65	Level 2	Level 3	Level 2	Level 1
Scenario 66	Level 2	Level 3	Level 2	Level 2
Scenario 67	Level 2	Level 3	Level 2	Level 3
Scenario 68	Level 2	Level 3	Level 2	Level 4
Scenario 69	Level 2	Level 3	Level 3	Level 1
Scenario 70	Level 2	Level 3	Level 3	Level 2
Scenario 71	Level 2	Level 3	Level 3	Level 3
Scenario 72	Level 2	Level 3	Level 3	Level 4
Scenario 73	Level 3	Level 1	Level 1	Level 1
Scenario 74	Level 3	Level 1	Level 1	Level 2
Scenario 75	Level 3	Level 1	Level 1	Level 3
Scenario 76	Level 3	Level 1	Level 1	Level 4
Scenario 77	Level 3	Level 1	Level 2	Level 1
Scenario 78	Level 3	Level 1	Level 2	Level 2
Scenario 79	Level 3	Level 1	Level 2	Level 3
Scenario 80	Level 3	Level 1	Level 2	Level 4
Scenario 81	Level 3	Level 1	Level 3	Level 1
Scenario 82	Level 3	Level 1	Level 3	Level 2
Scenario 83	Level 3	Level 1	Level 3	Level 3
Scenario 84	Level 3	Level 1	Level 3	Level 4
Scenario 85	Level 3	Level 2	Level 1	Level 1
Scenario 86	Level 3	Level 2	Level 1	Level 2
Scenario 87	Level 3	Level 2	Level 1	Level 3
Scenario 88	Level 3	Level 2	Level 1	Level 4
Scenario 89	Level 3	Level 2	Level 2	Level 1
Scenario 90	Level 3	Level 2	Level 2	Level 2
Scenario 91	Level 3	Level 2	Level 2	Level 3
Scenario 92	Level 3	Level 2	Level 2	Level 4
Scenario 93	Level 3	Level 2	Level 3	Level 1
Scenario 94	Level 3	Level 2	Level 3	Level 2
Scenario 95	Level 3	Level 2	Level 3	Level 3
Scenario 96	Level 3	Level 2	Level 3	Level 4

Scenario 97	Level 3	Level 3	Level 1	Level 1
Scenario 98	Level 3	Level 3	Level 1	Level 2
Scenario 99	Level 3	Level 3	Level 1	Level 3
Scenario 100	Level 3	Level 3	Level 1	Level 4
Scenario 101	Level 3	Level 3	Level 2	Level 1
Scenario 102	Level 3	Level 3	Level 2	Level 2
Scenario 103	Level 3	Level 3	Level 2	Level 3
Scenario 104	Level 3	Level 3	Level 2	Level 4
Scenario 105	Level 3	Level 3	Level 3	Level 1
Scenario 106	Level 3	Level 3	Level 3	Level 2
Scenario 107	Level 3	Level 3	Level 3	Level 3
Scenario 108	Level 3	Level 3	Level 3	Level 4
Scenario 109	Level 4	Level 1	Level 1	Level 1
Scenario 110	Level 4	Level 1	Level 1	Level 2
Scenario 111	Level 4	Level 1	Level 1	Level 3
Scenario 112	Level 4	Level 1	Level 1	Level 4
Scenario 113	Level 4	Level 1	Level 2	Level 1
Scenario 114	Level 4	Level 1	Level 2	Level 2
Scenario 115	Level 4	Level 1	Level 2	Level 3
Scenario 116	Level 4	Level 1	Level 2	Level 4
Scenario 117	Level 4	Level 1	Level 3	Level 1
Scenario 118	Level 4	Level 1	Level 3	Level 2
Scenario 119	Level 4	Level 1	Level 3	Level 3
Scenario 120	Level 4	Level 1	Level 3	Level 4
Scenario 121	Level 4	Level 2	Level 1	Level 1
Scenario 122	Level 4	Level 2	Level 1	Level 2
Scenario 123	Level 4	Level 2	Level 1	Level 3
Scenario 124	Level 4	Level 2	Level 1	Level 4
Scenario 125	Level 4	Level 2	Level 2	Level 1
Scenario 126	Level 4	Level 2	Level 2	Level 2
Scenario 127	Level 4	Level 2	Level 2	Level 3
Scenario 128	Level 4	Level 2	Level 2	Level 4
Scenario 129	Level 4	Level 2	Level 3	Level 1
Scenario 130	Level 4	Level 2	Level 3	Level 2
Scenario 131	Level 4	Level 2	Level 3	Level 3
Scenario 132	Level 4	Level 2	Level 3	Level 4
Scenario 133	Level 4	Level 3	Level 1	Level 1
Scenario 134	Level 4	Level 3	Level 1	Level 2
Scenario 135	Level 4	Level 3	Level 1	Level 3
Scenario 136	Level 4	Level 3	Level 1	Level 4
Scenario 137	Level 4	Level 3	Level 2	Level 1
Scenario 138	Level 4	Level 3	Level 2	Level 2
Scenario 139	Level 4	Level 3	Level 2	Level 3
Scenario 140	Level 4	Level 3	Level 2	Level 4
Scenario 141	Level 4	Level 3	Level 3	Level 1
Scenario 142	Level 4	Level 3	Level 3	Level 2
Scenario 143	Level 4	Level 3	Level 3	Level 3
Scenario 144	Level 4	Level 3	Level 3	Level 4

Appendix C: Experiment Generation Model

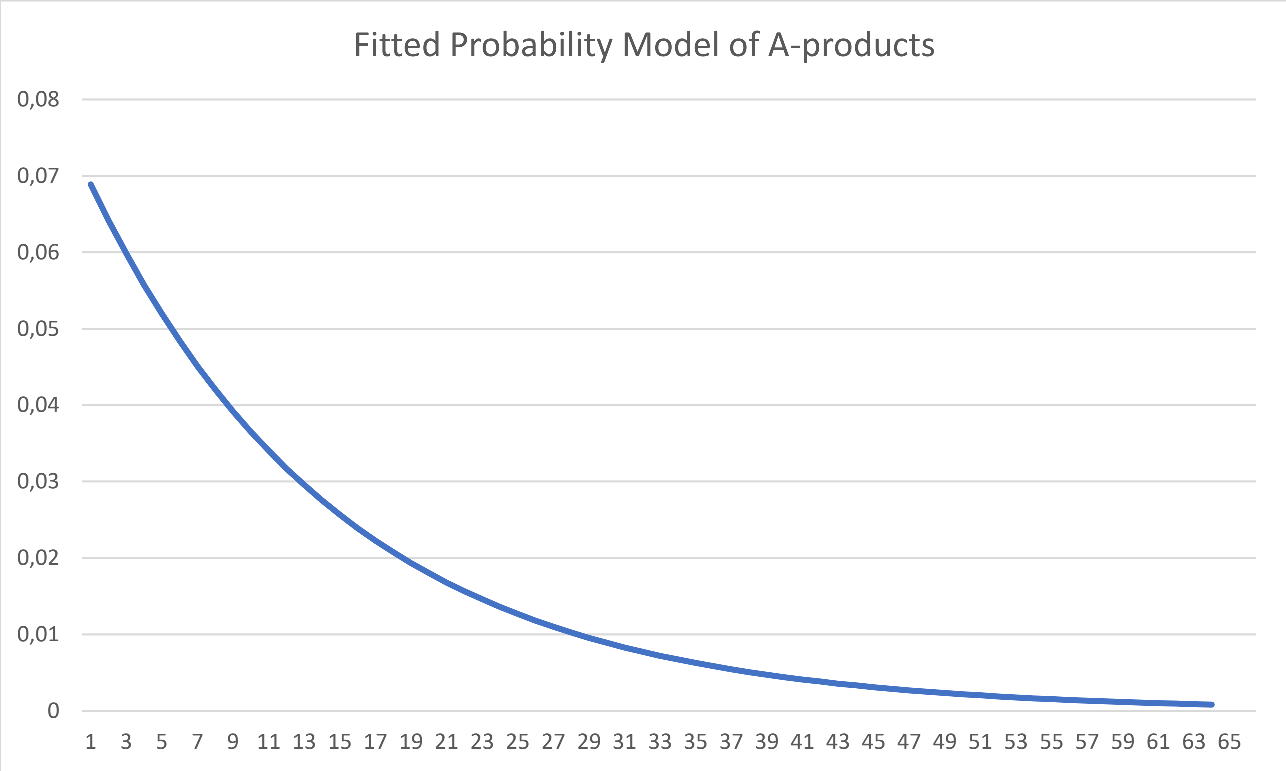

Figure C-1– Fitted probability of an A-product being picked in Tiel per SKU

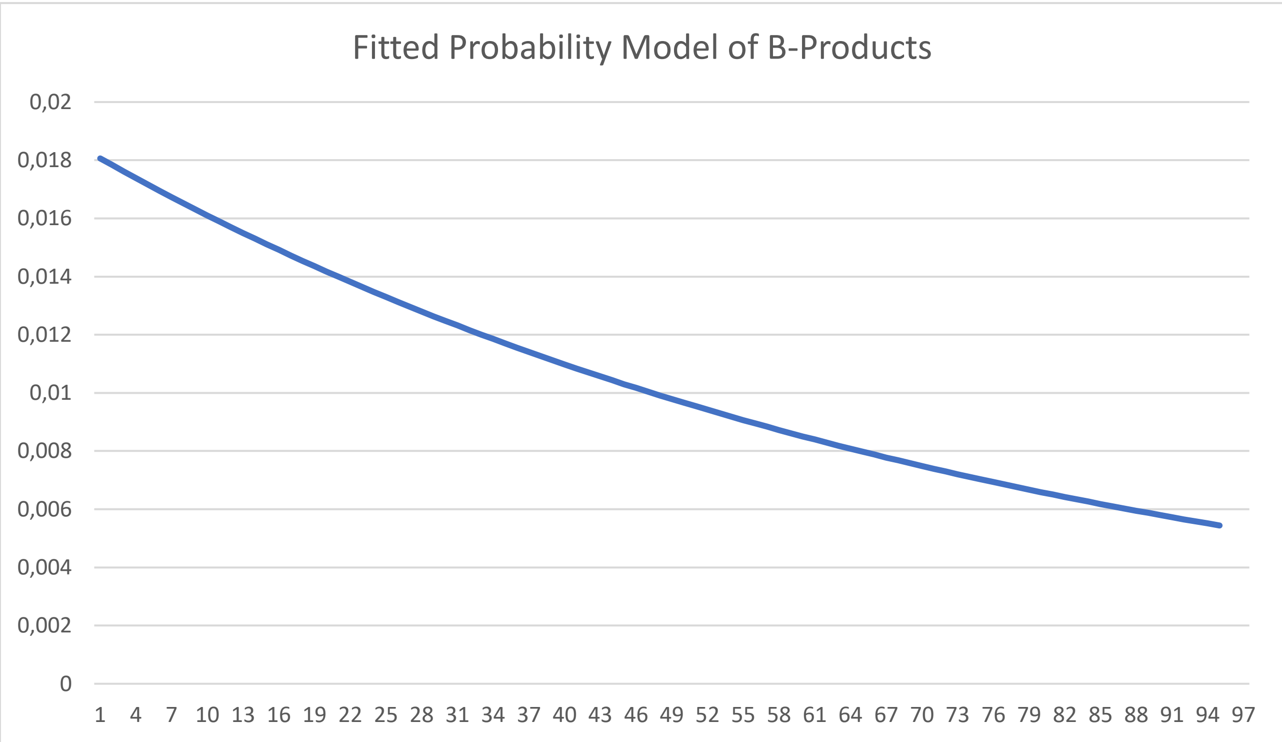

Figure C-2 – Fitted probability of a B-product being picked in Tiel per SKU

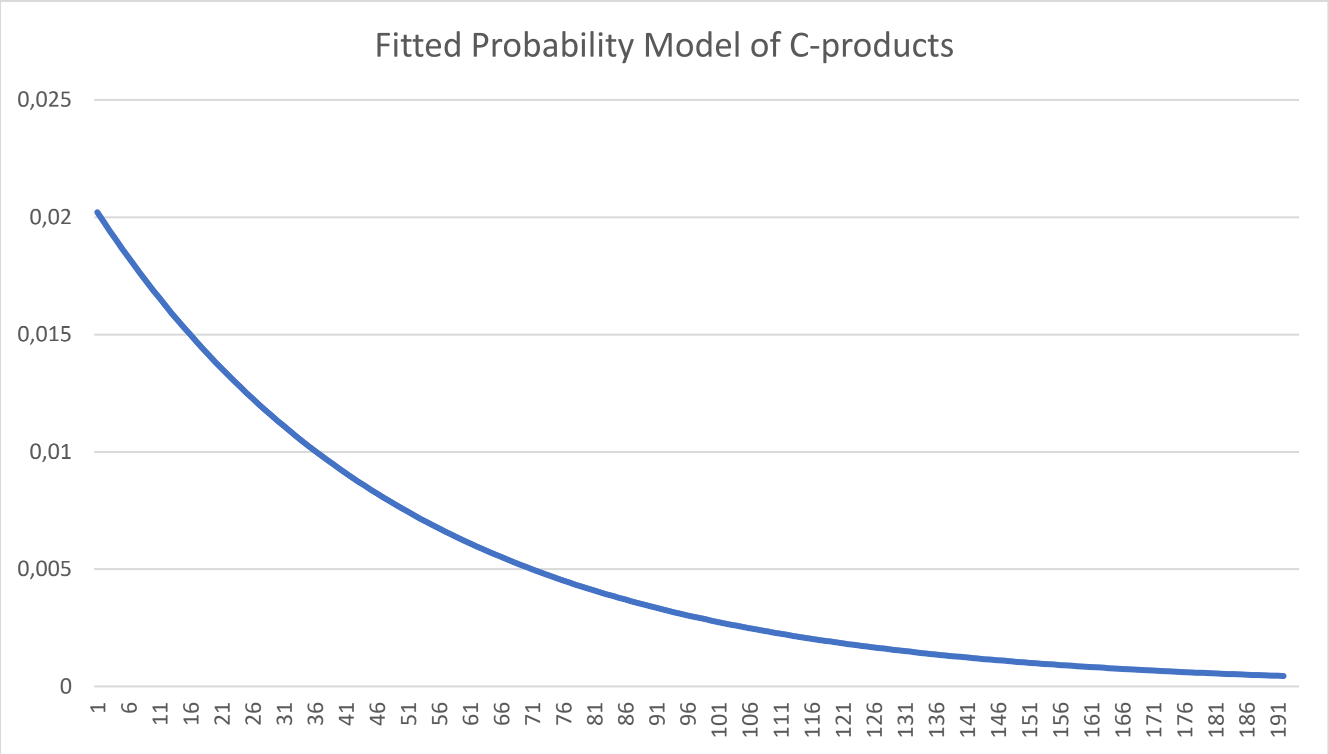

Figure C-3 – Fitted probability of an C-product being picked in Tiel per SKU

Appendix D: Configuration Model 2

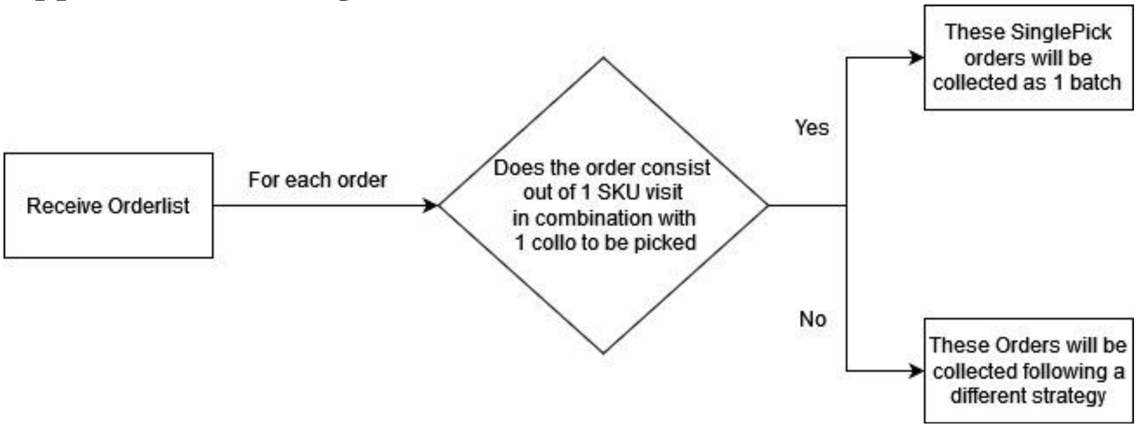

Figure D-1 – SinglePick Decision Chart

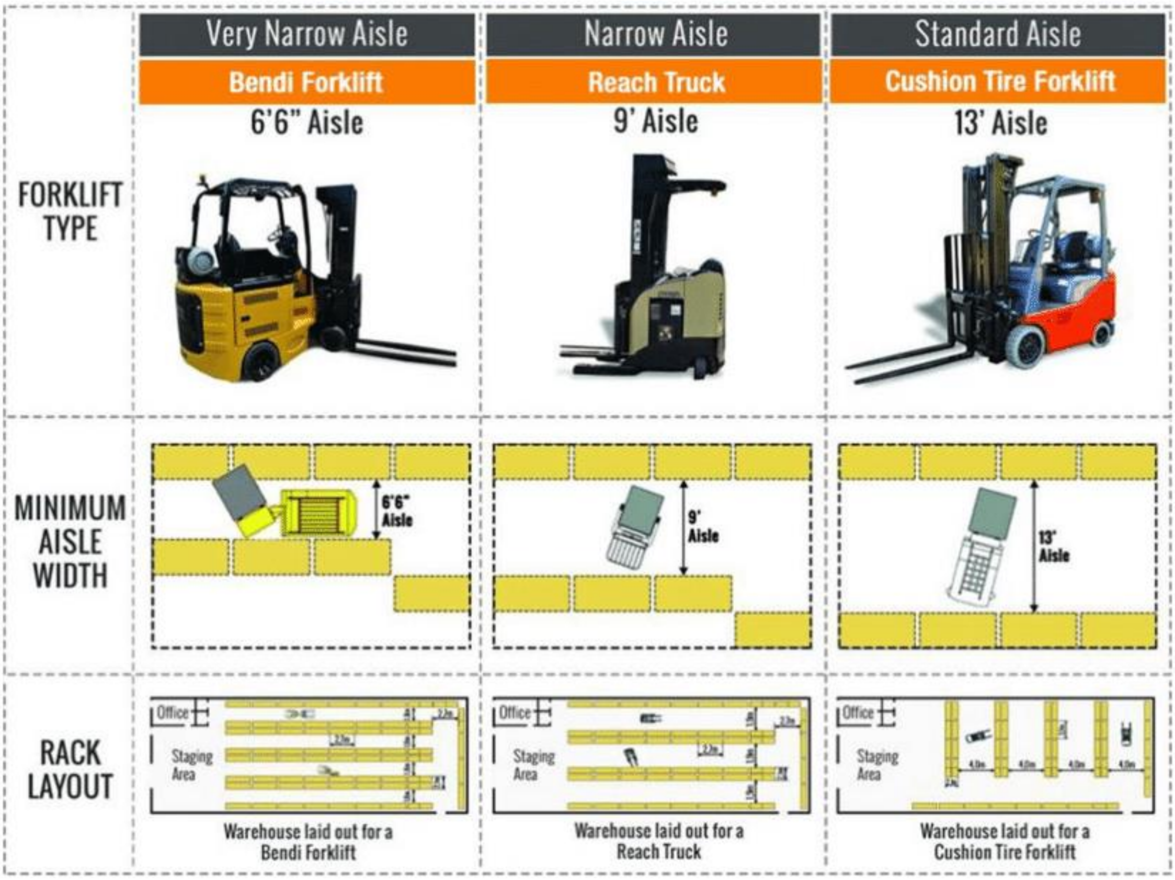

Figure D-2 – Width of Aisle per Forklift Type. In the configuration models Reach Truck is used.

Appendix E: Results and Analysis

E1. Results Current State Model Tiel

Table E-1. KPI's of the current state model of Tiel in comparison to configurations models with batch strategy and singlepicks

Configurations use Batch Strategy with SinglePicks				
	Tiel	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	65977	50553	50735	53090
Avg. Total Picking Time (min)	1100	843	846	885
Avg. Total Picking Time (h)	18,3	14,0	14,1	14,7
Avg. Total Colli	2302	2302	2302	2302
Avg. Colli/Hour	126	164	163	156
Avg. Total Pickers	3,0	2,00	2,0	2,0
Avg. Pick Time(h)/Picker	6,1	7,02	7,0	7,4
Avg. Distance Batch (m)	316	104	105	163
Avg. Total Distance (m)	23711	6238	6325	9782
Avg. Batching Time (s)	880	843	846	885

Table E-2. KPI's of the current state model of Tiel in comparison to configurations models with batch strategy

Configurations use Batch Strategy				
	Tiel	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	65977	55030	54745	57590
Avg. Total Picking Time (min)	1100	917	912	960
Avg. Total Picking Time (h)	18,3	15,3	15,2	16,0
Avg. Total Colli	2302	2302	2302	2302
Avg. Colli/Hour	126	151	152	144
Avg. Total Pickers	3,0	2,00	2,0	2,7
Avg. Pick Time(h)/Picker	6,1	7,64	7,6	6,0
Avg. Distance Batch (m)	316	91	90	155
Avg. Total Distance (m)	23711	6664	6487	11204
Avg. Batching Time (s)	880	749	761	800

Table E-3. KPI's of the current state model of Tiel in comparison of configurations models with FCFS strategy

Configurations use FCFS				
	Tiel	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	65977	57704	57033	61962
Avg. Total Picking Time (min)	1100	962	951	1033
Avg. Total Picking Time (h)	18,3	16,0	15,8	17,2
Avg. Total Colli	2302	2302	2302	2302
Avg. Colli/Hour	126	144	145	134
Avg. Total Pickers	3,0	2,40	2,3	3,0
Avg. Pick Time(h)/Picker	6,1	6,93	7,0	5,7
Avg. Distance Batch (m)	316	119	115	209
Avg. Total Distance (m)	23711	8939	8613	15657
Avg. Batching Time (s)	880	769	760	826

E2. Experimental Plans; Results from Experiment Generation Model

Table E-4. Experimental Plan for Scenario 50

	SKU per Order	*Distribution 2*	Number Of SKUs	*Level 1*	
	ABC-Ratio	*Level 2*	Colli per SKU	*Distribution 2*	
	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Orders	300	300	300	300	300
Orderlines	794	835	912	794	837
Total Colli	2176	2482	2536	2101	2281
Avg. Orderline/Order	2,65	2,78	3,04	2,65	2,79
Avg. Colli/Orderline	2,74	2,97	2,78	2,65	2,73
Avg. Colli/Order	7,25	8,27	8,45	7,00	7,60
Number of SinglePicks	74	72	62	83	67

Table E-5. Experimental Plan for Scenario 107

	SKU per Order	*Distribution 3*	Number Of SKUs	*Level 3*	
	ABC-Ratio	*Level 3*	Colli per SKU	*Distribution 3*	
	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Orders	300	300	300	300	300
Orderlines	734	706	711	816	766
Total Colli	1560	1640	1687	1736	1607
Avg. Orderline/Order	2,45	2,35	2,37	2,72	2,55
Avg. Colli/Orderline	2,13	2,32	2,37	2,13	2,10
Avg. Colli/Order	5,20	5,47	5,62	5,79	5,36
Number of SinglePicks	77	82	82	68	88

Table E-6. Experimental Plan for Scenario 10

	SKU per Order	*Distribution 1*	Number Of SKUs	*Level 3*	
	ABC-Ratio	*Level 1*	Colli per SKU	*Distribution 2*	
	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Orders	300	300	300	300	300
Orderlines	1665	1565	1438	1495	1636
Total Colli	4606	3937	3759	4048	4506
Avg. Orderline/Order	5,55	5,22	4,79	4,98	5,45
Avg. Colli/Orderline	2,77	2,52	2,61	2,71	2,75
Avg. Colli/Order	15,35	13,12	12,53	13,49	15,02
Number of SinglePicks	31	40	43	37	38

Table E-7. Experimental Plan for Scenario 77

	SKU per Order ABC-Ratio	*Distribution 3* *Level 1*	Number Of SKUs Colli per SKU	*Level 2* *Distribution 1*	
	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Orders	300	300	300	300	300
Orderlines	662	737	694	751	727
Total Colli	2819	3664	3262	3123	3388
Avg. Orderline/Order	2,21	2,46	2,31	2,50	2,42
Avg. Colli/Orderline	4,26	4,97	4,70	4,16	4,66
Avg. Colli/Order	9,40	12,21	10,87	10.41	11,29
Number of SinglePicks	59	55	57	65	60

Table E-8. Experimental Plan for Scenario 92

	SKU per Order ABC-Ratio	*Distribution 3* *Level 2*	Number Of SKUs Colli per SKU	*Level 2* *Distribution 4*	
	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Orders	300	300	300	300	300
Orderlines	742	736	709	721	764
Total Colli	2181	2217	2015	1981	2285
Avg. Orderline/Order	2,47	2,45	2,36	2,40	2,55
Avg. Colli/Orderline	2,94	3,01	2,84	2,75	2,99
Avg. Colli/Order	7,27	7,39	6,72	6,60	7,62
Number of SinglePicks	83	75	94	78	84

Table E-9. Experimental Plan for Scenario 123

	SKU per Order ABC-Ratio	*Distribution 4* *Level 2*	Number Of SKUs Colli per SKU	*Level 1* *Distribution 3*	
	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
Orders	300	300	300	300	300
Orderlines	1095	1130	1090	1000	1042
Total Colli	2312	2616	2544	2377	2110
Avg. Orderline/Order	3,65	3,77	3,63	3,33	3,47
Avg. Colli/Orderline	2,11	2,32	2,33	2,38	2,02
Avg. Colli/Order	7,71	8,72	8,48	7,92	7,03
Number of SinglePicks	75	79	72	79	83

E3. Overall Results of Configuration Models per Batching Strategy

Table E-10. KPI's of Configuration 1 with batching strategy and singlepicks in the multiple scenarios

Configuration 1	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Orders	300	300	300	300	300	300
Orderlines	834	747	1560	714	734	1071
Total Colli	2315	1646	4171	3251	2135	2391
Avg. Orderline/Order	2,78	2,21	5,20	2,38	2,45	3,57
Avg. Colli/Orderline	2,77	2,21	2,67	4,55	2,90	2,23
Avg. Colli/Order	7,71	5,49	13,90	10,94	7,12	7,97
Avg. SinglePicks	71,6	79,4	37,8	59,2	82,8	77,6
	Batch+SP					
Avg. Total Picking Time (s)	50973	47946	84267	56282	48055	55098
Avg. Total Picking Time (min)	850	799	1404	938	801	918
Avg. Total Picking Time (h)	14,2	13,3	23,4	15,6	13,3	15,3
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	163	124	178	208	160	156
Avg. Total Pickers	2	2,0	3,4	2	2	2
Avg. Pick Time(h)/Picker	7,1	6,7	7,0	7,2	6,7	7,3
Avg. Distance Batch (m)	113	186	200	103	131	126
Avg. Total Distance (m)	6647	10486	13401	6355	7283	7184
Avg. Batching Time (s)	869	850	1257	914	862	963
	Batching Strategy					
Avg. Total Picking Time (s)	55957	53512	86587	59970	53779	60151
Avg. Total Picking Time (min)	933	892	1443	999	896	1003
Avg. Total Picking Time (h)	15,5	14,9	24,1	16,7	14,9	16,7
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	149	111	173	195	143	143
Avg. Total Pickers	2	2,0	3,4	3	2	3
Avg. Pick Time(h)/Picker	7,0	7,4	7,1	6,1	7,5	5,8
Avg. Distance Batch (m)	99	157	186	92	109	107
Avg. Total Distance (m)	7267	11460	13822	6790	7975	7798
Avg. Batching Time (s)	763	732	1167	815	737	823
	FCFS					
Avg. Total Picking Time (s)	58548	57193	89736	62414	56730	63316
Avg. Total Picking Time (min)	976	953	1496	1040	946	1055
Avg. Total Picking Time (h)	16,3	15,9	24,9	17,3	15,8	17,6
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	142	104	167	187	135	136
Avg. Total Pickers	3	2,3	3,7	3	2	3
Avg. Pick Time(h)/Picker	6,4	7,2	6,8	6,0	7,0	5,9
Avg. Distance Batch (m)	126	206	231	123	145	139
Avg. Total Distance (m)	9479	15476	17352	9206	10880	10406
Avg. Batching Time (s)	781	763	1196	832	756	844

Table E-11. KPIs of Configuration 2 with batching strategy in the multiple scenarios

Configuration 2						
	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Orders	300	300	300	300	300	300
Orderlines	834	747	1560	714	734	1071
Total Colli	2315	1646	4171	3251	2135	2391
Avg. Orderline/Order	2,78	2,21	5,20	2,38	2,45	3,57
Avg. Colli/Orderline	2,77	2,21	2,67	4,55	2,90	2,23
Avg. Colli/Order	7,71	5,49	13,90	10,94	7,12	7,97
Avg. SinglePicks	71,6	79,4	37,8	59,2	82,8	77,6
	Batch+SP					
Avg. Total Picking Time (s)	50961	47842	84219	56413	48324	54853
Avg. Total Picking Time (min)	849	797	1404	940	805	914
Avg. Total Picking Time (h)	14,2	13,3	23,4	15,7	13,4	15,2
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	163	124	178	207	159	157
Avg. Total Pickers	2	2,0	3,4	2	2	2
Avg. Pick Time(h)/Picker	7,1	6,6	7,0	7,2	6,7	7,4
Avg. Distance Batch (m)	110	181	200	104	133	122
Avg. Total Distance (m)	6429	10184	13395	6376	7442	6960
Avg. Batching Time (s)	869	848	1256	916	866	959
	Batching Strategy					
Avg. Total Picking Time (s)	55851	53537	86480	60189	53903	60103
Avg. Total Picking Time (min)	931	892	1441	1003	898	1002
Avg. Total Picking Time (h)	15,5	14,9	24,0	16,7	15,0	16,7
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	149	111	173	194	143	143
Avg. Total Pickers	2	2,0	3,4	3	2	3
Avg. Pick Time(h)/Picker	7,2	7,4	7,2	6,2	7,4	5,9
Avg. Distance Batch (m)	95	155	184	93	112	104
Avg. Total Distance (m)	6927	11306	13652	6872	8177	7631
Avg. Batching Time (s)	762	733	1165	817	739	822
	FCFS					
Avg. Total Picking Time (s)	58268	56816	89878	62354	56995	63323
Avg. Total Picking Time (min)	971	947	1498	1039	950	1055
Avg. Total Picking Time (h)	16,2	15,8	25,0	17,3	15,8	17,6
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	143	104	167	187	135	136
Avg. Total Pickers	3	2,2	3,8	3	2	3
Avg. Pick Time(h)/Picker	6,4	7,3	6,7	5,9	6,7	5,9
Avg. Distance Batch (m)	121	200	230	122	147	136
Avg. Total Distance (m)	9099	15036	17252	9152	11022	10209
Avg. Batching Time (s)	777	758	1198	831	760	844

Table E-12. KPI's of Configuration 3 with FCFS strategy in the multiple scenarios

Configuration 3						
	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Orders	300	300	300	300	300	300
Orderlines	834	747	1560	714	734	1071
Total Colli	2315	1646	4171	3251	2135	2391
Avg. Orderline/Order	2,78	2,21	5,20	2,38	2,45	3,57
Avg. Colli/Orderline	2,77	2,21	2,67	4,55	2,90	2,23
Avg. Colli/Order	7,71	5,49	13,90	10,94	7,12	7,97
Avg. SinglePicks	71,6	79,4	37,8	59,2	82,8	77,6
	BatchSP					
Avg. Total Picking Time (s)	52736	49076	86080	63525	49635	56447
Avg. Total Picking Time (min)	879	818	1435	1059	827	941
Avg. Total Picking Time (h)	14,6	13,6	23,9	17,6	13,8	15,7
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	158	121	174	185	155	152
Avg. Total Pickers	2,0	2,0	3,4	3	2	2
Avg. Pick Time(h)/Picker	7,3	6,8	7,1	6,4	6,9	6,8
Avg. Distance Batch (m)	164	214	239	198	172	169
Avg. Total Distance (m)	9590	12089	15996	14009	9599	9665
Avg. Batching Time (s)	900	870	1284	913	890	987
	Batching Strategy					
Avg. Total Picking Time (s)	58767	55372	88497	63557	56168	62512
Avg. Total Picking Time (min)	979	923	1475	1059	936	1042
Avg. Total Picking Time (h)	16,3	15,4	24,6	17,7	15,6	17,4
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	142	107	169	184	137	138
Avg. Total Pickers	2,7	2,2	3,7	3	2	3
Avg. Pick Time(h)/Picker	6,3	7,2	6,7	5,9	6,8	5,9
Avg. Distance Batch (m)	156	195	225	158	160	158
Avg. Total Distance (m)	11461	14298	16670	11783	11695	11555
Avg. Batching Time (s)	801	758	1192	853	770	855
	FCFS					
Avg. Total Picking Time (s)	62694	61738	94953	67152	60914	67321
Avg. Total Picking Time (min)	1045	1029	1583	1119	1015	1122
Avg. Total Picking Time (h)	17,4	17,1	26,4	18,7	16,9	18,7
Avg. Total Colli	2315	1646	4171	3251	2136	2392
Avg. Colli/Hour	133	96	158	174	126	128
Avg. Total Pickers	3,0	3,0	4,0	3	3	3
Avg. Pick Time(h)/Picker	5,8	5,7	6,6	6,2	5,6	6,2
Avg. Distance Batch (m)	220	305	336	220	233	226
Avg. Total Distance (m)	16496	22854	25213	16475	17463	16919
Avg. Batching Time (s)	836	823	1266	895	812	898

E4. Average Results of Each Experiment per Scenario

Scenario 50

Table E-13. Average KPI Results per Picking Strategy of all Experiments of Scenario 50

Picking Strategy:	*BatchS + Singlepick*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	50973	50961	52736
Avg. Total Picking Time (min)	850	849	879
Avg. Total Picking Time (h)	14,2	14,2	14,6
Avg. Total Colli	2315	2315	2315
Avg. Colli/Hour	163	163	158
Avg. Total Pickers	2	2	2,0
Avg. Pick Time(h)/Picker	7,1	7,1	7,3
Avg. Distance Batch (m)	113	110	164
Avg. Total Distance (m)	6647	4429	9590
Avg. Batching Time (s)	869	869	900

Table E-14. Average KPI Results per Picking Strategy of all Experiments of Scenario 50

Picking Strategy:	*BatchS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	55957	55851	58767
Avg. Total Picking Time (min)	933	931	979
Avg. Total Picking Time (h)	15,5	15,5	16,3
Avg. Total Colli	2315	2315	2315
Avg. Colli/Hour	149	149	142
Avg. Total Pickers	2	2	2,7
Avg. Pick Time(h)/Picker	7,0	7,2	6,3
Avg. Distance Batch (m)	99	95	156
Avg. Total Distance (m)	7267	6927	11461
Avg. Batching Time (s)	763	762	801

Table E-15. Average KPI Results per Picking Strategy of all Experiments of Scenario 50

Picking Strategy:	*FCFS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	58548	58268	62694
Avg. Total Picking Time (min)	976	971	1045
Avg. Total Picking Time (h)	16,3	16,2	17,4
Avg. Total Colli	2315	2315	2315
Avg. Colli/Hour	142	143	133
Avg. Total Pickers	3	3	3,0
Avg. Pick Time(h)/Picker	6,4	6,4	5,8
Avg. Distance Batch (m)	126	121	220
Avg. Total Distance (m)	9479	9099	16496
Avg. Batching Time (s)	781	777	836

Table E-16. Average KPI Results of Configuration 1 of all Experiments of Scenario 50 per Picking Strategy

Configuration 1			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	50973	55957	58548
Avg. Total Picking Time (min)	850	933	976
Avg. Total Picking Time (h)	14,2	15,5	16,3
Avg. Total Colli	2315	2315	2315
Avg. Colli/Hour	163	149	142
Avg. Total Pickers	2	2	3
Avg. Pick Time(h)/Picker	7,1	7,0	6,4
Avg. Distance Batch (m)	113	99	126
Avg. Total Distance (m)	6647	7267	9479
Avg. Batching Time (s)	869	763	781

Table E-17. Average KPI Results of Configuration 2 of all Experiments of Scenario 50 per Picking Strategy

Configuration 2			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	50961	55851	58268
Avg. Total Picking Time (min)	849	931	971
Avg. Total Picking Time (h)	14,2	15,5	16,2
Avg. Total Colli	2315	2315	2315
Avg. Colli/Hour	163	149	143
Avg. Total Pickers	2	2	3
Avg. Pick Time(h)/Picker	7,1	7,2	6,4
Avg. Distance Batch (m)	110	95	121
Avg. Total Distance (m)	6429	6927	9099
Avg. Batching Time (s)	869	762	777

Table E-18. Average KPI Results of Configuration 3 of all Experiments of Scenario 50 per Picking Strategy

Configuration 3			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	52736	58767	62694
Avg. Total Picking Time (min)	879	979	1045
Avg. Total Picking Time (h)	14,6	16,3	17,4
Avg. Total Colli	2315	2315	2315
Avg. Colli/Hour	158	142	133
Avg. Total Pickers	2,0	2,7	3,0
Avg. Pick Time(h)/Picker	7,3	6,3	5,8
Avg. Distance Batch (m)	164	156	220
Avg. Total Distance (m)	9590	11461	16496
Avg. Batching Time (s)	900	801	836

Scenario 107

Table E-19. Average KPI Results per Picking Strategy of all Experiments of Scenario 107

Picking Strategy:	*BatchS + Singlepick*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	47946	47842	49076
Avg. Total Picking Time (min)	799	797	818
Avg. Total Picking Time (h)	13,3	13,3	13,6
Avg. Total Colli	1646	1646	1646
Avg. Colli/Hour	124	124	121
Avg. Total Pickers	2,0	2,0	2,0
Avg. Pick Time(h)/Picker	6,7	6,6	6,8
Avg. Distance Batch (m)	186	181	214
Avg. Total Distance (m)	10486	10184	12089
Avg. Batching Time (s)	850	848	870

Table E-20. Average KPI Results per Picking Strategy of all Experiments of Scenario 107

Picking Strategy:	*BatchS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	53512	53537	55372
Avg. Total Picking Time (min)	892	892	923
Avg. Total Picking Time (h)	14,9	14,9	15,4
Avg. Total Colli	1646	1646	1646
Avg. Colli/Hour	111	111	107
Avg. Total Pickers	2,0	2,0	2,2
Avg. Pick Time(h)/Picker	7,4	7,4	7,2
Avg. Distance Batch (m)	157	155	195
Avg. Total Distance (m)	11460	11306	14298
Avg. Batching Time (s)	732	733	758

Table E-21. Average KPI Results per Picking Strategy of all Experiments of Scenario 107

Picking Strategy:	*FCFS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	57193	56816	61738
Avg. Total Picking Time (min)	953	947	1029
Avg. Total Picking Time (h)	15,9	15,8	17,1
Avg. Total Colli	1646	1646	1646
Avg. Colli/Hour	104	104	96
Avg. Total Pickers	2,3	2,2	3,0
Avg. Pick Time(h)/Picker	7,2	7,3	5,7
Avg. Distance Batch (m)	206	200	305
Avg. Total Distance (m)	15476	15036	22854
Avg. Batching Time (s)	763	758	823

Table E-22. Average KPI Results of Configuration 1 of all Experiments of Scenario 107 per Picking Strategy

Configuration 1			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	47946	53512	57193
Avg. Total Picking Time (min)	799	892	953
Avg. Total Picking Time (h)	13,3	14,9	15,9
Avg. Total Colli	1646	1646	1646
Avg. Colli/Hour	124	111	104
Avg. Total Pickers	2,0	2,0	2,3
Avg. Pick Time(h)/Picker	6,7	7,4	7,2
Avg. Distance Batch (m)	186	157	206
Avg. Total Distance (m)	10486	11460	15476
Avg. Batching Time (s)	850	732	763

Table E-23. Average KPI Results of Configuration 2 of all Experiments of Scenario 107 per Picking Strategy

Configuration 2			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	47842	53537	56816
Avg. Total Picking Time (min)	797	892	947
Avg. Total Picking Time (h)	13,3	14,9	15,8
Avg. Total Colli	1646	1646	1646
Avg. Colli/Hour	124	111	104
Avg. Total Pickers	2,0	2,0	2,2
Avg. Pick Time(h)/Picker	6,6	7,4	7,3
Avg. Distance Batch (m)	181	155	200
Avg. Total Distance (m)	10184	11306	15036
Avg. Batching Time (s)	848	733	758

Table E-24. Average KPI Results of Configuration 3 of all Experiments of Scenario 107 per Picking Strategy

Configuration 3			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	49076	55372	61738
Avg. Total Picking Time (min)	818	923	1029
Avg. Total Picking Time (h)	13,6	15,4	17,1
Avg. Total Colli	1646	1646	1646
Avg. Colli/Hour	121	107	96
Avg. Total Pickers	2,0	2,2	3,0
Avg. Pick Time(h)/Picker	6,8	7,2	5,7
Avg. Distance Batch (m)	214	195	305
Avg. Total Distance (m)	12089	14298	22854
Avg. Batching Time (s)	870	758	823

Scenario 10

Table E-25. Average KPI Results per Picking Strategy of all Experiments of Scenario 10

Picking Strategy:	*BatchS + Singlepick*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	84267	84219	86080
Avg. Total Picking Time (min)	1404	1404	1435
Avg. Total Picking Time (h)	23,4	23,4	23,9
Avg. Total Colli	4171	4171	4171
Avg. Colli/Hour	178	178	174
Avg. Total Pickers	3,4	3,4	3,4
Avg. Pick Time(h)/Picker	7,0	7,0	7,1
Avg. Distance Batch (m)	200	200	239
Avg. Total Distance (m)	13401	13395	15996
Avg. Batching Time (s)	1257	1256	1284

Table E-26. Average KPI Results per Picking Strategy of all Experiments of Scenario 10

Picking Strategy:	*BatchS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	86587	86480	88497
Avg. Total Picking Time (min)	1443	1441	1475
Avg. Total Picking Time (h)	24,1	24,0	24,6
Avg. Total Colli	4171	4171	4171
Avg. Colli/Hour	173	173	169
Avg. Total Pickers	3,4	3,4	3,7
Avg. Pick Time(h)/Picker	7,1	7,2	6,7
Avg. Distance Batch (m)	186	184	225
Avg. Total Distance (m)	13822	13652	16670
Avg. Batching Time (s)	1167	1165	1192

Table E-27. Average KPI Results per Picking Strategy of all Experiments of Scenario 10

Picking Strategy:	*FCFS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	89736	89878	94953
Avg. Total Picking Time (min)	1496	1498	1583
Avg. Total Picking Time (h)	24,9	25,0	26,4
Avg. Total Colli	4171	4171	4171
Avg. Colli/Hour	167	167	158
Avg. Total Pickers	3,7	3,8	4,0
Avg. Pick Time(h)/Picker	6,8	6,7	6,6
Avg. Distance Batch (m)	231	230	336
Avg. Total Distance (m)	17352	17252	25213
Avg. Batching Time (s)	1196	1198	1266

Table E-28. Average KPI Results of Configuration 1 of all Experiments of Scenario 10 per Picking Strategy

Configuration 1			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	84267	86587	89736
Avg. Total Picking Time (min)	1404	1443	1496
Avg. Total Picking Time (h)	23,4	24,1	24,9
Avg. Total Colli	4171	4171	4171
Avg. Colli/Hour	178	173	167
Avg. Total Pickers	3,4	3,4	3,7
Avg. Pick Time(h)/Picker	7,0	7,1	6,8
Avg. Distance Batch (m)	200	186	231
Avg. Total Distance (m)	13401	13822	17352
Avg. Batching Time (s)	1257	1167	1196

Table E-29. Average KPI Results of Configuration 2 of all Experiments of Scenario 10 per Picking Strategy

Configuration 2			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	84219	86480	89878
Avg. Total Picking Time (min)	1404	1441	1498
Avg. Total Picking Time (h)	23,4	24,0	25,0
Avg. Total Colli	4171	4171	4171
Avg. Colli/Hour	178	173	167
Avg. Total Pickers	3,4	3,4	3,8
Avg. Pick Time(h)/Picker	7,0	7,2	6,7
Avg. Distance Batch (m)	200	184	230
Avg. Total Distance (m)	13395	13652	17252
Avg. Batching Time (s)	1256	1165	1198

Table E-30. Average KPI Results of Configuration 3 of all Experiments of Scenario 10 per Picking Strategy

Configuration 3			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	86080	88497	94953
Avg. Total Picking Time (min)	1435	1475	1583
Avg. Total Picking Time (h)	23,9	24,6	26,4
Avg. Total Colli	4171	4171	4171
Avg. Colli/Hour	174	169	158
Avg. Total Pickers	3,4	3,7	4,0
Avg. Pick Time(h)/Picker	7,1	6,7	6,6
Avg. Distance Batch (m)	239	225	336
Avg. Total Distance (m)	15996	16670	25213
Avg. Batching Time (s)	1284	1192	1266

Scenario 77

Table E-31. Average KPI Results per Picking Strategy of all Experiments of Scenario 77

Picking Strategy:	*BatchS + Singlepick*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	56282	56413	63525
Avg. Total Picking Time (min)	938	940	1059
Avg. Total Picking Time (h)	15,6	15,7	17,6
Avg. Total Colli	3251	3251	3251
Avg. Colli/Hour	208	207	185
Avg. Total Pickers	2	2	3
Avg. Pick Time(h)/Picker	7,2	7,2	6,4
Avg. Distance Batch (m)	103	104	198
Avg. Total Distance (m)	6355	6376	14009
Avg. Batching Time (s)	914	916	913

Table E-32. Average KPI Results per Picking Strategy of all Experiments of Scenario 77

Picking Strategy:	*BatchS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	59970	60189	63557
Avg. Total Picking Time (min)	999	1003	1059
Avg. Total Picking Time (h)	16,7	16,7	17,7
Avg. Total Colli	3251	3251	3251
Avg. Colli/Hour	195	194	184
Avg. Total Pickers	3	3	3
Avg. Pick Time(h)/Picker	6,1	6,2	5,9
Avg. Distance Batch (m)	92	93	158
Avg. Total Distance (m)	6790	6872	11783
Avg. Batching Time (s)	815	817	853

Table E-33. Average KPI Results per Picking Strategy of all Experiments of Scenario 77

Picking Strategy:	*FCFS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	62414	62354	67152
Avg. Total Picking Time (min)	1040	1039	1119
Avg. Total Picking Time (h)	17,3	17,3	18,7
Avg. Total Colli	3251	3251	3251
Avg. Colli/Hour	187	187	174
Avg. Total Pickers	3	3	3
Avg. Pick Time(h)/Picker	6,0	5,9	6,2
Avg. Distance Batch (m)	123	122	220
Avg. Total Distance (m)	9206	9152	16475
Avg. Batching Time (s)	832	831	895

Table E-34. Average KPI Results of Configuration 1 of all Experiments of Scenario 77 per Picking Strategy

Configuration 1			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	56282	59970	62414
Avg. Total Picking Time (min)	938	999	1040
Avg. Total Picking Time (h)	15,6	16,7	17,3
Avg. Total Colli	3251	3251	3251
Avg. Colli/Hour	208	195	187
Avg. Total Pickers	2	3	3
Avg. Pick Time(h)/Picker	7,2	6,1	6,0
Avg. Distance Batch (m)	103	92	123
Avg. Total Distance (m)	6355	6790	9206
Avg. Batching Time (s)	914	815	832

Table E-35. Average KPI Results of Configuration 2 of all Experiments of Scenario 77 per Picking Strategy

Configuration 2			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	56413	60189	62354
Avg. Total Picking Time (min)	940	1003	1039
Avg. Total Picking Time (h)	15,7	16,7	17,3
Avg. Total Colli	3251	3251	3251
Avg. Colli/Hour	207	194	187
Avg. Total Pickers	2	3	3
Avg. Pick Time(h)/Picker	7,2	6,2	5,9
Avg. Distance Batch (m)	104	93	122
Avg. Total Distance (m)	6376	6872	9152
Avg. Batching Time (s)	916	817	831

Table E-36. Average KPI Results of Configuration 3 of all Experiments of Scenario 77 per Picking Strategy

Configuration 3			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	63525	63557	67152
Avg. Total Picking Time (min)	1059	1059	1119
Avg. Total Picking Time (h)	17,6	17,7	18,7
Avg. Total Colli	3251	3251	3251
Avg. Colli/Hour	185	184	174
Avg. Total Pickers	3	3	3
Avg. Pick Time(h)/Picker	6,4	5,9	6,2
Avg. Distance Batch (m)	198	158	220
Avg. Total Distance (m)	14009	11783	16475
Avg. Batching Time (s)	913	853	895

Scenario 92

Table E-37. Average KPI Results per Picking Strategy of all Experiments of Scenario 92

Picking Strategy:	*BatchS + Singlepick*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	48055	48324	49635
Avg. Total Picking Time (min)	801	805	827
Avg. Total Picking Time (h)	13,3	13,4	13,8
Avg. Total Colli	2136	2136	2136
Avg. Colli/Hour	160	159	155
Avg. Total Pickers	2	2	2
Avg. Pick Time(h)/Picker	6,7	6,7	6,9
Avg. Distance Batch (m)	131	133	172
Avg. Total Distance (m)	7283	7442	9599
Avg. Batching Time (s)	862	866	890

Table E-38. Average KPI Results per Picking Strategy of all Experiments of Scenario 92

Picking Strategy:	*BatchS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	53779	53903	56168
Avg. Total Picking Time (min)	896	898	936
Avg. Total Picking Time (h)	14,9	15,0	15,6
Avg. Total Colli	2136	2136	2136
Avg. Colli/Hour	143	143	137
Avg. Total Pickers	2	2	2
Avg. Pick Time(h)/Picker	7,5	7,4	6,8
Avg. Distance Batch (m)	109	112	160
Avg. Total Distance (m)	7975	8177	11695
Avg. Batching Time (s)	737	739	770

Table E-39. Average KPI Results per Picking Strategy of all Experiments of Scenario 92

Picking Strategy:	*FCFS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	56730	56995	60914
Avg. Total Picking Time (min)	946	950	1015
Avg. Total Picking Time (h)	15,8	15,8	16,9
Avg. Total Colli	2136	2136	2136
Avg. Colli/Hour	135	135	126
Avg. Total Pickers	2	2	3
Avg. Pick Time(h)/Picker	7,0	6,7	5,6
Avg. Distance Batch (m)	145	147	233
Avg. Total Distance (m)	10880	11022	17463
Avg. Batching Time (s)	756	760	812

Table E-40. Average KPI Results of Configuration 1 of all Experiments of Scenario 92 per Picking Strategy

Configuration 1			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	48055	53779	56730
Avg. Total Picking Time (min)	801	896	946
Avg. Total Picking Time (h)	13,3	14,9	15,8
Avg. Total Colli	2136	2136	2136
Avg. Colli/Hour	160	143	135
Avg. Total Pickers	2	2	2
Avg. Pick Time(h)/Picker	6,7	7,5	7,0
Avg. Distance Batch (m)	131	109	145
Avg. Total Distance (m)	7283	7975	10880
Avg. Batching Time (s)	862	737	756

Table E-41. Average KPI Results of Configuration 2 of all Experiments of Scenario 92 per Picking Strategy

Configuration 2			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	48324	53903	56995
Avg. Total Picking Time (min)	805	898	950
Avg. Total Picking Time (h)	13,4	15,0	15,8
Avg. Total Colli	2136	2136	2136
Avg. Colli/Hour	159	143	135
Avg. Total Pickers	2	2	2
Avg. Pick Time(h)/Picker	6,7	7,4	6,7
Avg. Distance Batch (m)	133	112	147
Avg. Total Distance (m)	7442	8177	11022
Avg. Batching Time (s)	866	739	760

Table E-42. Average KPI Results of Configuration 3 of all Experiments of Scenario 92 per Picking Strategy

Configuration 3			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	49635	56168	60914
Avg. Total Picking Time (min)	827	936	1015
Avg. Total Picking Time (h)	13,8	15,6	16,9
Avg. Total Colli	2136	2136	2136
Avg. Colli/Hour	155	137	126
Avg. Total Pickers	2	2	3
Avg. Pick Time(h)/Picker	6,9	6,8	5,6
Avg. Distance Batch (m)	172	160	233
Avg. Total Distance (m)	9599	11695	17463
Avg. Batching Time (s)	890	770	812

Scenario 123

Table E-43. Average KPI Results per Picking Strategy of all Experiments of Scenario 123

Picking Strategy:	*BatchS + Singlepick*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	55098	54853	56447
Avg. Total Picking Time (min)	918	914	941
Avg. Total Picking Time (h)	15,3	15,2	15,7
Avg. Total Colli	2392	2392	2392
Avg. Colli/Hour	156	157	152
Avg. Total Pickers	2	2	2
Avg. Pick Time(h)/Picker	7,3	7,4	6,8
Avg. Distance Batch (m)	126	122	169
Avg. Total Distance (m)	7184	6960	9665
Avg. Batching Time (s)	963	959	987

Table E-44. Average KPI Results per Picking Strategy of all Experiments of Scenario 123

Picking Strategy:	*BatchS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	60151	60103	62512
Avg. Total Picking Time (min)	1003	1002	1042
Avg. Total Picking Time (h)	16,7	16,7	17,4
Avg. Total Colli	2392	2392	2392
Avg. Colli/Hour	143	143	138
Avg. Total Pickers	3	3	3
Avg. Pick Time(h)/Picker	5,8	5,9	5,9
Avg. Distance Batch (m)	107	104	158
Avg. Total Distance (m)	7798	7631	11555
Avg. Batching Time (s)	823	822	855

Table E-45. Average KPI Results per Picking Strategy of all Experiments of Scenario 123

Picking Strategy:	*FCFS*		
	Configuration 1	Configuration 2	Configuration 3
Avg. Total Picking Time (s)	63316	63323	67321
Avg. Total Picking Time (min)	1055	1055	1122
Avg. Total Picking Time (h)	17,6	17,6	18,7
Avg. Total Colli	2392	2392	2392
Avg. Colli/Hour	136	136	128
Avg. Total Pickers	3	3	3
Avg. Pick Time(h)/Picker	5,9	5,9	6,2
Avg. Distance Batch (m)	139	136	226
Avg. Total Distance (m)	10406	10209	16919
Avg. Batching Time (s)	844	844	898

Table E-46. Average KPI Results of Configuration 1 of all Experiments of Scenario 123 per Picking Strategy

Configuration 1			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	55098	60151	63316
Avg. Total Picking Time (min)	918	1003	1055
Avg. Total Picking Time (h)	15,3	16,7	17,6
Avg. Total Colli	2392	2392	2392
Avg. Colli/Hour	156	143	136
Avg. Total Pickers	2	3	3
Avg. Pick Time(h)/Picker	7,3	5,8	5,9
Avg. Distance Batch (m)	126	107	139
Avg. Total Distance (m)	7184	7798	10406
Avg. Batching Time (s)	963	823	844

Table E-47. Average KPI Results of Configuration 2 of all Experiments of Scenario 123 per Picking Strategy

Configuration 2			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	54853	60103	63323
Avg. Total Picking Time (min)	914	1002	1055
Avg. Total Picking Time (h)	15,2	16,7	17,6
Avg. Total Colli	2392	2392	2392
Avg. Colli/Hour	157	143	136
Avg. Total Pickers	2	3	3
Avg. Pick Time(h)/Picker	7,4	5,9	5,9
Avg. Distance Batch (m)	122	104	136
Avg. Total Distance (m)	6960	7631	10209
Avg. Batching Time (s)	959	822	844

Table E-48. Average KPI Results of Configuration 3 of all Experiments of Scenario 123 per Picking Strategy

Configuration 3			
	BatchS + Singlepick	BatchS	FCFS
Avg. Total Picking Time (s)	56447	62512	67321
Avg. Total Picking Time (min)	941	1042	1122
Avg. Total Picking Time (h)	15,7	17,4	18,7
Avg. Total Colli	2392	2392	2392
Avg. Colli/Hour	152	138	128
Avg. Total Pickers	2	3	3
Avg. Pick Time(h)/Picker	6,8	5,9	6,2
Avg. Distance Batch (m)	169	158	226
Avg. Total Distance (m)	9665	11555	16919
Avg. Batching Time (s)	987	855	898

E5. Results of each Experiment per Scenario per Configuration

Scenario 50

Table E-49. KPI Results of Configuration 1 of Experiment 1 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	48737	54183	56929
Total Picking Time (min)	812	903	949
Total Picking Time (h)	13,5	15,1	15,8
Total Colli	2176	2176	2176
Total Colli/Hour	161	145	138
Total Pickers	2,0	2,0	2,3
Pick Time(h)/Picker	6,8	7,5	7,0
Avg. Distance Batch (m)	115	98	125
Total Distance (m)	6646	7194	9373
Avg. Batching Time (s)	840	740	759

Table E-50. KPI Results of Configuration 1 of Experiment 2 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	51588	57171	59397
Total Picking Time (min)	860	953	990
Total Picking Time (h)	14,3	15,9	16,5
Total Colli	2482	2482	2482
Total Colli/Hour	173	156	150
Total Pickers	2,0	2,5	3,0
Pick Time(h)/Picker	7,2	6,5	5,5
Avg. Distance Batch (m)	104	96	120
Total Distance (m)	6054	7013	9035
Avg. Batching Time (s)	889	781	792

Table E-51. KPI Results of Configuration 1 of Experiment 3 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	55038	59148	62074
Total Picking Time (min)	917	986	1035
Total Picking Time (h)	15,3	16,4	17,2
Total Colli	2536	2536	2536
Total Colli/Hour	166	154	147
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,6	5,7	5,7
Avg. Distance Batch (m)	121	107	136
Total Distance (m)	7403	7834	10226
Avg. Batching Time (s)	902	804	828

Table E-52. KPI Results of Configuration 1 of Experiment 4 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47906	53737	56275
Total Picking Time (min)	798	896	938
Total Picking Time (h)	13,3	14,9	15,6
Total Colli	2101	2101	2101
Total Colli/Hour	158	141	134
Total Pickers	2,0	2,0	2,1
Pick Time(h)/Picker	6,7	7,5	7,5
Avg. Distance Batch (m)	111	96	122
Total Distance (m)	6219	7037	9170
Avg. Batching Time (s)	855	736	750

Table E-53. KPI Results of Configuration 1 of Experiment 5 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	51596	55547	58064
Total Picking Time (min)	860	926	968
Total Picking Time (h)	14	15	16
Total Colli	2281	2281	2281
Total Colli/Hour	159	148	141
Total Pickers	2,0	2,0	2,7
Pick Time(h)/Picker	7,2	7,7	6,3
Avg. Distance Batch (m)	115	99	128
Total Distance (m)	6914	7257	9591
Avg. Batching Time (s)	860	756	774

Table E-54. KPI Results of Configuration 2 of Experiment 1 in Scenario 50

Iterations	*10*		
Number of Changes	*3*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49034	53874	56187
Total Picking Time (min)	817	898	936
Total Picking Time (h)	13,6	15,0	15,6
Total Colli	2176	2176	2176
Total Colli/Hour	160	146	139
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,8	7,5	7,8
Avg. Distance Batch (m)	110	92	119
Total Distance (m)	6386	6724	8926
Avg. Batching Time (s)	845	735	749

Table E-55. KPI Results of Configuration 2 of Experiment 2 in Scenario 50

Iterations	*10*		
Number of Changes	*3*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	52291	56846	58991
Total Picking Time (min)	872	947	983
Total Picking Time (h)	14,5	15,8	16,4
Total Colli	2482	2482	2482
Total Colli/Hour	171	157	151
Total Pickers	2,0	2,2	3,0
Pick Time(h)/Picker	7,3	7,4	5,5
Avg. Distance Batch (m)	107	92	119
Total Distance (m)	6190	6727	8891
Avg. Batching Time (s)	902	777	787

Table E-56. KPI Results of Configuration 2 of Experiment 3 in Scenario 50

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	54545	59501	61336
Total Picking Time (min)	909	992	1022
Total Picking Time (h)	15,2	16,5	17,0
Total Colli	2536	2536	2536
Total Colli/Hour	167	154	149
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,6	5,7	5,7
Avg. Distance Batch (m)	113	100	124
Total Distance (m)	6876	7342	9301
Avg. Batching Time (s)	894	809	818

Table E-57. KPI Results of Configuration 2 of Experiment 4 in Scenario 50

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47664	53459	56181
Total Picking Time (min)	794	891	936
Total Picking Time (h)	13,2	14,8	15,6
Total Colli	2101	2101	2101
Total Colli/Hour	159	142	135
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,6	7,4	7,8
Avg. Distance Batch (m)	108	92	120
Total Distance (m)	6063	6706	8966
Avg. Batching Time (s)	851	732	749

Table E-58. KPI Results of Configuration 2 of Experiment 5 in Scenario 50

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	51272	55573	58646
Total Picking Time (min)	855	926	977
Total Picking Time (h)	14	15	16
Total Colli	2281	2281	2281
Total Colli/Hour	160	148	140
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	7,1	7,7	5,4
Avg. Distance Batch (m)	110	97	125
Total Distance (m)	6630	7135	9408
Avg. Batching Time (s)	855	756	782

Table E-59. KPI Results of Configuration 3 of Experiment 1 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	50403	57148	61040
Total Picking Time (min)	840	952	1017
Total Picking Time (h)	14,0	15,9	17,0
Total Colli	2176	2176	2176
Total Colli/Hour	155	137	128
Total Pickers	2,0	2,5	3,0
Pick Time(h)/Picker	7,0	6,7	5,7
Avg. Distance Batch (m)	160	156	220
Total Distance (m)	9285	11490	16503
Avg. Batching Time (s)	869	780	814

Table E-60. KPI Results of Configuration 3 of Experiment 2 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	53875	59890	64041
Total Picking Time (min)	898	998	1067
Total Picking Time (h)	15,0	16,6	17,8
Total Colli	2482	2482	2482
Total Colli/Hour	166	149	140
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,5	5,8	5,9
Avg. Distance Batch (m)	162	157	220
Total Distance (m)	9402	11487	16488
Avg. Batching Time (s)	929	818	854

Table E-61. KPI Results of Configuration 3 of Experiment 3 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56352	62068	65668
Total Picking Time (min)	939	1034	1094
Total Picking Time (h)	15,7	17,2	18,2
Total Colli	2536	2536	2536
Total Colli/Hour	162	147	139
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,8	6,0	6,1
Avg. Distance Batch (m)	167	157	229
Total Distance (m)	10206	11587	17146
Avg. Batching Time (s)	924	843	876

Table E-62. KPI Results of Configuration 3 of Experiment 4 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49773	56628	60358
Total Picking Time (min)	830	944	1006
Total Picking Time (h)	13,8	15,7	16,8
Total Colli	2101	2101	2101
Total Colli/Hour	152	134	125
Total Pickers	2,0	2,2	3,0
Pick Time(h)/Picker	6,9	7,4	5,6
Avg. Distance Batch (m)	165	155	208
Total Distance (m)	9249	11334	15575
Avg. Batching Time (s)	889	775	805

Table E-63. KPI Results of Configuration 3 of Experiment 5 in Scenario 50

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	53279	58103	62363
Total Picking Time (min)	888	968	1039
Total Picking Time (h)	15	16	17
Total Colli	2281	2281	2281
Total Colli/Hour	154	141	132
Total Pickers	2,0	2,8	3,0
Pick Time(h)/Picker	7,4	5,8	5,8
Avg. Distance Batch (m)	164	155	224
Total Distance (m)	9811	11405	16766
Avg. Batching Time (s)	888	791	832

Scenario 107

Table E-64. KPI Results of Configuration 1 of Experiment 1 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47726	53252	56730
Total Picking Time (min)	795	888	945
Total Picking Time (h)	13,3	14,8	15,8
Total Colli	1560	1560	1560
Total Colli/Hour	118	106	99
Total Pickers	2,0	2,0	2,1
Pick Time(h)/Picker	6,6	7,4	7,6
Avg. Distance Batch (m)	194	161	210
Total Distance (m)	11038	11778	15776
Avg. Batching Time (s)	837	728	756

Table E-65. KPI Results of Configuration 1 of Experiment 2 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	46635	52210	56049
Total Picking Time (min)	777	870	934
Total Picking Time (h)	13,0	14,5	15,6
Total Colli	1640	1640	1640
Total Colli/Hour	127	113	105
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,5	7,3	7,8
Avg. Distance Batch (m)	176	152	198
Total Distance (m)	9851	11086	14884
Avg. Batching Time (s)	833	715	747

Table E-66. KPI Results of Configuration 1 of Experiment 3 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47160	52967	56624
Total Picking Time (min)	786	883	944
Total Picking Time (h)	13,1	14,7	15,7
Total Colli	1687	1687	1687
Total Colli/Hour	129	115	107
Total Pickers	2,0	2,0	2,1
Pick Time(h)/Picker	6,5	7,4	7,6
Avg. Distance Batch (m)	191	158	207
Total Distance (m)	10678	11540	15556
Avg. Batching Time (s)	842	725	755

Table E-67. KPI Results of Configuration 1 of Experiment 4 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	51292	55935	59204
Total Picking Time (min)	855	932	987
Total Picking Time (h)	14,2	15,5	16,4
Total Colli	1736	1736	1736
Total Colli/Hour	122	112	106
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	7,1	7,8	5,5
Avg. Distance Batch (m)	185	159	210
Total Distance (m)	10887	11677	15762
Avg. Batching Time (s)	869	763	789

Table E-68. KPI Results of Configuration 1 of Experiment 5 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	46918	53195	57359
Total Picking Time (min)	782	887	956
Total Picking Time (h)	13	15	16
Total Colli	1607	1607	1607
Total Colli/Hour	123	109	101
Total Pickers	2,0	2,0	2,2
Pick Time(h)/Picker	6,5	7,4	7,4
Avg. Distance Batch (m)	185	154	205
Total Distance (m)	9977	11217	15403
Avg. Batching Time (s)	869	731	765

Table E-69. KPI Results of Configuration 2 of Experiment 1 in Scenario 107

Iterations	*10*		
Number of Changes	*4*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47405	53052	56299
Total Picking Time (min)	790	884	938
Total Picking Time (h)	13,2	14,7	15,6
Total Colli	1560	1560	1560
Total Colli/Hour	118	106	100
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,6	7,4	7,8
Avg. Distance Batch (m)	186	157	206
Total Distance (m)	10620	11473	15413
Avg. Batching Time (s)	832	726	751

Table E-70. KPI Results of Configuration 2 of Experiment 2 in Scenario 107

Iterations	*10*		
Number of Changes	*3*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	46532	52339	55581
Total Picking Time (min)	776	872	926
Total Picking Time (h)	12,9	14,5	15,4
Total Colli	1640	1640	1640
Total Colli/Hour	127	113	106
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,5	7,3	7,7
Avg. Distance Batch (m)	171	152	192
Total Distance (m)	9581	11095	14414
Avg. Batching Time (s)	831	717	741

Table E-71. KPI Results of Configuration 2 of Experiment 3 in Scenario 107

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47874	53185	56542
Total Picking Time (min)	798	886	942
Total Picking Time (h)	13,3	14,8	15,7
Total Colli	1687	1687	1687
Total Colli/Hour	127	114	107
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,6	7,4	7,9
Avg. Distance Batch (m)	187	157	200
Total Distance (m)	10458	11475	15017
Avg. Batching Time (s)	855	729	754

Table E-72. KPI Results of Configuration 2 of Experiment 4 in Scenario 107

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	50697	55675	58578
Total Picking Time (min)	845	928	976
Total Picking Time (h)	14,1	15,5	16,3
Total Colli	1736	1736	1736
Total Colli/Hour	123	112	107
Total Pickers	2,0	2,0	2,8
Pick Time(h)/Picker	7,0	7,7	6,0
Avg. Distance Batch (m)	181	158	204
Total Distance (m)	10689	11578	15288
Avg. Batching Time (s)	859	759	781

Table E-73. KPI Results of Configuration 2 of Experiment 5 in Scenario 107

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	46701	53434	57078
Total Picking Time (min)	778	891	951
Total Picking Time (h)	13	15	16
Total Colli	1607	1607	1607
Total Colli/Hour	124	108	101
Total Pickers	2,0	2,0	2,3
Pick Time(h)/Picker	6,5	7,4	7,0
Avg. Distance Batch (m)	177	150	201
Total Distance (m)	9573	10911	15050
Avg. Batching Time (s)	865	734	761

Table E-74. KPI Results of Configuration 3 of Experiment 1 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	48872	54720	61749
Total Picking Time (min)	815	912	1029
Total Picking Time (h)	13,6	15,2	17,2
Total Colli	1560	1560	1560
Total Colli/Hour	115	103	91
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	6,8	7,6	5,7
Avg. Distance Batch (m)	219	196	315
Total Distance (m)	12455	14368	23654
Avg. Batching Time (s)	857	749	823

Table E-75. KPI Results of Configuration 3 of Experiment 2 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47887	54514	60745
Total Picking Time (min)	798	909	1012
Total Picking Time (h)	13,3	15,1	16,9
Total Colli	1640	1640	1640
Total Colli/Hour	123	108	97
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	6,7	7,6	5,6
Avg. Distance Batch (m)	214	192	302
Total Distance (m)	12010	14049	22654
Avg. Batching Time (s)	855	747	810

Table E-76. KPI Results of Configuration 3 of Experiment 3 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	48136	54457	60681
Total Picking Time (min)	802	908	1011
Total Picking Time (h)	13,4	15,1	16,9
Total Colli	1687	1687	1687
Total Colli/Hour	126	112	100
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	6,7	7,6	5,6
Avg. Distance Batch (m)	211	198	294
Total Distance (m)	11842	14478	22054
Avg. Batching Time (s)	860	746	809

Table E-77. KPI Results of Configuration 3 of Experiment 4 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	52499	57730	63855
Total Picking Time (min)	875	962	1064
Total Picking Time (h)	14,6	16,0	17,7
Total Colli	1736	1736	1736
Total Colli/Hour	119	108	98
Total Pickers	2,0	2,8	3,0
Pick Time(h)/Picker	7,3	5,8	5,9
Avg. Distance Batch (m)	215	197	314
Total Distance (m)	12697	14470	23516
Avg. Batching Time (s)	890	787	851

Table E-78. KPI Results of Configuration 3 of Experiment 5 in Scenario 107

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47986	55437	61661
Total Picking Time (min)	800	924	1028
Total Picking Time (h)	13	15	17
Total Colli	1607	1607	1607
Total Colli/Hour	121	105	94
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	6,7	7,7	5,7
Avg. Distance Batch (m)	212	194	299
Total Distance (m)	11440	14123	22391
Avg. Batching Time (s)	889	762	822

Scenario 10

Table E-79. KPI Results of Configuration 1 of Experiment 1 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	90441	91781	95014
Total Picking Time (min)	1507	1530	1584
Total Picking Time (h)	25,1	25,5	26,4
Total Colli	4606	4606	4606
Total Colli/Hour	183	181	175
Total Pickers	4,0	4,0	4,0
Pick Time(h)/Picker	6,3	6,4	6,6
Avg. Distance Batch (m)	205	192	241
Total Distance (m)	14124	14278	18053
Avg. Batching Time (s)	1311	1233	1267

Table E-80. KPI Results of Configuration 1 of Experiment 2 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	82795	85521	88831
Total Picking Time (min)	1380	1425	1481
Total Picking Time (h)	23,0	23,8	24,7
Total Colli	3937	3937	3937
Total Colli/Hour	171	166	160
Total Pickers	3,0	3,1	4,0
Pick Time(h)/Picker	7,7	7,7	6,2
Avg. Distance Batch (m)	206	192	233
Total Distance (m)	13590	14263	17501
Avg. Batching Time (s)	1254	1154	1184

Table E-81. KPI Results of Configuration 1 of Experiment 3 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	79085	81889	84688
Total Picking Time (min)	1318	1365	1411
Total Picking Time (h)	22,0	22,7	23,5
Total Colli	3759	3759	3759
Total Colli/Hour	171	165	160
Total Pickers	3,0	3,0	3,0
Pick Time(h)/Picker	7,3	7,6	7,8
Avg. Distance Batch (m)	200	184	231
Total Distance (m)	13213	13618	17294
Avg. Batching Time (s)	1198	1105	1129

Table E-82. KPI Results of Configuration 1 of Experiment 4 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	81864	84073	86912
Total Picking Time (min)	1364	1401	1449
Total Picking Time (h)	22,7	23,4	24,1
Total Colli	4048	4048	4048
Total Colli/Hour	178	173	168
Total Pickers	3,0	3,0	3,7
Pick Time(h)/Picker	7,6	7,8	6,7
Avg. Distance Batch (m)	187	174	219
Total Distance (m)	12533	12928	16406
Avg. Batching Time (s)	1222	1133	1159

Table E-83. KPI Results of Configuration 1 of Experiment 5 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	87149	89673	93233
Total Picking Time (min)	1452	1495	1554
Total Picking Time (h)	24	25	26
Total Colli	4506	4506	4506
Total Colli/Hour	186	181	174
Total Pickers	3,9	4,0	4,0
Pick Time(h)/Picker	6,3	6,2	6,5
Avg. Distance Batch (m)	202	189	233
Total Distance (m)	13547	14026	17506
Avg. Batching Time (s)	1301	1208	1243

Table E-84. KPI Results of Configuration 2 of Experiment 1 in Scenario 10

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	90332	91998	95451
Total Picking Time (min)	1506	1533	1591
Total Picking Time (h)	25,1	25,6	26,5
Total Colli	4606	4606	4606
Total Colli/Hour	184	180	174
Total Pickers	4,0	4,0	4,0
Pick Time(h)/Picker	6,3	6,4	6,6
Avg. Distance Batch (m)	204	189	240
Total Distance (m)	14080	14087	17963
Avg. Batching Time (s)	1309	1236	1273

Table E-85. KPI Results of Configuration 2 of Experiment 2 in Scenario 10

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	82513	84930	88682
Total Picking Time (min)	1375	1415	1478
Total Picking Time (h)	22,9	23,6	24,6
Total Colli	3937	3937	3937
Total Colli/Hour	172	167	160
Total Pickers	3,0	3,0	4,0
Pick Time(h)/Picker	7,6	7,9	6,2
Avg. Distance Batch (m)	206	187	232
Total Distance (m)	13586	13826	17409
Avg. Batching Time (s)	1250	1146	1182

Table E-86. KPI Results of Configuration 2 of Experiment 3 in Scenario 10

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	78929	81446	85109
Total Picking Time (min)	1315	1357	1418
Total Picking Time (h)	21,9	22,6	23,6
Total Colli	3759	3759	3759
Total Colli/Hour	171	166	159
Total Pickers	3,0	3,0	3,0
Pick Time(h)/Picker	7,3	7,5	7,9
Avg. Distance Batch (m)	200	183	230
Total Distance (m)	13173	13540	17213
Avg. Batching Time (s)	1196	1099	1135

Table E-87. KPI Results of Configuration 2 of Experiment 4 in Scenario 10

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	81565	84033	86959
Total Picking Time (min)	1359	1401	1449
Total Picking Time (h)	22,7	23,3	24,2
Total Colli	4048	4048	4048
Total Colli/Hour	179	173	168
Total Pickers	3,0	3,0	3,9
Pick Time(h)/Picker	7,6	7,8	6,3
Avg. Distance Batch (m)	187	172	218
Total Distance (m)	12507	12799	16316
Avg. Batching Time (s)	1217	1132	1159

Table E-88. KPI Results of Configuration 2 of Experiment 5 in Scenario 10

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	87756	89993	93191
Total Picking Time (min)	1463	1500	1553
Total Picking Time (h)	24	25	26
Total Colli	4506	4506	4506
Total Colli/Hour	185	180	174
Total Pickers	4,0	4,0	4,0
Pick Time(h)/Picker	6,1	6,2	6,5
Avg. Distance Batch (m)	203	189	231
Total Distance (m)	13628	14009	17360
Avg. Batching Time (s)	1310	1213	1243

Table E-89. KPI Results of Configuration 3 of Experiment 1 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	91969	93574	100453
Total Picking Time (min)	1533	1560	1674
Total Picking Time (h)	25,5	26,0	27,9
Total Colli	4606	4606	4606
Total Colli/Hour	180	177	165
Total Pickers	4,0	4,0	4,0
Pick Time(h)/Picker	6,4	6,5	7,0
Avg. Distance Batch (m)	242	229	345
Total Distance (m)	16693	17071	25875
Avg. Batching Time (s)	1333	1257	1339

Table E-90. KPI Results of Configuration 3 of Experiment 2 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	84437	87186	93550
Total Picking Time (min)	1407	1453	1559
Total Picking Time (h)	23,5	24,2	26,0
Total Colli	3937	3937	3937
Total Colli/Hour	168	163	152
Total Pickers	3,0	3,9	4,0
Pick Time(h)/Picker	7,8	6,2	6,5
Avg. Distance Batch (m)	241	228	335
Total Distance (m)	15896	16892	25108
Avg. Batching Time (s)	1279	1176	1247

Table E-91. KPI Results of Configuration 3 of Experiment 3 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	80903	83387	90298
Total Picking Time (min)	1348	1390	1505
Total Picking Time (h)	22,5	23,2	25,1
Total Colli	3759	3759	3759
Total Colli/Hour	167	162	150
Total Pickers	3,0	3,0	4,0
Pick Time(h)/Picker	7,5	7,7	6,3
Avg. Distance Batch (m)	234	221	342
Total Distance (m)	15443	16406	25663
Avg. Batching Time (s)	1226	1125	1204

Table E-92. KPI Results of Configuration 3 of Experiment 4 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	83875	86911	92618
Total Picking Time (min)	1398	1449	1544
Total Picking Time (h)	23,3	24,1	25,7
Total Colli	4048	4048	4048
Total Colli/Hour	174	168	157
Total Pickers	3,0	3,7	4,0
Pick Time(h)/Picker	7,8	6,6	6,4
Avg. Distance Batch (m)	237	222	330
Total Distance (m)	15867	16498	24772
Avg. Batching Time (s)	1252	1171	1235

Table E-93. KPI Results of Configuration 3 of Experiment 5 in Scenario 10

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	89216	91428	97848
Total Picking Time (min)	1487	1524	1631
Total Picking Time (h)	25	25	27
Total Colli	4506	4506	4506
Total Colli/Hour	182	177	166
Total Pickers	4,0	4,0	4,0
Pick Time(h)/Picker	6,2	6,3	6,8
Avg. Distance Batch (m)	240	222	329
Total Distance (m)	16079	16484	24648
Avg. Batching Time (s)	1332	1232	1305

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Table E-94. KPI Results of Configuration 1 of Experiment 1 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	52113	56278	58102
Total Picking Time (min)	869	938	968
Total Picking Time (h)	14,5	15,6	16,1
Total Colli	2819	2819	2819
Total Colli/Hour	195	181	175
Total Pickers	2,0	2,3	2,6
Pick Time(h)/Picker	7,2	7,1	6,6
Avg. Distance Batch (m)	95	88	115
Total Distance (m)	5876	6474	8642
Avg. Batching Time (s)	841	764	775

Table E-95. KPI Results of Configuration 1 of Experiment 2 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	59981	63127	65465
Total Picking Time (min)	1000	1052	1091
Total Picking Time (h)	16,7	17,5	18,2
Total Colli	3664	3664	3664
Total Colli/Hour	220	209	202
Total Pickers	3,0	3,0	3,0
Pick Time(h)/Picker	5,6	5,8	6,1
Avg. Distance Batch (m)	101	88	121
Total Distance (m)	6384	6481	9104
Avg. Batching Time (s)	952	856	873

Table E-96. KPI Results of Configuration 1 of Experiment 3 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56243	59613	61890
Total Picking Time (min)	937	994	1031
Total Picking Time (h)	15,6	16,6	17,2
Total Colli	3262	3262	3262
Total Colli/Hour	209	197	190
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,8	5,8	5,7
Avg. Distance Batch (m)	103	93	121
Total Distance (m)	6398	6875	9101
Avg. Batching Time (s)	907	809	825

Table E-97. KPI Results of Configuration 1 of Experiment 4 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	55942	59812	63113
Total Picking Time (min)	932	997	1052
Total Picking Time (h)	15,5	16,6	17,5
Total Colli	3123	3123	3123
Total Colli/Hour	201	188	178
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,8	5,8	5,8
Avg. Distance Batch (m)	112	98	134
Total Distance (m)	6747	7219	10047
Avg. Batching Time (s)	932	815	842

Table E-98. KPI Results of Configuration 1 of Experiment 5 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	57134	61018	63502
Total Picking Time (min)	952	1017	1058
Total Picking Time (h)	16	17	18
Total Colli	3388	3388	3388
Total Colli/Hour	213	200	192
Total Pickers	2,1	2,9	3,0
Pick Time(h)/Picker	7,7	5,9	5,9
Avg. Distance Batch (m)	104	94	122
Total Distance (m)	6370	6900	9133
Avg. Batching Time (s)	937	830	847

Table E-99. KPI Results of Configuration 2 of Experiment 1 in Scenario 77

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	52295	56125	58036
Total Picking Time (min)	872	935	967
Total Picking Time (h)	14,5	15,6	16,1
Total Colli	2819	2819	2819
Total Colli/Hour	194	181	175
Total Pickers	2,0	2,0	2,8
Pick Time(h)/Picker	7,3	7,8	6,0
Avg. Distance Batch (m)	95	88	113
Total Distance (m)	5913	6502	8493
Avg. Batching Time (s)	843	762	774

Table E-100. KPI Results of Configuration 2 of Experiment 2 in Scenario 77

Iterations	*10*		
Number of Changes	*3*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	60065	63473	65034
Total Picking Time (min)	1001	1058	1084
Total Picking Time (h)	16,7	17,6	18,1
Total Colli	3664	3664	3664
Total Colli/Hour	220	208	203
Total Pickers	3,0	3,0	3,0
Pick Time(h)/Picker	5,6	5,9	6,0
Avg. Distance Batch (m)	99	89	121
Total Distance (m)	6265	6587	9095
Avg. Batching Time (s)	953	860	867

Table E-101. KPI Results of Configuration 2 of Experiment 3 in Scenario 77

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56494	60026	61466
Total Picking Time (min)	942	1000	1024
Total Picking Time (h)	15,7	16,7	17,1
Total Colli	3262	3262	3262
Total Colli/Hour	208	196	191
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,8	5,8	5,7
Avg. Distance Batch (m)	104	94	121
Total Distance (m)	6432	6919	9086
Avg. Batching Time (s)	911	815	820

Table E-102. KPI Results of Configuration 2 of Experiment 4 in Scenario 77

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56109	60409	63845
Total Picking Time (min)	935	1007	1064
Total Picking Time (h)	15,6	16,8	17,7
Total Colli	3123	3123	3123
Total Colli/Hour	200	186	176
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,8	5,8	5,9
Avg. Distance Batch (m)	115	101	132
Total Distance (m)	6875	7408	9892
Avg. Batching Time (s)	935	823	851

Table E-103. KPI Results of Configuration 2 of Experiment 5 in Scenario 77

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	57100	60913	63390
Total Picking Time (min)	952	1015	1057
Total Picking Time (h)	16	17	18
Total Colli	3388	3388	3388
Total Colli/Hour	214	200	192
Total Pickers	2,1	2,9	3,0
Pick Time(h)/Picker	7,7	5,9	5,9
Avg. Distance Batch (m)	105	94	123
Total Distance (m)	6394	6943	9196
Avg. Batching Time (s)	936	828	845

Table E-104. KPI Results of Configuration 3 of Experiment 1 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	54723	58978	62790
Total Picking Time (min)	912	983	1047
Total Picking Time (h)	15,2	16,4	17,4
Total Colli	2819	2819	2819
Total Colli/Hour	185	172	162
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,6	5,7	5,8
Avg. Distance Batch (m)	158	151	207
Total Distance (m)	9818	11167	15546
Avg. Batching Time (s)	883	800	837

Table E-105. KPI Results of Configuration 3 of Experiment 2 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	70210	67190	70572
Total Picking Time (min)	1170	1120	1176
Total Picking Time (h)	19,5	18,7	19,6
Total Colli	3664	3664	3664
Total Colli/Hour	188	196	187
Total Pickers	3,0	3,0	3,0
Pick Time(h)/Picker	6,5	6,2	6,5
Avg. Distance Batch (m)	219	161	219
Total Distance (m)	16422	12046	16422
Avg. Batching Time (s)	936	896	941

Table E-106. KPI Results of Configuration 3 of Experiment 3 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	66756	63381	66467
Total Picking Time (min)	1113	1056	1108
Total Picking Time (h)	18,5	17,6	18,5
Total Colli	3262	3262	3262
Total Colli/Hour	176	185	177
Total Pickers	3,0	3,0	3,0
Pick Time(h)/Picker	6,2	5,9	6,2
Avg. Distance Batch (m)	223	161	223
Total Distance (m)	16751	12089	16751
Avg. Batching Time (s)	890	845	886

Table E-107. KPI Results of Configuration 3 of Experiment 4 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	67382	64226	68144
Total Picking Time (min)	1123	1070	1136
Total Picking Time (h)	18,7	17,8	18,9
Total Colli	3123	3123	3123
Total Colli/Hour	167	175	165
Total Pickers	3,0	3,0	3,0
Pick Time(h)/Picker	6,2	5,9	6,3
Avg. Distance Batch (m)	233	165	233
Total Distance (m)	17452	12392	17452
Avg. Batching Time (s)	898	856	909

Table E-108. KPI Results of Configuration 3 of Experiment 5 in Scenario 77

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	58554	64009	67784
Total Picking Time (min)	976	1067	1130
Total Picking Time (h)	16	18	19
Total Colli	3388	3388	3388
Total Colli/Hour	208	191	180
Total Pickers	2,9	3,0	3,0
Pick Time(h)/Picker	5,7	5,9	6,3
Avg. Distance Batch (m)	157	152	216
Total Distance (m)	9599	11220	16203
Avg. Batching Time (s)	960	870	904

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Table E-109. KPI Results of Configuration 1 of Experiment 1 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49084	54399	57359
Total Picking Time (min)	818	907	956
Total Picking Time (h)	13,6	15,1	15,9
Total Colli	2181	2181	2181
Total Colli/Hour	160	144	137
Total Pickers	2,0	2,0	2,6
Pick Time(h)/Picker	6,8	7,6	6,5
Avg. Distance Batch (m)	133	110	149
Total Distance (m)	7434	8057	11201
Avg. Batching Time (s)	877	746	765

Table E-110. KPI Results of Configuration 1 of Experiment 2 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49431	54935	57626
Total Picking Time (min)	824	916	960
Total Picking Time (h)	13,7	15,3	16,0
Total Colli	2217	2217	2217
Total Colli/Hour	161	145	139
Total Pickers	2,0	2,0	2,6
Pick Time(h)/Picker	6,9	7,6	6,5
Avg. Distance Batch (m)	129	114	148
Total Distance (m)	7500	8355	11136
Avg. Batching Time (s)	852	750	768

Table E-111. KPI Results of Configuration 1 of Experiment 3 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	45560	52006	55784
Total Picking Time (min)	759	867	930
Total Picking Time (h)	12,7	14,4	15,5
Total Colli	2015	2015	2015
Total Colli/Hour	159	140	130
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,3	7,2	7,7
Avg. Distance Batch (m)	128	104	143
Total Distance (m)	6794	7533	10709
Avg. Batching Time (s)	860	716	744

Table E-112. KPI Results of Configuration 1 of Experiment 4 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	46859	52662	55168
Total Picking Time (min)	781	878	919
Total Picking Time (h)	13,0	14,6	15,3
Total Colli	1981	1981	1981
Total Colli/Hour	152	136	129
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,5	7,3	7,7
Avg. Distance Batch (m)	130	111	143
Total Distance (m)	7423	8120	10695
Avg. Batching Time (s)	822	720	736

Table E-113. KPI Results of Configuration 1 of Experiment 5 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49339	54893	57713
Total Picking Time (min)	822	915	962
Total Picking Time (h)	14	15	16
Total Colli	2285	2285	2285
Total Colli/Hour	167	150	143
Total Pickers	2,0	2,0	2,6
Pick Time(h)/Picker	6,9	7,6	6,5
Avg. Distance Batch (m)	132	107	142
Total Distance (m)	7267	7808	10658
Avg. Batching Time (s)	897	754	770

Table E-114. KPI Results of Configuration 2 of Experiment 1 in Scenario 92

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49179	54392	57840
Total Picking Time (min)	820	907	964
Total Picking Time (h)	13,7	15,1	16,1
Total Colli	2181	2181	2181
Total Colli/Hour	160	145	136
Total Pickers	2,0	2,0	2,7
Pick Time(h)/Picker	6,8	7,6	6,2
Avg. Distance Batch (m)	135	113	151
Total Distance (m)	7551	8226	11344
Avg. Batching Time (s)	878	745	771

Table E-115. KPI Results of Configuration 2 of Experiment 2 in Scenario 92

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49916	54637	57794
Total Picking Time (min)	832	911	963
Total Picking Time (h)	13,9	15,2	16,1
Total Colli	2217	2217	2217
Total Colli/Hour	160	146	138
Total Pickers	2,0	2,0	2,7
Pick Time(h)/Picker	6,9	7,6	6,2
Avg. Distance Batch (m)	134	114	147
Total Distance (m)	7782	8352	11062
Avg. Batching Time (s)	861	746	771

Table E-116. KPI Results of Configuration 2 of Experiment 3 in Scenario 92

Iterations	*10*		
Number of Changes	*3*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	45905	52301	55602
Total Picking Time (min)	765	872	927
Total Picking Time (h)	12,8	14,5	15,4
Total Colli	2015	2015	2015
Total Colli/Hour	158	139	130
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,4	7,3	7,7
Avg. Distance Batch (m)	130	107	146
Total Distance (m)	6896	7732	10918
Avg. Batching Time (s)	866	721	741

Table E-117. KPI Results of Configuration 2 of Experiment 4 in Scenario 92

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	47276	52561	55802
Total Picking Time (min)	788	876	930
Total Picking Time (h)	13,1	14,6	15,5
Total Colli	1981	1981	1981
Total Colli/Hour	151	136	128
Total Pickers	2,0	2,0	2,0
Pick Time(h)/Picker	6,6	7,3	7,8
Avg. Distance Batch (m)	135	114	148
Total Distance (m)	7702	8362	11066
Avg. Batching Time (s)	829	719	744

Table E-118. KPI Results of Configuration 2 of Experiment 5 in Scenario 92

Iterations	*10*		
Number of Changes	*3*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	49344	55625	57935
Total Picking Time (min)	822	927	966
Total Picking Time (h)	14	15	16
Total Colli	2285	2285	2285
Total Colli/Hour	167	148	142
Total Pickers	2,0	2,1	2,9
Pick Time(h)/Picker	6,9	7,5	5,7
Avg. Distance Batch (m)	132	113	143
Total Distance (m)	7282	8213	10721
Avg. Batching Time (s)	897	764	772

Table E-119. KPI Results of Configuration 3 of Experiment 1 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	50959	56995	61426
Total Picking Time (min)	849	950	1024
Total Picking Time (h)	14,2	15,8	17,1
Total Colli	2181	2181	2181
Total Colli/Hour	154	138	128
Total Pickers	2,0	2,5	3,0
Pick Time(h)/Picker	7,1	6,4	5,7
Avg. Distance Batch (m)	179	166	243
Total Distance (m)	10023	12135	18205
Avg. Batching Time (s)	910	780	819

Table E-120. KPI Results of Configuration 3 of Experiment 2 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	50899	57131	61689
Total Picking Time (min)	848	952	1028
Total Picking Time (h)	14,1	15,9	17,1
Total Colli	2217	2217	2217
Total Colli/Hour	157	140	129
Total Pickers	2,0	2,5	3,0
Pick Time(h)/Picker	7,1	6,7	5,7
Avg. Distance Batch (m)	169	160	232
Total Distance (m)	9796	11762	17379
Avg. Batching Time (s)	878	780	823

Table E-121. KPI Results of Configuration 3 of Experiment 3 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	46931	54425	59962
Total Picking Time (min)	782	907	999
Total Picking Time (h)	13,0	15,1	16,7
Total Colli	2015	2015	2015
Total Colli/Hour	155	134	121
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	6,5	7,6	5,6
Avg. Distance Batch (m)	171	158	236
Total Distance (m)	9073	11537	17730
Avg. Batching Time (s)	885	749	799

Table E-122. KPI Results of Configuration 3 of Experiment 4 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	48315	54609	59614
Total Picking Time (min)	805	910	994
Total Picking Time (h)	13,4	15,2	16,6
Total Colli	1981	1981	1981
Total Colli/Hour	148	131	120
Total Pickers	2,0	2,0	3,0
Pick Time(h)/Picker	6,7	7,6	5,5
Avg. Distance Batch (m)	166	156	227
Total Distance (m)	9490	11436	17036
Avg. Batching Time (s)	848	747	795

Table E-123. KPI Results of Configuration 3 of Experiment 5 in Scenario 92

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	51072	57679	61878
Total Picking Time (min)	851	961	1031
Total Picking Time (h)	14	16	17
Total Colli	2285	2285	2285
Total Colli/Hour	161	143	133
Total Pickers	2,0	2,8	3,0
Pick Time(h)/Picker	7,1	5,8	5,7
Avg. Distance Batch (m)	175	159	226
Total Distance (m)	9614	11606	16963
Avg. Batching Time (s)	929	792	825

Scenario 123

Table E-124. KPI Results of Configuration 1 of Experiment 1 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	55409	60278	63493
Total Picking Time (min)	923	1005	1058
Total Picking Time (h)	15,4	16,7	17,6
Total Colli	2312	2312	2312
Total Colli/Hour	150	138	131
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,7	5,8	5,9
Avg. Distance Batch (m)	130	110	140
Total Distance (m)	7514	8061	10463
Avg. Batching Time (s)	955	824	847

Table E-125. KPI Results of Configuration 1 of Experiment 2 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56927	62311	65619
Total Picking Time (min)	949	1039	1094
Total Picking Time (h)	15,8	17,3	18,2
Total Colli	2616	2616	2616
Total Colli/Hour	165	151	144
Total Pickers	2,3	2,9	3,0
Pick Time(h)/Picker	7,1	6,0	6,1
Avg. Distance Batch (m)	126	108	142
Total Distance (m)	7183	7880	10649
Avg. Batching Time (s)	999	853	875

Table E-126. KPI Results of Configuration 1 of Experiment 3 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	57388	61924	65013
Total Picking Time (min)	956	1032	1084
Total Picking Time (h)	15,9	17,2	18,1
Total Colli	2544	2544	2544
Total Colli/Hour	160	148	141
Total Pickers	2,4	3,0	3,0
Pick Time(h)/Picker	6,9	5,7	6,0
Avg. Distance Batch (m)	134	114	144
Total Distance (m)	7755	8380	10792
Avg. Batching Time (s)	989	846	867

Table E-127. KPI Results of Configuration 1 of Experiment 4 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	53308	58619	61184
Total Picking Time (min)	888	977	1020
Total Picking Time (h)	14,8	16,3	17,0
Total Colli	2377	2377	2377
Total Colli/Hour	161	146	140
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,4	5,7	5,7
Avg. Distance Batch (m)	115	98	127
Total Distance (m)	6578	7145	9509
Avg. Batching Time (s)	935	802	816

Table E-128. KPI Results of Configuration 1 of Experiment 5 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	52457	57624	61270
Total Picking Time (min)	874	960	1021
Total Picking Time (h)	15	16	17
Total Colli	2110	2110	2110
Total Colli/Hour	145	132	124
Total Pickers	2,0	2,8	3,0
Pick Time(h)/Picker	7,3	5,8	5,7
Avg. Distance Batch (m)	123	103	142
Total Distance (m)	6893	7524	10618
Avg. Batching Time (s)	937	789	817

Table E-129. KPI Results of Configuration 2 of Experiment 1 in Scenario 123

Iterations	*10*		
Number of Changes	*2*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	55580	60136	63183
Total Picking Time (min)	926	1002	1053
Total Picking Time (h)	15,4	16,7	17,6
Total Colli	2312	2312	2312
Total Colli/Hour	150	139	132
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,7	5,8	5,9
Avg. Distance Batch (m)	125	108	138
Total Distance (m)	7242	7896	10358
Avg. Batching Time (s)	958	821	842

Table E-130. KPI Results of Configuration 2 of Experiment 2 in Scenario 123

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56874	62237	65654
Total Picking Time (min)	948	1037	1094
Total Picking Time (h)	15,8	17,3	18,2
Total Colli	2616	2616	2616
Total Colli/Hour	166	151	143
Total Pickers	2,3	2,9	3,0
Pick Time(h)/Picker	7,1	6,0	6,1
Avg. Distance Batch (m)	125	106	138
Total Distance (m)	7141	7766	10349
Avg. Batching Time (s)	998	852	875

Table E-131. KPI Results of Configuration 2 of Experiment 3 in Scenario 123

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56662	61702	65356
Total Picking Time (min)	944	1028	1089
Total Picking Time (h)	15,7	17,1	18,2
Total Colli	2544	2544	2544
Total Colli/Hour	162	149	140
Total Pickers	2,1	2,9	3,0
Pick Time(h)/Picker	7,6	5,9	6,1
Avg. Distance Batch (m)	127	111	142
Total Distance (m)	7360	8107	10636
Avg. Batching Time (s)	977	842	871

Table E-132. KPI Results of Configuration 2 of Experiment 4 in Scenario 123

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	53151	58636	61446
Total Picking Time (min)	886	977	1024
Total Picking Time (h)	14,8	16,3	17,1
Total Colli	2377	2377	2377
Total Colli/Hour	161	146	139
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,4	5,6	5,7
Avg. Distance Batch (m)	111	95	123
Total Distance (m)	6314	6974	9258
Avg. Batching Time (s)	932	802	819

Table E-133. KPI Results of Configuration 2 of Experiment 5 in Scenario 123

Iterations	*10*		
Number of Changes	*1*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	51996	57803	60977
Total Picking Time (min)	867	963	1016
Total Picking Time (h)	14	16	17
Total Colli	2110	2110	2110
Total Colli/Hour	146	132	125
Total Pickers	2,0	2,7	3,0
Pick Time(h)/Picker	7,2	6,1	5,6
Avg. Distance Batch (m)	120	102	139
Total Distance (m)	6742	7413	10447
Avg. Batching Time (s)	929	792	813

Table E-134. KPI Results of Configuration 3 of Experiment 1 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	56872	62640	67434
Total Picking Time (min)	948	1044	1124
Total Picking Time (h)	15,8	17,4	18,7
Total Colli	2312	2312	2312
Total Colli/Hour	146	133	123
Total Pickers	2,2	2,9	3,0
Pick Time(h)/Picker	7,4	6,0	6,2
Avg. Distance Batch (m)	172	159	232
Total Distance (m)	9957	11691	17387
Avg. Batching Time (s)	981	856	899

Table E-135. KPI Results of Configuration 3 of Experiment 2 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	58757	64437	69409
Total Picking Time (min)	979	1074	1157
Total Picking Time (h)	16,3	17,9	19,3
Total Colli	2616	2616	2616
Total Colli/Hour	160	146	136
Total Pickers	2,9	3,0	3,0
Pick Time(h)/Picker	5,7	6,0	6,4
Avg. Distance Batch (m)	167	157	220
Total Distance (m)	9526	11485	16503
Avg. Batching Time (s)	1031	882	925

Table E-136. KPI Results of Configuration 3 of Experiment 3 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	58749	63763	69068
Total Picking Time (min)	979	1063	1151
Total Picking Time (h)	16,3	17,7	19,2
Total Colli	2544	2544	2544
Total Colli/Hour	156	144	133
Total Pickers	2,9	3,0	3,0
Pick Time(h)/Picker	5,7	5,9	6,4
Avg. Distance Batch (m)	172	161	233
Total Distance (m)	9950	11796	17504
Avg. Batching Time (s)	1013	871	921

Table E-137. KPI Results of Configuration 3 of Experiment 4 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	54344	61244	65675
Total Picking Time (min)	906	1021	1095
Total Picking Time (h)	15,1	17,0	18,2
Total Colli	2377	2377	2377
Total Colli/Hour	157	140	130
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,5	5,9	6,1
Avg. Distance Batch (m)	165	155	218
Total Distance (m)	9380	11339	16357
Avg. Batching Time (s)	953	837	876

Table E-138. KPI Results of Configuration 3 of Experiment 5 in Scenario 123

Iterations	*10*		
	BatchS + Singlepick	BatchS	FCFS
Total Picking Time (s)	53515	60477	65020
Total Picking Time (min)	892	1008	1084
Total Picking Time (h)	15	17	18
Total Colli	2110	2110	2110
Total Colli/Hour	142	126	117
Total Pickers	2,0	2,9	3,0
Pick Time(h)/Picker	7,4	5,8	6,0
Avg. Distance Batch (m)	170	157	225
Total Distance (m)	9512	11464	16846
Avg. Batching Time (s)	956	829	867

Appendix F. Analysis of Results

In this Appendix the different performance indicators are shown and compared what the sensitivity is in output of the according KPIs. It is shown per configuration and strategy. How each scenario will react to a change in batching strategy per KPI.

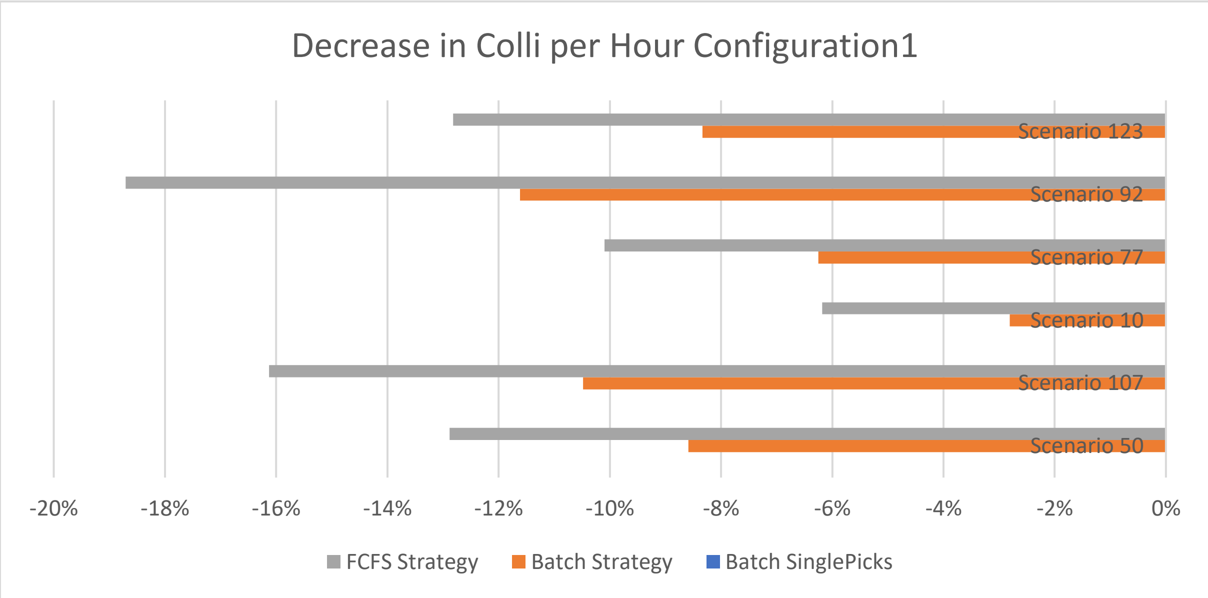

Figure F-1 – Percentage decrease in Colli per Hour configuration 1 if switched to another picking strategy

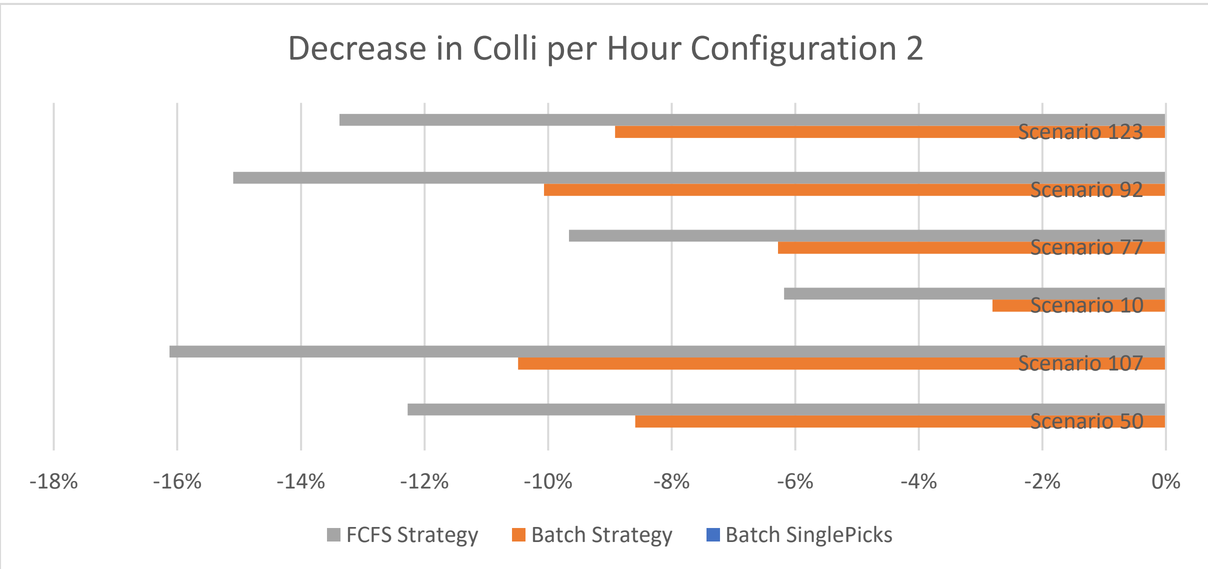

Figure F-2 – Percentage decrease in Colli per Hour configuration 2 if switched to another picking strategy

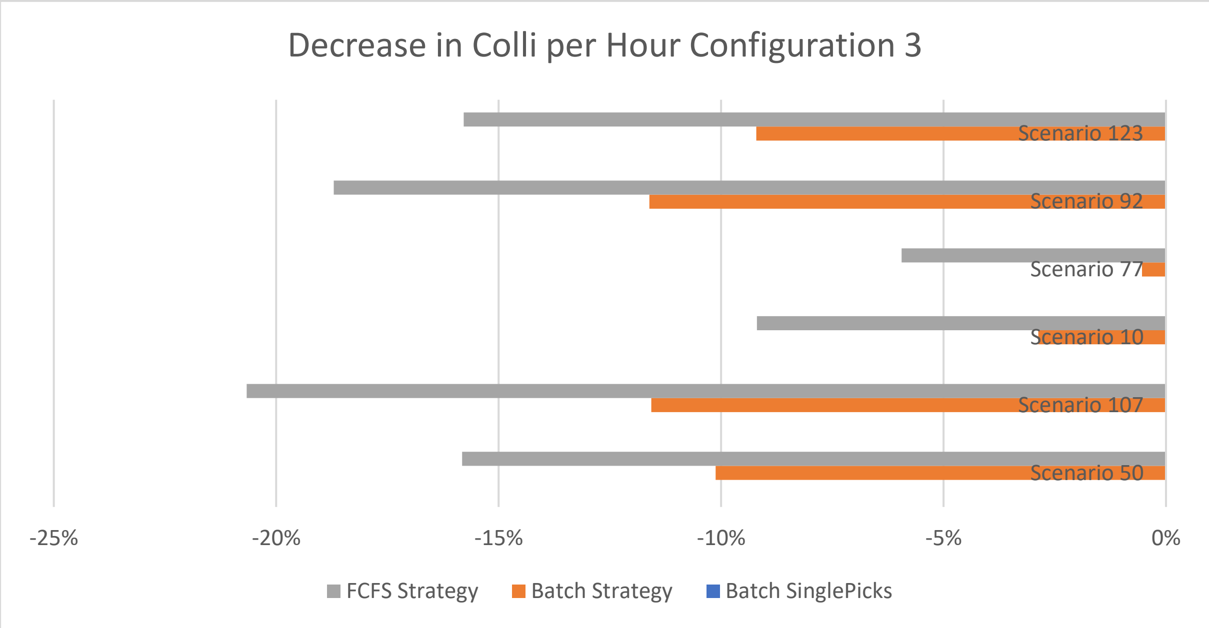

Figure F-3 – Percentage decrease in Colli per Hour configuration 3 if switched to another picking strategy

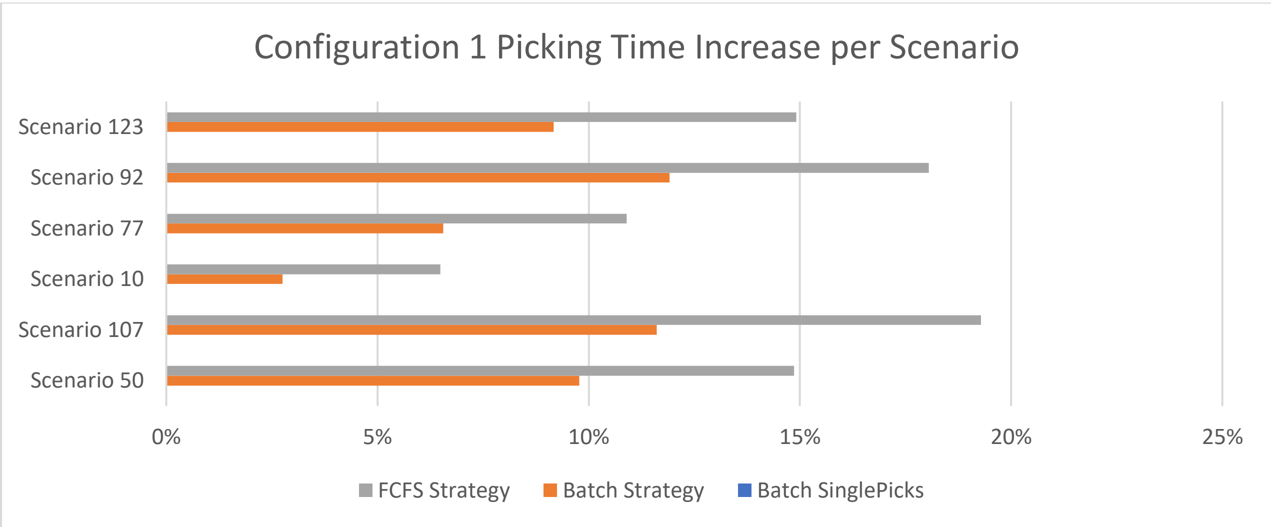

Figure F-4 – Percentage increase in Picking Time configuration 1 if switched to another picking strategy

As can be seen in the figure is, in each scenario, the Batch SinglePicks strategy the best strategy in each scenario if we look at the picking time. Therefore we analyse how much increase in picking time there will be if we use another picking strategy. As can be seen in the figure, scenario 92 and scenario 107 significantly increase if another strategy is being used. In scenario 10, the increase in picking time is a lot less.

The same analysis is done for configuration 2 in the graph below.

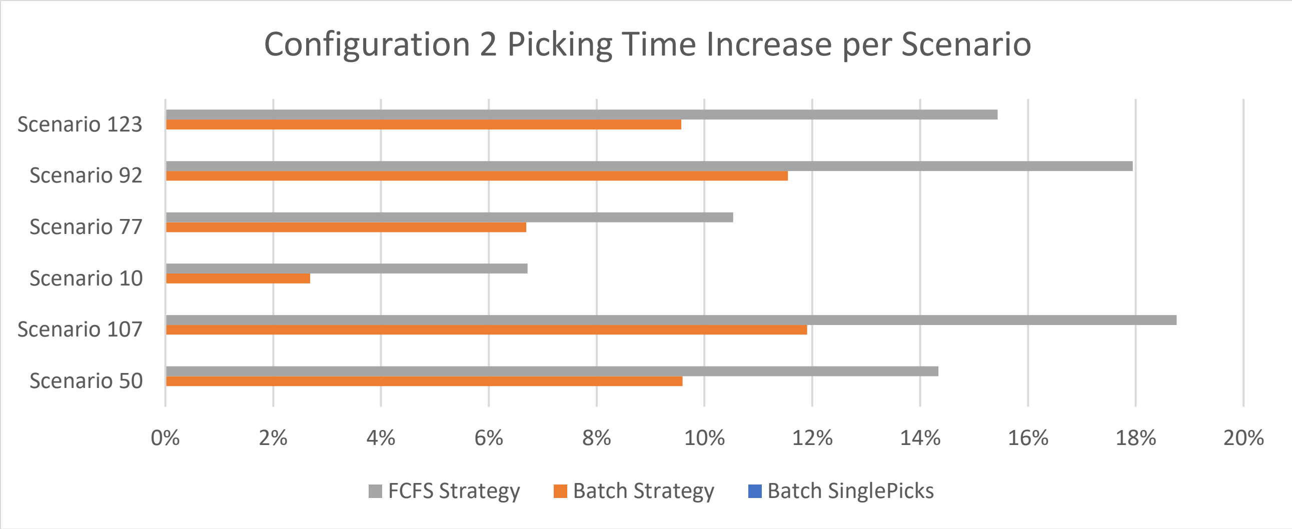

Figure F-5 – Percentage increase in Picking Time configuration 2 if switched to another picking strategy

Configuration 2 very much looks like configuration 1. Here also, the best strategy in each scenario is the star aisle batching with SinglePicks. Later on in the analysis, we will further look into the comparison between configurations 1 and 2 for each strategy.

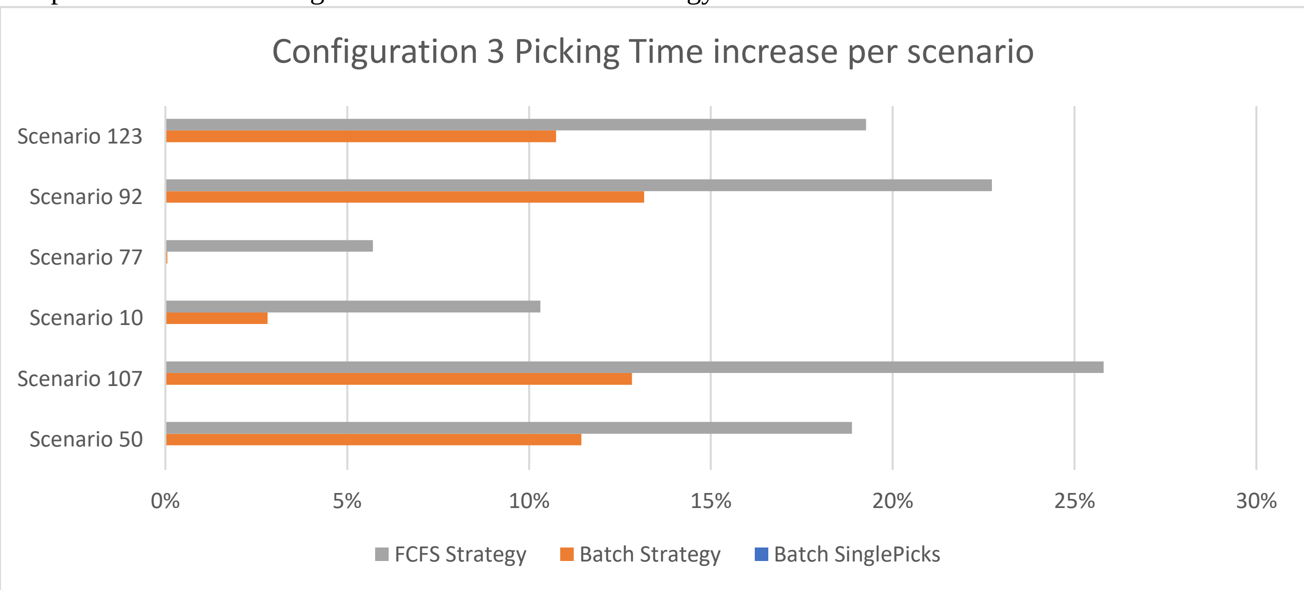

Figure F-6 – Percentage increase in Picking Time configuration 2 if switched to another picking strategy

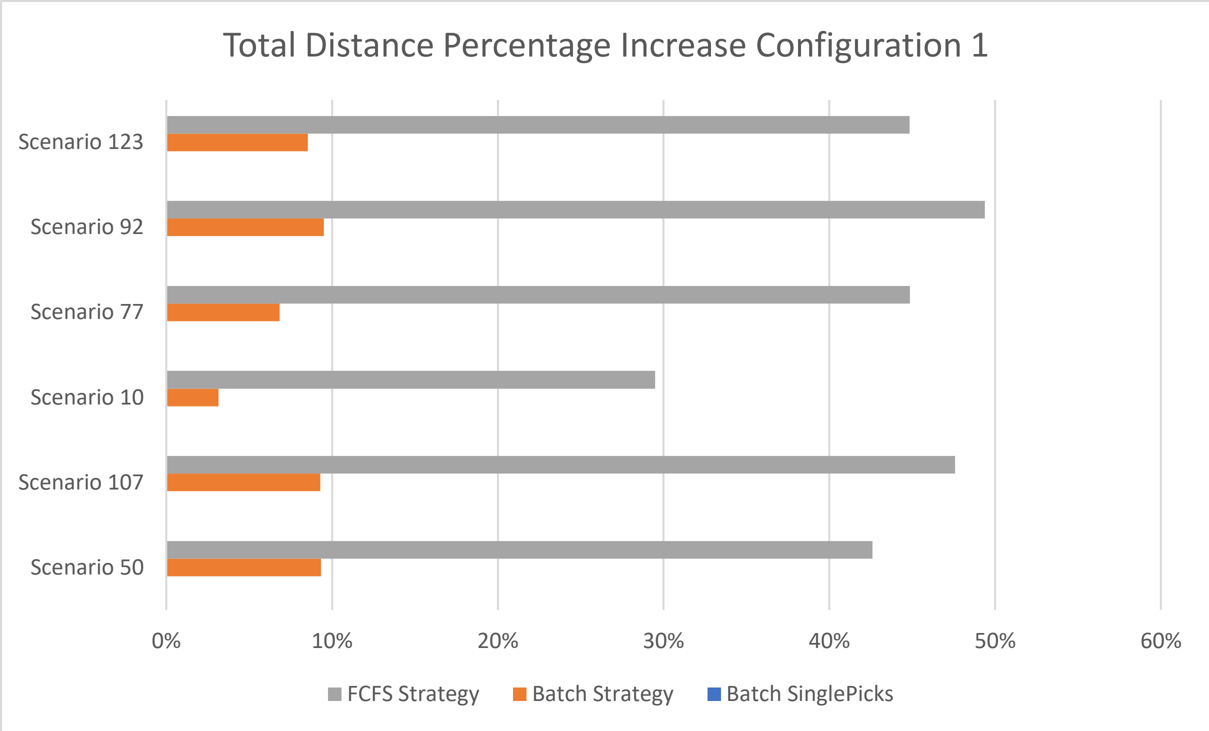

Figure F-7 – Percentage increase in Total Distance configuration 1 if switched to another picking strategy

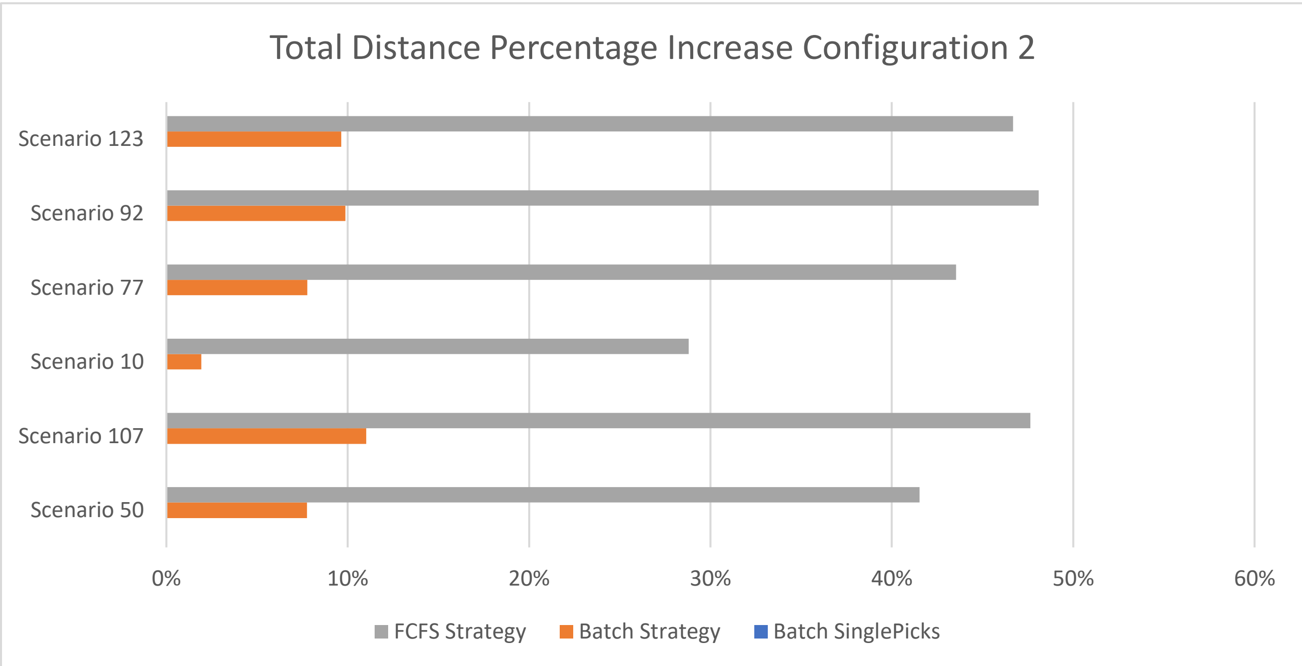

Figure F-8 – Percentage increase in Total Distance configuration 2 if switched to another picking strategy

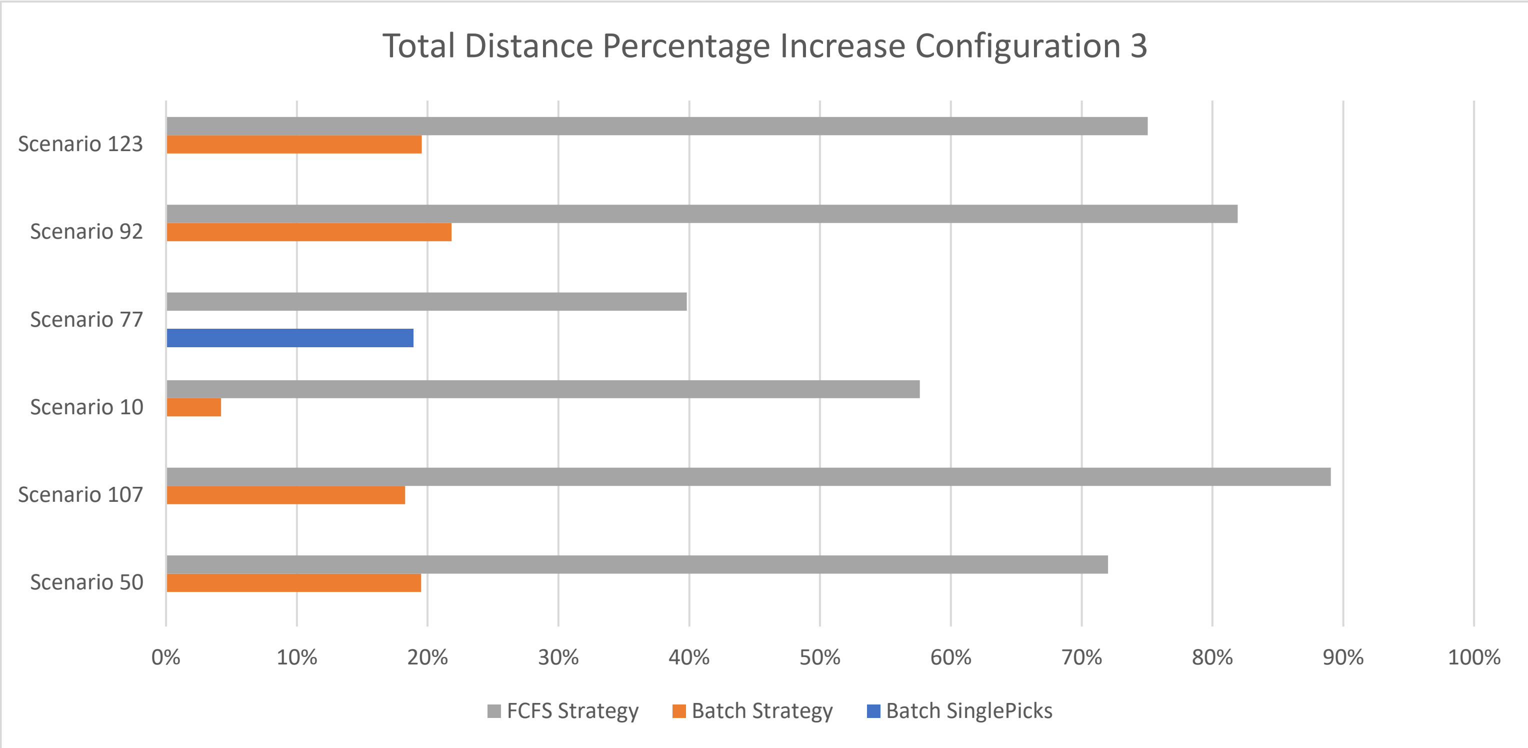

Figure F-9 – Percentage increase in Total Distance configuration 3 if switched to another picking strategy

Appendix G. Scientific Paper

Thesis Paper

The Impact of Order Characteristics Uncertainty on Different Configurations of the Outbound Logistics of a 3PL Warehouse

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Abstract

This paper examines the impact of order characteristics on the performance of different configurations of the outbound logistics of a 3PL warehouse. A contingency approach combined with a proof of configuration method is used to answer this question. The contingency variables in this study are the order characteristics, which are uncertain for the future state of the newly built e-commerce warehouse Haaften III for Nedcargo Logistics, A third-party logistics provider in the Netherlands. Six contingency scenarios are chosen, and a model transforms them into experiments. Three different potential warehouse configuration models process these experiments, and their productivity performance is compared and analysed. Our results showed that the compactness of the layout, ABC-class-based storage and a new picking strategy, *Star Aisle Batch combined with Singlepicks*, provides the best productivity in each scenario. Next, between each scenario, the productivity is impacted differently. The productivity is higher if the order characteristics contain a low percentage of A-type products, the amount of colli is high, or orderlines per order are low. A change in configuration or strategy within each scenario also influences productivity differently. Lastly, it is also proved that the new proposed configuration and picking strategy can improve its current productivity by over 30%

Keywords: 3PL Warehouse, Order Characteristics, Uncertainty, Warehouse Configurations, Modelling, Contingency Approach, Proof of Configuration, Outbound Logistics

1. Introduction

Warehouses are a crucial component in the supply chain. This is especially true for third-party logistics providers (3PL), which specialise in the integrated logistics of warehousing and transportation services. Clients of 3PL providers outsource their warehousing operations and, therefore, must be scaled and adapted to fulfil the expectations and requirements for their products. Consequently, a growing interest in improving the efficiency of warehouses has grown.

The complexity of warehousing has increased significantly with the emerging trend of e-commerce orders, which requires fast processing at warehouses to assure on-time delivery and enhance client satisfaction. This e-commerce trend also increases the uncertainty aspect of the order characteristics because the e-commerce trend is not a homogenous concept. It affects the order characteristics differently. For example, the customer now orders low quantities of product per order due to the easiness, which is also becoming time-critical due to competition.

Warehouses fulfil operations like receiving, put-away, storage, picking, sorting, packing, and shipping (Kembro et al., 2020). Warehouse operations, design, and resources together can be mentioned as the configuration of a warehouse. These configurations should allow a flexible response to the varying and uncertain needs in the future. Warehouse configuration and the way it is operated determines its efficiency. So, understanding the warehouse's current - and future state and goals is crucial before selecting the suitable configuration.

1.1. Research Purpose

This study aims to investigate the fit between the future context and configuration of a soon to be built warehouse. The uncertainty of handling specific order characteristics of potential clients is a contextual factor. The fit between the warehouse's configuration and the context in which it operates is an essential driver for its performance and must be explored.

1.2. Case Study

This paper focuses on the newly built warehouse for Nedcargo, a 3PL provider in The Netherlands, named Haaften III. The new warehouse in Haaften allows Nedcargo to re-evaluate its current warehousing and improve its configuration to be efficient and robust. The

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focus will be on outbound logistics, including storing, sorting, picking, and packing. The performance of a warehouse is impacted by how it is configured, yet the pre-build development of warehouse systems has not been quantified

1.3. Research Question

As mentioned, it is suggested that the warehouse configuration must be tailored to its particular context. The contingency factor in this research is the order characteristics, and the configuration focuses on the outbound logistics. The following research question is established:

What is the impact of context uncertainty of order characteristics on the different outbound configurations of an order-picking warehouse?

1.4. Research Methodology

This research uses a contingency approach combined with the proof of configuration method to answer the research question. The proof of configuration method, also known as the proof of concept but renamed for this study's purpose, is focused on determining if an idea is feasible or if an idea will function as envisioned. This so-called idea is the three proposed configurations of Haaften III in this study.

The contingency approach is a theory that suggests that a warehouse configuration must be tailored to its particular context (Donaldson, 2001). It is applied to connect decisions concerning warehouse configurations to match their context to improve their performance (Woodward, 1965). How do these contextual order characteristics influence the performance of warehouse configurations in the rapidly advancing and changing e-commerce market? This approach is based on modelling three variables, namely the contingency, response, and performance variables. These are respectively modelled as a scenario experiment model, configuration models, and the performance as output. Before this, an extensive current state analysis is performed to investigate the current characteristics and configuration located in their warehouse Tiel. Further elaboration on this is in chapter 3.

1.5. Research Approach

The proof of configuration - and contingency approach is incorporated into an overall research approach, the adapted SIMILAR approach method. The SIMILAR approach is a System Engineering approach and can be seen as an iterative process roadmap. The SIMILAR approach is short for the following process steps: State the problem, Investigate, Model the System, Integrate, Launch the system, Assess performance, and Re-evaluate. The last three processes are combined in this research's evaluation process step. This is because this research is more based on proving the warehouse configuration than implementing a new system. This research approach can be seen as an abbreviated SIMILAR approach, denoted as SIMIE. This System Engineering approach is founded on system thinking, which is a mode of thinking that considers not the whole system but also how the pieces of that system interact.

1.6. Research Objective

This research will prove that specific configurations perform differently in a given context. This aim should provide scientific insights into the different configuration choices and how they affect the performance, the contextual importance of warehouses on their performance, and whether knowledge gaps from literature can be filled. In addition to practice, this study tries to create tools for Nedcargo to eliminate uncertainty in their decision-making for Haaften III. By experimenting with different scenarios regarding order characteristics uncertainty and how potential configurations perform in these scenarios.

2. Literature Review

In section 2, essential previous research findings are discussed based on several topics. These findings pave the way for the methodology of this paper.

2.1. Warehouse Logistics

The warehouse represents a significant role in the modern supply chain. Azadnia et al. (2013) state that 20% of the logistics costs of companies come from warehouse operations. In this manner, a warehouse's in-house logistics (or intralogistics) are integral to the organisation's operations. Therefore, it can be seen as a vital opportunity to improve optimisation, physical - and information flows, reduce inventory levels, and enable more agile distribution (Vrijhoef & Koselka, 2000). An appropriate strategy, layout, warehouse operations, and material handling system must be achieved (Lehrer et al., 2010).

2.2. Warehouse Configuration

Warehouse configuration refers to the combination of operations, design aspects, and resources (Kembro and Norrman, 2020; see also, e.g., Rouwenhorst et al., 2000). The focus of this research is, as said, on the outbound logistics of this warehouse configuration. First is the outbound operations; Klumpp and Heragu (2019) defined outbound logistics as moving and storing goods from production to the point where they are delivered to the customer. So, the warehouse's storage, sorting, picking, and packing operations. Important to mention that the outbound logistics are different for every warehouse. The chances of warehouses having almost the same outbound logistics process due to other order characteristics are minimum (Baretto et al., 2017). Therefore the current state analysis is mandatory.

Secondly, the warehouse design aspects. Gu et al. (2010) classified these warehouse design decisions into different categories: The overall structure of the warehouse, sizing, throughput, layout design, utilised number of workforce, equipment selection, and selection of operational policies. Next to that, a warehouse design project should include definitions of policies such as order fulfilment, picking, packing, stocking, and stock rotation (Chan & Chan, 2011).

Lastly, the resources of the warehouse. Manual warehouses, like Nedcargo, rely on human operators for their order picking system (OPS). The equipment selection decisions in a manual warehouse are expressed, e.g., number of human resources, number of carts, utilisation, etc. Order picking is one of the most time-intensive processes in outbound logistics, so human factors play a crucial role in OPS performance (Tompkins et al., 2010).

2.3. Warehouse Context

Kembro et al. (2018) stated that it is emphasised in many recent studies that the role of a warehouse in meeting its customers' expectations is growing. Mainly due to the shorter lead times and e-commerce trend, it has become more common to rely on the functioning of a warehouse to fulfil the client's wishes. Kembro et al. (2020) stress that more research is needed to analyse and test managerial practices and solutions. Particularly "the need to understand where certain configurations might fit better and which future path to pick" The important context in which a warehouse operates is therefore of great significance. Several researchers emphasise the importance of context in warehousing. Faber et al. (2013) studied external factors that influence the planning and control of WMS systems. They consider two sets of variables: the external warehouse environment (i.e., the market it operates in) and the internal warehouse system. Next, they address five contextual factors: the number of SKUs, assortment fluctuations, demand unpredictability, number of SKUs per order (or amount of orderlines), and process diversity. These factor claims are backed up in several other warehouse studies. Sousa and Voss (2008) pointed out that contingency studies consist of three types of variables: (1) contingency variables, which represent the context, (2) response variables, which represent the organisational actions to respond to the context, (3) and performance variables, which measure the effectiveness of the operations of the system

2.4. Warehouse Performance

The Overwhelming quantity of technological equipment, strategies, components, etc., and the difficulty in assessing them motivates the search for better and more effective warehouse configuration tools (Heragu, 2016). This difficulty in determining is where warehouse modelling comes in. In order to make the right choices in design, strategies and resource models for warehouses are desirable. Therefore multiple studies were conducted to model warehouse components. Table 1 shows the literature table of studies in which warehouse modelling was performed. There is a distinction made between the modelling method, the warehouse components that were modelled, and if the model accounted for uncertainty. Here you can see that most of the studies use a deterministic approach. This research combines this deterministic approach with a probabilistic modelling approach. Next, most of the studies of warehouse modelling considered only a single design method, with the focus mostly on improving the picking strategy. This optimisation approach is limited wherein an attempt to improve one performance may craft wastage in other warehouse processes. This research takes all the warehouse components into account so that it is more of a synthesis than an analysis. Finally, there are not many studies that account for uncertainty in their model. In this study, the uncertainty of its warehouse context is accounted for, namely the order characteristics. The general methodology chapter will further elaborate on this.

In warehouse modelling, there is not a single, one-size-fits-all solution. Optimal solutions can only be applied to particular settings and therefore are non-generalisable. And therefore, of importance to Nedcargo.

Table 1. Research Gap Table for Warehouse Modelling

		Method			*Component*					*External*
Reference	Focus	Deterministic	Probabilistic	Stochastic	Layout	Storage	Picking Strategy	Equipment	Routing	Uncertainty
Aboelfotoh et al. (2019)	Order Batching Optimization	X			X		X		X	
Altarazi et al (2018)	Different Warehouse Design Simulation		X	X	X	X	X	X	X	
Amorim-Lopes et al. (2021)	Probabilistic Simulation of Picking Warehouse		X		X	X	X			
Burinskiene et al. (2018)	Reduction of Waste in Warehouse Logistics	X		X	X	X	X	X	X	
Colla & Nastasi (2010)	Automated Warehouse Storage Strategy	X	X			X				
De La Fuente et al. (2019)	Staffing Strategy and Capacity of Warehouse simulation			X		X		X		
Gagliardi et al. (2008)	Warehouse Simulation to Allocate SKUs	X		X		X	X			
Gong (2009)	Stochastic Modelling Warehouse Operations			X		X	X			X
Gray et al. (1992)	Design of order-consolidation Warehouse	X	X		X		X			
Guo et al. (2007)	Narrow Aisle Pick Density		X		X		X	X	X	
He et al. (2020)	Uncertain Warehouse Layout Problem	X			X	X				X
Hwang & Cho (2006)	Performance model for Order Picking		X				X			
Kachitvichyanaku et al. (2005)	Batches of Customer Orders in Warehouse	X					X			
Le Duc (2005)	Design and Control of Order Picking	X	X		X	X	X	X	X	
Merkuryev et al. (2009)	Warehouse Order Picking Process	X			X	X	X	X	X	
Park & Webster (1989)	3D Warehouse Modelling			X	X	X				
Ratliff & Rosenthal (1983)	Order Picking in Warehouse with TSP	X					X		X	
Saderova et al. (2022)	Simulation modelling of Selected activity	X		X				X	X	
Sadownski et al. (2021	Contingent Nature of Warehouse Flexibility	X				X		X		X
Thi et al. (2021)	Optimizing Warehouse Storage Location under Uncertainty			X		X		X		X
This Research	The Impact of Order Characteristics Uncertainty on Performance of Warehouse Configurations	X	X		X	X	X	~	X	X

3. General Methodology

In section 3, the general methodology of the paper is presented. Each paragraph will discuss a particular step in the research approach. The results obtained from each method are then compared in sections 4 and 5.

3.1. Current State Analysis; Tiel

To develop new configurations for the newly built warehouse of Haaften. We need to have knowledgeable insight into their current outbound logistics operations in their currently active e-commerce warehouse. Because there is no single one-size-fits-all solution. The warehouse in Tiel currently handles the e-commerce orders for Nedcargo. This picker-to-good manually operated warehouse handles the e-commerce orders of Jacob Douwe Egberts (JDE). This study focuses on new configurations and the order characteristics uncertainty of Haaften III. But before confident future choices can be made, the current state must be analysed. This current state analysis is conducted by process description and followed by extensive data analysis in the research.

First is the process description. Since this research focuses on outbound logistics, we will confine to the storing, picking, and packing operations. The storing in Tiel is based on an ABC-class-based strategy, but it is not compact. Six aisles are used for only 351 products, or Stock-Keeping Units (SKU), that need to be stored. This storage should be more compact in the future configuration. Because now, a total of 351 SKUs are stored in 130 pick locations, where each pick location can exist out of 4 SKUs. So, if we look at the compactness of that storage, if we divide 351 by four, only 88 pick locations are needed. This reasoning is vital to consider in future configurations.

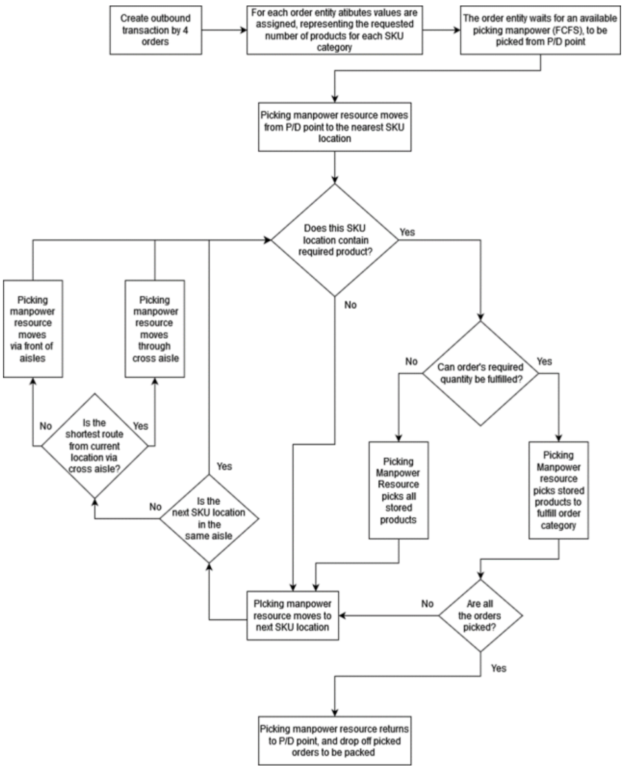


Figure 1- Logistics flow decision chart per picking tour

Next are the picking operations, shown in figure 1. The orders in Tiel are batched per four orders, and it follows a First Come, First Serve strategy. This simple batch construction method is based that orders are sequentially assigned to batches depending on their arrival. The figure shows the decision that must be made for the pickers when moving through the picking circuit. The picker follows the route with the use of the shortest route algorithm. It must be explored if this batching/picking strategy can be executed more efficiently.

Concerning the packing operations, the following has been noticed. Namely, maintaining a *SinglePick* strategy is beneficial for the packing operation. The *SinglePick* strategy is a batching strategy that batches all the orders consisting of a single SKU and a single colli; colli is the number of packages of a particular SKU. If these orders are collected as a bulk batch, the packer now can pack-per-colli instead of pack-per-customer. Because the packer does not have to include multiple SKUs in the shipping box, it can now scan the colli and see to which customer it belongs. Instead of collecting colli from the picking cart based on the customer's order. This strategy should fasten the picking and packing performance. The figure below shows the picker's decision chart concerning the *SinglePick* strategy.

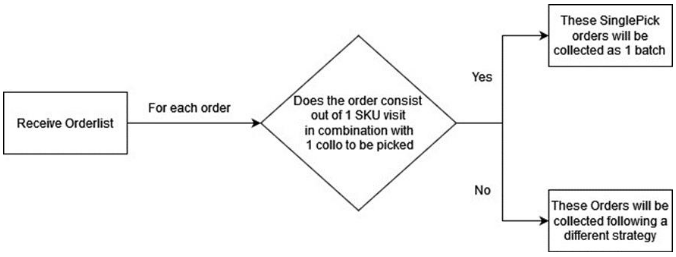


Figure 2- Logistics flow decision chart for SinglePicks

3.2. Data Analysis of Tiel

After the current state analysis of Tiel is explored. It is time to look deeper into the data of Tiel. Tiel's warehouse management system (WMS) allowed us to analyse the collected data from the warehouse over a half year, the second semester of 2021. The data was gathered and analysed using Microsoft Access. This access database allowed the possibility to link data nodes and perform analyses the WMS could not function.

The following data was collected:

1. The data of the distance travelled
2. The data of all the orders
3. The data of the movements in the warehouse
4. The data of time measurements

By the distance travelled is meant the total distance that the pickers travel within the warehouse. The data of all the orders consist of the order characteristics, the product characteristics, and an ABC analysis of the SKUs. With the movements in the warehouse, is meant the storage of all the SKUs and the allocation of SKUs, both by using a heat map. Lastly, the data of the time measurements included the pick time per picking tour, the fixed time per SKU visit, the variable time per colli pick, and the performance of the pickers in colli per hour. The below figure shows that these data together form the current state model of Tiel.

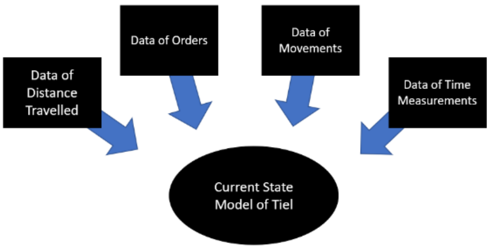


Figure 3- Data from Tiel Access Database, which shapes the Current State Model

The current state model of Tiel is a simulation model representing the current state warehouse of Tiel that has been made to make it possible to measure the (simulated) performance. It is a computer simulation which can process an order list based on the collected data. The below table compares the simulated performance with the real-life performance. This model will be used to prove that the configurational changes should improve the current state as well.

Table 1. The model results of the Tiel Warehouse.

	Real-Life Day	Simulated Day
Avg. Performance (Colli/Hour)	112,4	116,7
Avg. Batching Distance (m)	264	299

3.3. Proof of Configuration

The proof of configuration approach in combination with the contingency approach is pursued because it can prove that specific configurations better fit and perform in certain contexts. The proof of concept, or in this research's case configuration, constituted the scope of this research project. As part of a robust systems engineering process, conducting a proof-of-concept initial study to identify potential system limitations is critical to understanding the system's expected usefulness before incurring additional costs. This approach can benefit the pre-design phase of Nedcargo by highlighting potential limitations of the configurations in specific contextual settings. These configuration models must represent the outbound logistics of a warehouse; thus, storage, layout, picking strategy, routing, and equipment must be modelled within the models.

3.4. Contingency Approach

Sousa and Voss (2008) pointed out that contingency studies consist of three types of variables: (1) contingency variables, which represent the context, (2) response variables, which represent the organisational actions to respond to the context, (3) and performance variables, which measure the effectiveness of the operations of the system. These three variables will each represent a specific aspect of the warehouse, and all will be modelled.

The contingency variables will represent the order characteristics, which are contextual factors influencing a warehouse's performance. The order characteristics are measured in four types of contingency variables:

1. Number of SKUs
2. SKU per Order
3. Colli per SKU
4. ABC-Ratio

The response variables are the proposed configurations. The configurations represent the different components in a warehouse and will process the orders influenced by the contingency variables.

The performance variables, which are in this paper: the productivity (colli per hour), the distance travelled, the picking time, the number of pickers, and the average batching time.

Based on these proof of configuration and contingency approaches, the following method of this research can be visualised in figure 4.

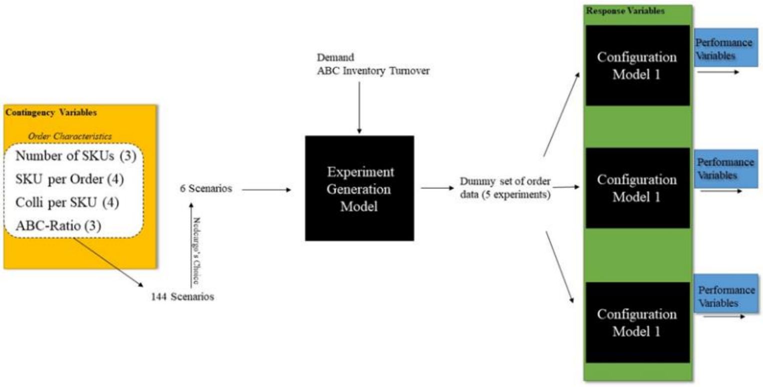


Figure 4- Overview of Method of Study

3.5. Scenarios

As can be seen in figure 4, out of the four order characteristics variables, 144 scenarios are presented. These contingency variables are each distributed at different levels. We will each discuss them separately.

The first contingency variable is the "Number of SKUs". This variable represents the number of SKUs that needs to be handled in the warehouse. It can be chosen from three levels, namely 350, 500 or 750 SKUs in the warehouse.

The second contingency variable is the "SKU per Order". This variable represents the probability that an order consists of X amount of SKUs. This variable is based on four distributions where each distribution differs in likelihood for the amount of 1 -, 2 till 3 -, 4 till 7 -, 8 till 10 -, 11 till 20 -, and 20 till 50 SKUs per order.

The third contingency variable is the colli per SKU. This variable represents the probability of how many colli an SKU visit consists of. During the data analysis, it was discovered that the type of SKU influences the colli per SKU probability. So if an SKU is an A-type, B-type or C-type, thus, it is chosen to have four probability distributions for each type of SKU.

The last contingency variable is the ABC Ratio. The ABC ratio is based on the ABC analysis performed in the data analysis. Tiel has an ABC ratio of 18%-27%-55%, with an inventory turnover of the Tiel warehouse being 75%-20%-5%. This means that 18% of the SKUs account for 75% of the SKU visits. This 18% of the SKUs are called A-type SKUs. But what if we change the ABC ratio to other ratios? The latter is what this contingency variable represents, namely three levels of different ABC ratios.

Based on the different levels and distributions of the contingency variables, 144 context scenarios were created. Nedcargo could choose the six most applicable or plausible scenarios for Haaften. The chosen scenarios are 50, 107, 10,77, 92 and 123. As shown in figure 4, these scenarios are being transformed into experiments by the Experiment Generation Model. The next chapter will explain how this and further steps in the method are carried out.

4. Models

The 4 models created in this research will be explained in this chapter. The experiment generation model, which transforms the scenarios into experiments, will be discussed first—followed by the three configuration models that will process the experiments quantifying their performance.

4.1. Experiment Generation Model

As mentioned in the previous chapter, each scenario is a different combination of contingency levels and distributions. Each of these context scenarios must be transformed into experiments that the configuration models can process.

A model must therefore be created to generate a dummy order data set based on the various contingency characteristics. Each scenario will have five generated experiments. The model is implemented using Excel VBA in combination with macros and PowerPivot functions.

This dummy order data set can be compared with an actual order list received at the beginning of a picking day. This will function as the input of the proposed configuration models

This "Experiment Generation Model" consists of several steps. Each step will be discussed in short.

The first step is to decide how many orders should be generated. In this research, it is assumed that 300 orders are generated for each experiment. This is assumed because we do not want to see the impact of the demand characteristics but rather the impact of order characteristics on the performance of the proposed configurations.

The second step is to generate out of how many order lines the order consists of. An order line is also the number of SKUs per order. The model assigns an amount of SKUs to each order based on the probability distribution of the scenario. For example, order-1 has 5 SKUs to pick and order-2 only 1 SKU. These orderlines are based on the chosen distribution of the "SKU per Order" contingency variable.

Now that for each order, the amount of SKUs is known. We must decide whether each SKU is an A-type, B-type or C-type SKU. For this step, two contingency variables are essential: the ABC ratio and the Number of SKUs. Based on these two variables, how many SKUs are A, B or C can be decided.

If that step is completed, it is known how many SKUs are A, how many are B, and how many are C. The next step is to decide the probability of an SKU being visited. If that probability is known, a specific SKU can be assigned to each orderline generated in step 2.

For this step, we have to use the data analysis of Tiel. The probability per SKU and type of SKUs have been analysed during the data analysis. For the experiment generation model, the probability that a particular SKU is visited. It was seen that this probability followed an exponential decay. So for each type of SKU, a growth factor was decomposed out of the data analysis, which was scaled and fitted for the chosen contingency variables. Then the probability for each SKU was awarded by the following formula:

$$y(pt) = a * g^{p} \qquad (1)$$

$$where$$

$$y(pt) = probability\ value\ for\ SKU_{p}\ of\ type\ \mathrm{t}$$

$$a = probability\ of\ most\ picked\ SKU$$

$$g = rate\ of\ decay$$

$$p = SKU\ number\ (e.g. for\ A{:}\ 1\ till\ 64)$$

This formula assigns to each SKU a certain probability of being picked.

After this step, each order now has the amount of SKU(s) it needs to pick and which specific SKU(s) they are. The last step is that based on the "Colli per SKU", how many colli the pickers have to collect at each SKU visit is generated. This is decided by the probability distribution per type- of SKU of the particular scenario.

The average results of all the generated experiments per scenario are shown in table 2. These characteristics are the average results of each dummy order set that the model generates.

4.2. Configuration Models

In this paragraph, the three proposed configuration models will be elaborated on. Each of the configuration components will be discussed per configuration. Based on literature findings, consultation with Nedcargo, data analysis, and personal insights, these configurations are configured. Out of the consultation with Nedcargo, the following functional and non-functional requirements were presented:

Table 2. Average results of experiments per scenario

	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Orders	300	300	300	300	300	300
Orderlines	834	747	1560	714	734	1071
Total Colli	2315	1646	4171	3251	2135	2391
Avg. Orderline/Order	2,78	2,21	5,20	2,38	2,45	3,57
Avg. Colli/Orderline	2,77	2,21	2,67	4,55	2,90	2,23
Avg. Colli/Order	7,71	5,49	13,90	10,94	7,12	7,97
Avg. SinglePicks	71,6	79,4	37,8	59,2	82,8	77,6

- Productivity as high as possible
- As few pickers as possible
- Insight beforehand how many pickers needed
- All orders picked in about 8 working hours
- The layout must fit its context.
- *SinglePick* type orders must be collected as a batch
- Conventional racking is not necessary
- Future possibility for automation

Next to these requirements, there were also assumptions to be made. These were divided into numerical, mathematical and conceptual assumptions, which can be found in the full research report.

Configuration 1 has the most configurational changes compared to the current state. Configuration models 2 and 3 are mostly tweaked compared to configuration 1. Each of the configurations is created by using Visual Basics for Applications (VBA) for Microsoft Excel (MS Excel 2019). This is a programming language tailored to act as a macro language found in most spreadsheets.

We will now discuss each of the configurations per configurational component.

Configuration Model 1

This section is structured as follows: for configuration 1, its choice of layout, storage, picking strategy, and equipment will be elaborated.

First, we take a look at the picking strategy. We have already discussed the *FCFS* and the *SinglePick* strategy. But this configuration considers three types of picking strategies which will be compared. *The First Come, First Serve* strategy, the *Star Aisle Batch* strategy and the *Star Aisle Batch combined with SinglePick* strategy. We will discuss the last two strategies.

The Star Aisle Batch strategy is a batching heuristic presented by Aboelfotoh et al. (2019). This batching strategy focuses on batching orders located in the same aisle. This aisle-by-aisle heuristic considers various parameters such as item location, order details, detailed layout of pick area, and the maximum number of orders allowed per batch. The heuristic is based on six steps which are shown below in the algorithm:

Step 1: Define star aisle k
Step 2: Generate star aisle vector X^*
Step 3: Generate order aisle vector X^i for each order
Step 4: Choose the first order for this assignment based on the minimum sum of squared distance S_i of order i
Step 5: Update the star aisle vector X^*
Step 6: Group next order
For each order i, calculate its sum of the squared distance S_i to star aisles and assign the order with the least S_i.
Is the number of orders grouped greater than the maximum number of orders that van de assigned in one batch assignment?
Then go to Step 1
Else, go to Step 5

$$S_i = \sum_{j=1}^{a} \sum_{j*=1}^{a} (j - j^*)^2 \qquad \forall x_j^i = 1 \ \ \forall x_j^* = 1 \quad (2)$$

$$i = order\ index$$
$$k = batch\ index$$
$$j = aisle\ index$$
$$n = number\ of\ orders$$
$$a = number\ of\ aisles$$
$$B = Batch\ Size$$

The *Star Aisle Batch combined with the SinglePick* strategy is a new strategy proposed. This first batches all the SinglePick orders in a so-called "SPBatch". So that the pickers first collect all the SinglePick orders in one picking tour. Then the remaining orders are batched following the Star Aisle Batching Algorithm.

Now that the picking strategies are clear, we move to the routing strategy. Just as in the current warehouse of Tiel, the shortest route strategy is maintained for configuration 1. The shortest path algorithm finds the shortest path between two nodes (SKUs), and the pickers follow that path.

The storage assignment is based on the ABC-class-based storage strategy from Yu & Koster (2010). This is visualised in figure 5.

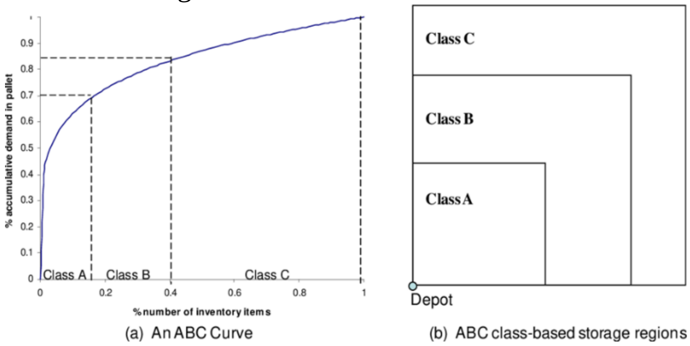


Figure 5- ABC-Class-Based Storage strategy

In this layout, the A-class SKUs are the nearest to the packing depot. The only thing that is added to this is that there are AA-products., which are the twelve most ordered SKUs. Those SKUs are the closest to the depot, and the rest is randomly assigned based on their class type.

The warehouse layout is based on almost the same characteristics as the Tiel warehouse. Only in configuration 1, it is as compact as possible. That means that only as many aisles are used as SKUs that are needed. Each pick location can store three SKUs, so the number of aisles that are needed can be calculated because the aisles consist of the same amount of pick locations as in Tiel. Next to that, a cross-aisle is located at 60% of the warehouse's length; this is the same as the current state.

The equipment that is used is the same as in Tiel. So the data of the time measurements of the data analysis are also implemented in this model.

Configuration Model 2

Configuration 1 has made some significant changes from the current state, substantiated by literature and data analysis to improve its current configuration of Tiel. Configuration 2 copies all of these changes and adds an extra element to this, namely, in the storage assignment.

This new storage strategy is called "Dynamic SKU Location." The dynamic SKU locations are two locations in the warehouse where at the beginning of each working day, the stored SKUs could be different than the day before. This strategy is decided by first performing an affinity analysis, which checks if a pair of SKUs are often paired in orders on that specific day. And secondly, by looking at the daily demand of the SKUs

Configuration Model 3

Configuration 3 focuses on decreasing the possibility of congestion in the warehouse. This decongestion is achieved by changing the routing strategy of configuration 1. Instead of using the shortest route algorithm, configuration 3 uses a different strategy: The S-Shape routing strategy. The s-shape routing strategy leads to a route in which the aisles that need to be visited to complete the batch are traversed in a single direction. That is why it is called an S-shape strategy; aisles are visited in a shape of an S. As a result, the cross-aisle is removed, and the aisle width will be narrowed down slightly. The same is assumed for the other warehouse components as in configuration 1. Formula 3 shows the calculation needed to calculate the distance between and within the aisles.

$$d_b = 2\left(\left\lceil\frac{\mathrm{N}^{\mathrm{b}}_{aisles}}{2}\right\rceil \cdot d_{wl} + d_{cw} * A_{last}\right) \qquad (3)$$

$Where:$

$d_b = distance\ covered\ in\ batch\ b \qquad b \in B$

$d_{cw} = cross\ lenght\ between\ 2\ aisles\ (or\ distance\ between)$

$A^b_{last} = Last\ aisle\ to\ be\ visited\ in\ batch\ b \qquad b \in B$

$d_{wl} = Lenght\ of\ the\ warehouse$

$N^b_{aisles} = number\ of\ aisles\ visited\ in\ batch\ b \qquad b \in B$

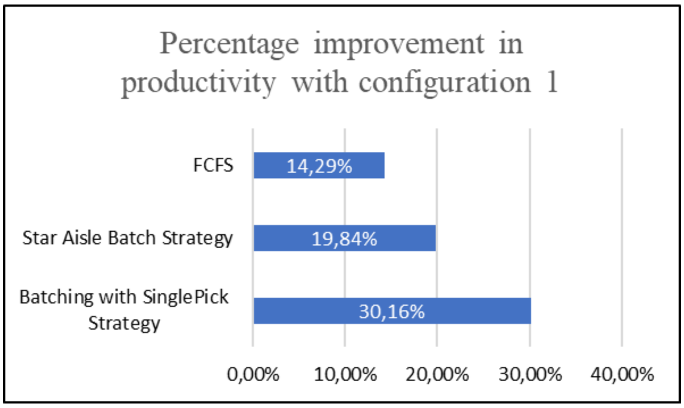
5. Analysis and Results

In this chapter, the results of the configuration models will be discussed. In this research, several performance indicators were addressed. But it is chosen for this paper to only focus on one of the performance indicators, namely productivity. The productivity is measured in colli per hour for each picker. If anyone wants to know more about the results of the other performance indicators measured, please contact the author. It was also seen that configuration 1 outperformed configurations 2 and 3. So, the focus will be on configuration 1 as well.

5.1. Current State Comparison

The first thing that we wanted to achieve with the configuration models was to prove that the new configurations perform better in the same context as Tiel. Therefore we needed to compare the configuration models with the current state model. For each configuration, we simulated the productivity if the contextual order characteristics were the same as in Tiel. There it was seen that configuration 1 outperformed configurations 2 and 3 in terms of productivity increase compared to the current state model of Tiel. Therefore, we will now continue to address configuration 1.

This comparison resulted that if configuration 1 was used with the same order set data of the context of Tiel, the *FCFS* strategy resulted in a productivity increase of 15%. This is due to the improvements with ABC-class based storage and compacter layout choices compared to the current state. If configuration 1 was implemented with the *Star Aisle Batching Strategy*, it would increase productivity by 20%. And if configuration 1 were implemented in Tiel with the *Star Aisle combined with the SinglePicks* strategy, it would increase by 30% in terms of productivity. This improvement is visualised in the graph below.



So, if this configuration is implemented in combination with the new picking strategy *Star Aisle combined with the SinglePicks*, the current operations will increase its productivity by over 30%. This increase in productivity also means that Nedcargo now only requires two pickers to complete the picking operations. If we take the current state average number of 4 pickers, as seen in the data analysis. Nedcargo (at least) can save two pickers using configuration 1 and the proposed strategy. Consequently, saving costs due to fewer pickers needed.

Table 3. Results of Configuration 1 and *Star Aisle combined with SinglePicks* strategy

Batch+SP	Scenario 50	Scenario 107	Scenario 10	Scenario 77	Scenario 92	Scenario 123
Configuration 1						
Avg. Colli/Hour	163	124	178	208	160	156

5.2. Results Context Experiments

This paragraph will reflect on the main research question and answer it. The main research question was: *What is the impact of context uncertainty of order characteristics on the different outbound configurations of an order-picking warehouse?*

As shown in Table 3, in each scenario, the productivity is different per scenario in configuration 1 with the *Star Aisle combined with SinglePicks.* This combination of configuration and strategy is chosen to reflect on because it results in the highest productivity of all the combinations possible. How can this difference between productivity and the scenarios be explained? And how can we trace that back to the order characteristics of the scenarios presented in Table 2.

The results showed that the ABC-Ratio contingency variable has a significant impact on the productivity of the chosen configurations. Respectively, high productivity is reached if the warehouse consists of a lower percentage of A-type SKUs and lower productivity if the warehouse has a high rate of A-type SKUs.

Next to that, a context scenario where the amount of colli is high and the orderlines per order are low will result in higher performance. These contingencies can be explained since the picker can grab more colli during an SKU visit, which decreases the travel distance and thus increases the performance. Table 1 shows the difference in performance between the scenarios, but how do they react to configuration and/or strategy differences?

Figure 6 shows that the change between configuration and picking strategy affects each scenario. In some scenarios, such as 10 and 77, another picking strategy or configuration does not have an as significant impact as, e.g., 107 and 92. In those scenarios, the percentage decrease in productivity is much higher when not the best configuration and picking strategy option is implemented. This is an essential insight because now it is shown that the order characteristics influence how well the warehouse functions per configuration and picking strategy. Each order characteristics scenario is differently sensitive to a change in configuration or strategy.

The different context in which a configuration is placed in combination with the strategy impacts its productivity. In this way, we can state that the experiments show that different configurations perform differently in specific scenarios.

5.3. Case Analysis

It is proven that the context in which a warehouse operates is essential to see whether some configurations perform better or worse. This insight can help in the pre-design phase of a warehouse design. To see how specific configurations will perform and react to confident configurational choices. Nedcargo can do this using the proposed method with each experiment and configuration of their liking. The order characteristics of the future state for Haaften III are uncertain, and therefore Nedcargo can use the findings of this study to be prepared. The experiments show that it is essential to test different configurations on their performance before you start designing.

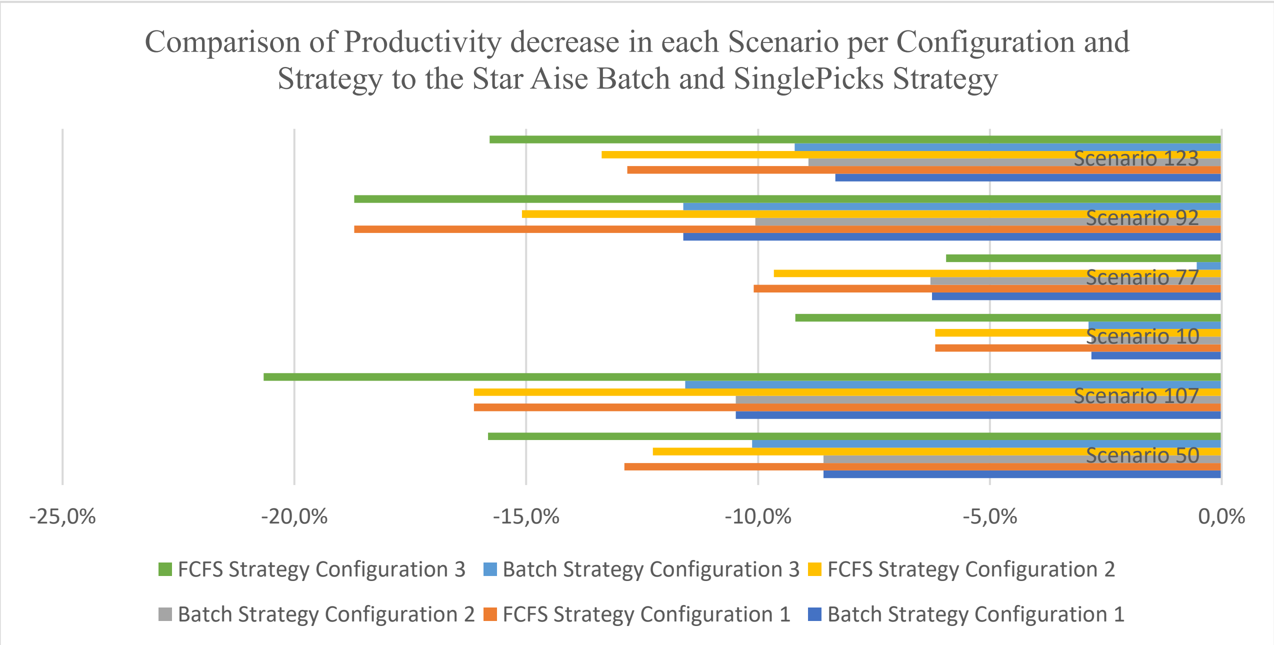


Figure 6- Productivity decrease other configurations/strategies

6. Discussion and Conclusion

In this chapter, the key findings from the research are presented. Next, the scientific relevance of this study will be highlighted. Finally, some limitations of this study will be discussed.

6.1. Key Findings

Several key conclusions can be drawn up from this study. We will highlight some of them. The first key finding was that it was proven that configuration 1 outperformed configurations 2 and 3 in each of the context scenarios. Thus, it can be concluded that the "Dynamic SKU locations" and the S-Shape routing strategy do not improve productivity. However, the chance of congestion with the S-shape strategy is lower, which can be considered if this should be avoided.

Suppose we compare the configuration 1 model with the current state model with the order characteristics of Tiel. If the same picking strategy is used (FCFS), the improvements from the current state analysis in the storage and layout choices cause an improvement of 15% in productivity. If the picking strategies *Star Aisle Batch* or the combination with *SinglePick* strategy is used, respectively, a productivity increase of 20% and 30% is achieved. This configuration and strategy options could be implemented during the pre-design phase for Haaften. The models can help to reflect and quantify certain configurational and contextual choices.

Next, if we reflect on the main research question, it is proven that the context in which a configuration operates influences its productivity. The order characteristics have an influence between the scenarios for the same configurations and also within scenarios in different configurations. This also proved that *Star Aisle Batching Strategy combined with the SinglePick* and *configuration 1* is the best combination to have the highest productivity. Respectively, high productivity is reached if the warehouse' order characteristics consist of a lower percentage of A-type SKUs and/or where the amount of colli is high, and the orderlines per order are low.

So, the context in which an order-picking warehouse operates, based on the order characteristics uncertainty, has a significant impact on the performance of different configurations. Each configuration performs differently considering its context scenario. This is shown using the contingency approach. The contingency variables represent the uncertainty of the order characteristics, the response variables, which are the three configurations and picking strategies modelled, and the performance variables, which are the output of these models.

6.2. Scientific Relevance

The *SinglePick* strategy is a picking strategy that has not yet been quantified in the warehousing literature. It is described as a strategy option but not quantified what its specific impact on the productivity it causes. Also, the literature stated that warehouse strategies are non-generalisable and are very case specific. Therefore each quantification could benefit Nedcargo because it reflects their operation.

The *Star Aisle Batching Strategy combined with the SinglePick* strategy is a new strategy proposed. The combination of the two has not been seen in literature before. This strategy outperforms the other two strategies in each of the experiments. Hence, it is exciting to carry out further research on this strategy. This, of course, is context-dependent, which has also been concluded in this research.

Quantification of the contingency approach has only been seen once in literature (Sadowski et al., 2021). The research approach of this thesis, the combination with the proof of configuration aim, is a new approach that could benefit the stage before the design process of a new warehouse starts. This approach could prove that confident configurational choices would improve or deteriorate performance in a particular context. This can be executed preliminary to the design phase of a warehouse.

"*Develop scales to measure different contextual factors and configuration elements for warehouses more precisely.".* This literature gap by Kembro (2020) is filled with the experiment generation and configuration models. These models give an insight into the scales of contextual factors, although only those of the contingency of order characteristics. The configurational elements were modelled as response variables. A Modelling approach that integrates multiple components of warehouse configurations as response variables is not yet been developed in previously conducted research. Next to that, multiple components were implemented in the model. While in other warehouse modelling studies, mostly one or few specific component(s) were investigated.

6.3. Discussion

Further research should focus on implementing more contingency variables, for example, demand characteristics, which are set as a constant in this model. Furthermore, the picking time is chosen to be continuously uniform and distributed in the configuration models. This is due to the data that was collected and analysed. This is acceptable, but it is recommended that Nedcargo and future researchers further look into the data gathering of the picking activities. Next to that, the experiment generation - and configuration models give a substantial amount of data as output. Only several analyses were made regarding this study's context and chosen KPIs. For further research, the models could be used to answer other types of questions. The quantity of the data provides the opportunity for new insights.

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