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Master Thesis

Assessing Efficiency in Warehouse Order Picking: A Simulation-Based Approach

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Management Summary

This study provides a simulation model capable of evaluating order picking policies in warehouse operations. Order picking is the most time-consuming and costly activity in the warehouse, meaning efficiency improvements can lead to significant cost savings. Models in current literature mostly focus on a fix set of polices, where this study develops a simulation model that can test a wide variety of policies and can incorporate multiple relevant variables. The primary research question addressed in this study is: "How can order picking policies be evaluated on efficiency using a simulation model to support decision-making in warehouse management?". This is answered through four sub questions that explore the metrics for measuring efficiency, methods to enhance efficiency, and how to assess and evaluate using a simulation model to eventually support decision making. The research employs a custom-made simulation model tailored to the specific operations of the case company's warehouse. The model uses historical order data to simulate various scenarios, evaluating the impact of different improvement policies on travel distance and other significant variables. A combination of literature review and warehouse expertise is utilized to compile a set of order picking improvement policies, that are tested in the simulation model.

Literature identifies travel distance as the primary metric for measuring order picking efficiency. However, for the case company, additional variables such as the number of bins utilized are also relevant. Literature identifies five key areas for improvement: storage, batching, routing, zoning, and layout. For this study we select three policies, based on literature and suggestions from warehouse management. The selected policies with the yielded results in the simulation model are as follows:

- A new storage assignment method did not improve efficiency, showing an increase in travel distance instead.
- Splitting the warehouse into zones significantly improved efficiency
- Introducing small bins also showed notable improvements in efficiency
- Combining zoning and small bins yielded the greatest reduction in travel distance

Three business cases were developed based on the simulation results. A cost-benefit analysis presents the potential cost savings and considerations for each scenario. The efficiency gains result in savings in labor cost, while the implementation of policies can also lead to additional

labor cost and one-time investments. Dividing the warehouse into zones results in an estimated net savings of €59,175 after one year. For the implementation of small bins this is €26,805. The combination of the above policies already shows the greatest reduction in travel time, and also presents the best business case with an estimated net savings of €87,406 after one year.

Based on the results and business cases described above, order picking policies can be evaluated on efficiency gains and estimates cost savings, thereby validating the use of a simulation model for this purpose. By considering variables such as the number of bins and labor hours spent on handling, warehouse management can be supplied with all relevant information to make informed decisions. This emphasizes the importance of tailoring models to specific organizational context. It is found that picking cart capacity can have a significant effect on order picking efficiency. Where current literature mostly focusses on (a subset) of the five above-mentioned key areas of improvement, this study demonstrates that picking cart capacity is a critical factor in enhancing overall efficiency. The findings underscore the benefit of using zones in warehouses, consistent with existing literature. For the case company, this study advocates a hybrid approach for storage location assignment, as a practical contribution. More general, this study contributes by demonstrating how companies can leverage data for decision-making, serving as a valuable example for those looking to become more data driven.

Table of contents

List of figures

List of tables

1. Introduction

Warehouses strive for high efficiency in their operations, to ensure a streamlined and cost-effective logistics process. Nowadays, supply chains must rely on efficient logistical systems with low turnaround times, to meet customer expectations (van Gils et al., 2018b). To meet the demands of rapid delivery within these tight timeframes, less time is available for warehouse operations, like order picking, packing, and shipping (Koster et al., 2007). Given that order picking is known as the most labor-intensive and most expensive activity in the warehouse, it often becomes the primary focus for enhancing efficiency (Koster et al., 2007). In conventional warehouses, on average almost 90% of the time is spent on order picking and 55% of the operating cost is attributed to order picking (Dukic & Oluic, 2007). Therefore, enhancing the efficiency of order picking is vital for improving overall warehouse productivity and cost-effectiveness. Literature offers various approaches to achieve this. The literature review from Van Gils et al (2018) summarizes the order picking (planning) problems in the category's storage, batching, zone picking, and routing. The layout of the warehouse is a fifth issue that can be added as a factor impacting the order picking performance (Yu & de Koster, 2009). In these categories, there are a variety of policies that can be implemented to increase order picking efficiency.

Even in modern warehouses, decisions on these order picking problems are often based on simple heuristics or rules of thumb (Gademann & Velde, 2005). To make informed decisions on which improvements can be made, the changes to the current situation need to be tested on performance to compare with the current situation. A proven method to evaluate such changes is to implement the change and compare the performance in the new situation with the performance in the old situation. However, in this situation, conducting such experiments is expensive and time-consuming. Consequently, in the majority of studies investigating warehouse efficiency, the preferred approach is to simulate the impact of changes in a model (e.g. Chan & Chan, 2011; Petersen & Aase, 2004; Tsai et al., 2008). The available software and more importantly data, make it possible to replicate the warehouse processes in a model and evaluate its performance. Building on historic data, companies can use prescriptive analysis and simulation, that helps them answer the questions what changes they should implement.

Utilizing such a data-driven approach, decision makers can make informed decisions on the warehouse operations, so not based on heuristics and rules of thumb (Granillo-Macías, 2020). It supports them in how to deal with warehouse operation and how to manage the wide amount of available data (Antomarioni et al., 2021). McAfee & Brynjolfsson (2012) found that the more companies characterize themselves as data-driven, the better they perform on objective measures of operational and financial results. As a result, data is nowadays recognized as a valuable asset for companies, yet many remain uncertain about how to effectively integrate data-driven decision-making into their operations (Gupta & George, 2016). While the objective is there, also leading companies seem to be failing in their struggle to become data-driven (Bean & Davenport, 2019). In today's modern warehouses, the available technology and practices, like scanning each item during picking, generate a rich repository of data points. However, having the data available does not mean it is automatically deployed to create value for the company, by for example providing insights on how to make the warehouse process more efficient.

To evaluate the effectiveness of efficiency improvement methods, a simulation model is a proven method in literature on order picking efficiency. Van Gils et al., (2018b) simulate the combined performance of multiple storage, batching, zoning, and routing policies in a simulation model, tested on a real-life case-study. Chan & Chan (2011) also use a simulation model to find the most efficient warehouse setup, looking at order retrieval time and travel distance. These studies, next to several other studies using simulation (Petersen & Aase, (2004); Tsai et al., (2008)), focus on finding the optimal set of policies with the highest efficiency for the specific warehouse or layout that is being studied. Although this offers grounded suggestions to management to improve their order picking process, it does not provide a versatile model that could support warehouse management with future decision-making. Chen et al., (2010) developed a unified framework for warehouse managers to analyze and evaluate order picking problems, based on the following factors: storage assignment, routing polices, picking cart capacity, and order sequencing. This provides a warehouse manager with flexibility in evaluating and selecting order picking policies, applicable across various scenarios and repeat uses. The model, however, is limited to the above policies and does not offer the versatility to test and simulate suggestions from warehouse management. Although De Santis et al. (2018) takes into account each of the main categories in literature, the focus of the study lies in proposing a new routing algorithm. Yu & de Koster (2009) also recognize the same categories, yet their proposed model primarily addresses batching and zoning. This research studies the effect of various order picking policies on efficiency, evaluating proposed methods using a simulation model. Hereby, this study will contribute to the existing literature by providing a model capable of evaluating order picking improvements across a broad spectrum of policies. Moreover, the aim is to provide a model designed for decision-making that incorporates all relevant factors influencing decisions. Unlike the previously mentioned models, which often consider only one variable as a metric for efficiency, this model integrates multiple variables to enhance decision-making accuracy. The model can assess improvement strategies recommended by both literature and warehouse management, thereby supporting decision-making processes in warehouse management. The purpose of this research is to answer the following research question: How can order picking policies be evaluated on efficiency using a simulation model to support decision making in warehouse management? To answer this research questions the below sub questions are formulated:

1. What metric(s) should be used to measure order picking efficiency in a simulation model?
2. What methods to improve order picking efficiency exists, according to literature?
3. How can the suggested order picking improvement methods be evaluated in a simulation model?
4. How can the simulation model support warehouse managers in decision making?

The remainder of this research is organized as follows. Chapter Two reviews the current literature on order picking, measuring order picking, and order picking policies. Chapter Three describes the methodology, followed by an introduction to the case study company in Chapter Four. Chapter Five presents the simulation model, with the simulation results detailed in Chapter Six and further discussed in the context of a business case in Chapter Seven. Finally, Chapter Eight includes the conclusions and discussion.

2. Literature review

2.1 Order picking

The warehouse is a place where goods are received, stored, picked, and shipped from (Dawe, 1995). The primary role of a warehouse is to have storage from which the customer orders can be fulfilled. Contrary to a distribution center, a warehouse is meant to have inventory from which orders are picked (Koster et al., 2007). This buffer can ensure a stable supply chain, but also represents a substantial cost factor. Therefore, next to transportation, warehousing is one of the largest cost drivers in supply chains (Dukic & Oluic, 2007). Among the above-described activities occurring in a warehouse, order picking is the most time-consuming and thus the primary opportunity for enhancing efficiency (van Gils et al., 2018b)

Order picking can be defined as the process of retrieving items from storage locations in the warehouse, following a customer request or pick list (Dukic & Oluic, 2007). In literature on performance management in warehouses it is the most discussed topic, by far (van Gils et al., 2018b). The reason for this is that from all warehouse activities, order picking is the most labor-intense operation, and therefore the most time-consuming (Koster et al., 2007; Dukic & Oluic, 2007; van Gils et al., 2018b). This is especially the case for warehouses that have a picker-to-parts system, (i.e. a system where items are picked from storage locations and brought to packing stations). Alternatives to this would be a parts-to-picker systems or automated storage and retrieval systems, where the order picker can stay at one location where the items that need to be picked are presented by the system. The second distinction lies in low-level versus mid-level order picking. In low-level picking, goods are stored within easy reach, allowing pickers to access and pick items without the need for equipment like forklifts or reach trucks. Mid-level picking requires such machinery, as the goods are stored beyond manual reach (Koster et al., 2007). A third distinction can be made between sort-while-pick systems and pick-and-sort system, which is only applicable when orders are batched for picking. Batched picking means that the order picker picks more than one order on its route, instead of returning each time after completing the items on one order. Sort-while-pick means that the order picker sorts the separate orders while picking them at once, while pick-and-sort means all items are picked without sorting them and the items are being sorted per order afterwards (Parikh &

Meller, 2010). This study focuses on low-level, manual order picking in a system that combines a picker-to-parts with a sort-while-pick system.

2.2 Measuring efficiency order picking efficiency

The reason why order picking is the most labor-intense, and therefore the most expensive, is the travel component. Order pickers are travelling between locations a significant amount of their time: from the start location to the storage location, between the storage locations, and to the end point. On average, total order picking time consists of 10% setup time, 15% pick time, 20% search time, 5% other, and 50% travelling time (van Gils et al., 2018b). Next to that, Aboelfotoh et al. (2019) found that it accumulates to 60% of the total cost of order picking on average. Improving order picking efficiency directly contributes to cost savings, making it a critical focus area for process improvement (de Koster et al., 2007).

In order to evaluate the efficiency of the current state of the order picking process, or to test changes, an objective indicator is needed. To measure the efficiency of the order picking process, the travel distance is the most used indicator in literature. Table 1 below shows the frequency of several variables used, based on a literature review. This can be either the total travel distance (e.g. of a time period) or the average travel distance (per order) (Koster et al., 2007). An alternative is the order picking time, which shows the same results under the assumption that the order picking speed is the same throughout the warehouse (van Gils et al., 2018a). Chan & Chan (2011) adds order retrieval time as a metric and states that measured with different performance indicators, the performance of combinations of factors can be different. This can be the case when indicators as total order retrieval time versus travel distance are used. Since travel distance is the most objective and consistent metric which cannot be influenced by other factors like disruptions or worker fatigue, this metric is used in this study.

Table 1

Order picking efficiency indicators in literature

Variable	Count	Sources
Travel distance	7	(Koster et al., 2007; van Gils et al., 2018b; Dukic & Oluic, 2007; De Santis et al., 2018; Aboelfotoh et al., 2019; Petersen, 2002; Caron et al., 1998)
Travel time	2	(Van Gils et al., 2018; Chan, 2011)
Order throughput time	1	(Yu & de Koster, 2009)
Order retrieval time	1	(Chan, 2011)

2.3 Improving order picking efficiency

In academic studies focused on advancing order picking efficiency, the literature consistently recognizes five key categories that represent challenges or concerns within the order picking process. Table 2 shows which categories are studied by other literature that study two or more categories. These are the factors impacting the order picking productivity.

1. Storage: assigning products to storage locations.
2. Batching: the process of grouping customer orders together and jointly releasing them for picking.
3. Routing: the sequence of the items on the picking list which determines the route for the order picker in combination with the general routing policy.
4. Zoning: dividing the whole picking area into a number of smaller areas (zones) and assigning order pickers to pick requested items within the zone.
5. Layout: the quantity and the arrangement of blocks and aisles

Table 2

Order picking problem categories in literature

Category	Sources
Storage	(De Santis et al., 2018; van Gils et al., 2018b; Koster et al., 2007; Chen et al., 2010; Yu & de Koster, 2009; Henn, 2012; Dukic & Oluic, 2007)

Batching	(De Santis et al., 2018;van Gils et al., 2018b; Koster et al., 2007; Yu & de Koster, 2009; Henn, 2012; Dukic & Oluic, 2007)
Routing	(De Santis et al., 2018; van Gils et al., 2018b; Koster et al., 2007; Chen et al., 2010; Yu & de Koster, 2009; Henn, 2012; Dukic & Oluic, 2007)
Zoning	(De Santis et al., 2018; van Gils et al., 2018b; Koster et al., 2007; Yu & de Koster, 2009)
Layout	(De Santis et al., 2018; Yu & de Koster, 2009)

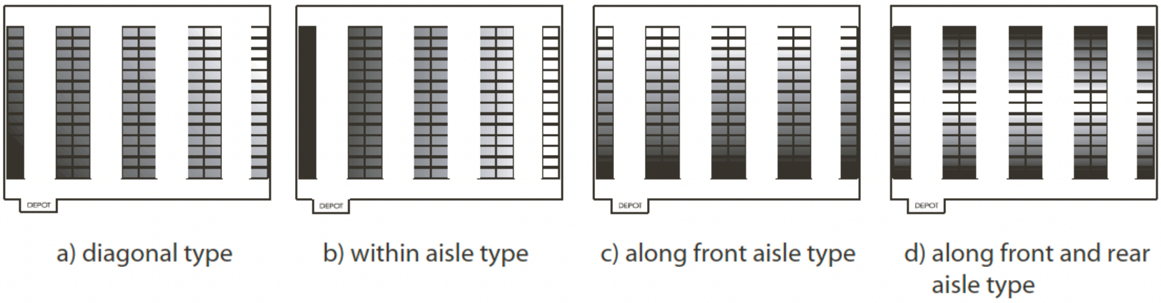
2.3.1 Storage

It is proven that storage assignment can be an effective measure to improve order picking efficiency, but there is a variety of methods that could be applied. What method is the most efficient depends on the variables like the type of products and the order composition, but also the zoning, routing, etc. Chan & Chan (2011) found that the picking density (i.e. the variety of items in an order) has an influence on which storage assignment method is the most effective. One way of storage assignment is through grouping, which according to Liu (1999) can be done in three ways: based on complementarity (i.e. items often ordered together should be located next to each other), based on compatibility (i.e. based on practical conditions), or based on popularity (items that are picked often should be located close to outbound point). This last option is also known as a volume-based storage policy, that assigns items to locations based on the picking volume. A proven method to apply this, is to combine an IQ (order quantity of each item) analysis with an ABC classification (Chan & Chan, 2011). ABC classification sorts products into three categories based on their contribution to turnover, the number of picks, or other relevant variables. A-items, which have high turnover or are frequently picked, are positioned close to the in- and outbound points for easy access. In contrast, C-items are less accessible due to their lower turnover or pick frequency. The distribution of these categories varies depending on specific operational circumstances. Alongside item quantity, factors such as storage space and customer orders are also considered to optimize storage assignment. The Cube-per-order index (COI) combines the items' required storage space with the picking volume (Dukic & Oluic, 2007). The COI method is the most beneficial when combined with the within-aisle placement, as shown on the figure 1 below.

Criticism on the COI method is that it in principle it assumes that every pick is a direct return trip, where in reality most picks are followed by another pick, except the last one (Mantel et al., 2007). The Order Oriented Slotted strategy (OOS) introduced by Mantel et al. (2007) approaches this differently, so that the total travelling time of all tours is minimized.

Figure 1

Placement of items with a storage assignment policy



Note. Figure from Dukic & Oluic (2007) p.4. The dark squares indicate items with a high COI.

Battini et al. (2015) introduces a storage assignment and travel distance estimation (SA&TDE) method that provides guidelines for warehouse design to reduce travelling time by improving efficiency. In a case study, items were assigned to other storage locations, leading to a significant decrease in travel distance. In conclusion, an appropriate inventory classification method is of vital importance to divide products into classes to increase efficiency, regardless the type of order picking system (Chan & Chan, 2011).

2.3.2 Batching

There is a high variety of batching methods that has been studied in literature, with order batching in general being an effective way to reduce travel distances (M. B. M. De Koster et al., 1999; Dukic & Oluic, 2007). According to Koster et al (1999), the best batching method is by applying a seed selection rule, which creates a batch by selecting the initial and the additional order based on a specified rule. In a simulation, this was proven more effective than for example the Clarke and Wright algorithm, that groups orders into batches based on the savings that can be made on the travel distance. Henn (2012) also tested this algorithm together with other options and found the Iterated Local Search (ILS) method to be the most efficient method. This method refines batches of orders by making small changes to the current method and then searching nearby solutions, aiming to minimize the total picking time or distance. Another option is batching by a selection of heuristics, which was proven to be more efficient than a First Come First Serve (FCFS) method or a mathematical model by Aboelfotoh (2019). In all studies, FCFS turned out to be less efficient compared to its alternatives. According to Dukic and Olic (2007), order batching in general is the measure showing the greatest potential in reducing travel distances.

2.3.3 Routing

A general routing policy determines in what sequence the items will appear on the order pickers' (digital) pick list and how to navigate through the warehouse aisles. In the literature several routing heuristics are discussed. Their effectiveness is not universally applicable but varies depending on other variables, such as the storage assignment and the order batching. Table 3 shows the list of heuristics discussed in four studies.

Table 3

Routing policies with definitions

Routing policy	Definition	Mentioned by
Aisle-by-aisle	Picker visits every aisle containing at least one pick	(van Gils et al., 2018b)
S-shape	Picker goes through aisles with at least one pick in an S-shape	(Henn, 2012; Koster et al., 2007)
Traversal	Picker traverses every subaisle containing at least one pick	(van Gils et al., 2018b)
Return	Picker enters and leaves every aisle on the same end containing at least on pick	(van Gils et al., 2018b; Koster et al., 2007)
Largest gap	Picker enters an aisle as far as the start of the largest gap within an aisle	(van Gils et al., 2018b; Koster et al., 2007)
Optimal	Based on an algorithm or calculation	(van Gils et al., 2018b; Koster et al., 2007)

Midpoint	Picker enters aisles from one side and picks items till the midpoint and does the same from the other side.	(van Gils et al., 2018b; Koster et al., 2007)
Combined	Picker either traverses or returns	(van Gils et al., 2018b, Koster et al., 2007)

The optimal routing to minimize the travel distances in some cases can be found by an algorithm (De Santis et al., 2018). However, the most optimal routing can be complex for the order picker when there is no apparent logic behind it. According to Dukic & Oluic, routing has some effect on efficiency, but it is insignificant for practical purposes in that specific case study. In a simulation by Chan & Chan (2011), a combination of the transversal and the return routing heuristics turned out to be the most effective policy.

2.3.4 Zoning

The concept of zoning has been identified as a critical factor influencing efficiency. Van Gils et al. (2018) highlighted the significance of warehouse zoning, a topic that had not been given as much attention as storage assignment, batching, and routing in previous literature. The configuration of zones within a warehouse is not a one-size-fits-all solution; it requires careful analysis and consideration of various parameters, such as product categories, the space available, etc. However, Van Gils (2007) makes a general claim that making the zones in a warehouse smaller is an effective way to improve efficiency. Koster et al. (2010) conducted a detailed investigation into the optimal zone configuration for a retail warehouse in the Netherlands, yielding valuable insights into the ideal number of zones, as well as associated layout and routing policies. The findings of Petersen (2002) suggest that the optimal zone setup is contingent upon several factors, including average order size and batch size. It is important to make the distinction between sequential and simultaneous zone picking. Sequential zone picking is where the picking in one zone begins only after the completion in the preceding zone, typically suited to smaller order sizes, while simultaneous zone picking allows for the picking of different parts of an order to occur concurrently across various zones, with consolidation occurring subsequently (Parikh & Meller, 2008; Petersen, 2002).

2.3.5 Layout

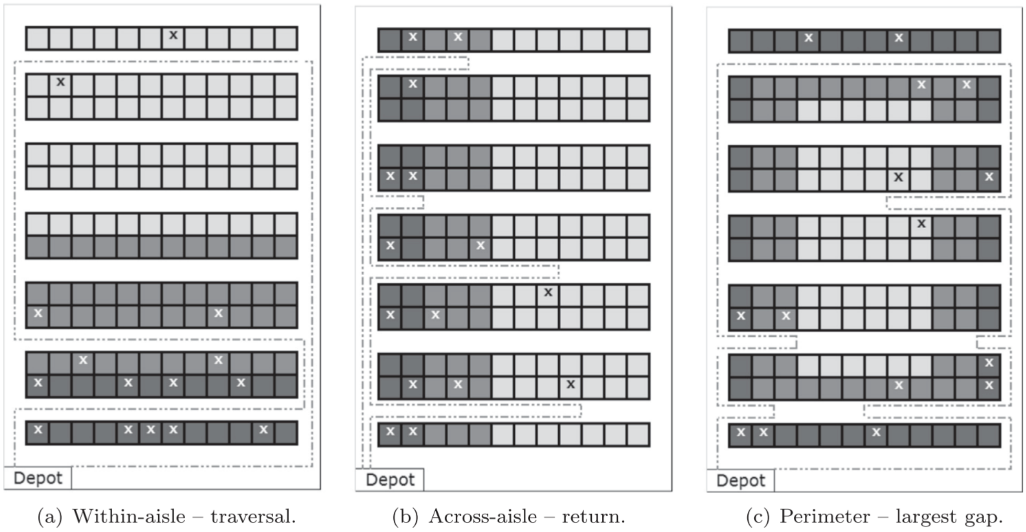
While some studies do not include layout when discussing methods to improve order picking efficiency, Yu & de Koster (2009) includes it with the other four categories. Layout is less often mentioned in literature, because it is simply easier to change the routing or assign products to different storage locations, compared to moving racks or changing the shape of a building. A distinction can be made between the facility layout, concerning the locating of several departments in the building, and the internal layout, concerning the number of blocks, the width of aisles, etc. (Koster et al., 2007). This study only focuses on the internal layout. The use of cross-aisles has proven to improve efficiency significantly. Layout is compared to the other order picking problems highly dependent on the warehouse structure (Battini et al., 2015). This is why layout decisions are important when designing a warehouse from scratch but difficult to change once implemented.

2.3.6 Combining storage, batching, routing, and zoning problems

To achieve efficiency in the order picking process, warehouse managers have to look beyond single-dimensional performance and consider trade-offs among the four different problems of storage, batching, routing, zoning, and layout (Chen et al., 2010). A combined approach is more effective to increase efficiency (van Gils et al., 2018a). Where most literature that studies them in relation to each other only include storage, batching and routing, Van Gils et al (2018) stated the importance of integrating zoning. In the above-mentioned case study by Petersen (2002), the zone configuration was studied, also taking into account the storage assignment policies. It was found that different combinations have different impacts. The same goes for storage and routing, which should be considered as combined decision problems, because the storage assignment impacts the routing method according to De Koster et al. (1999) and Koster et al. (2007). Figure 2 below shows examples of how storage and routing policies can be combined. While in most literature studied separately, Yu et al. (2009) found batching and zoning are also closely related and are therefore often simultaneously applied in warehouses.

Figure 2

Examples of combing storage and routing policies



Note. Figure from van Gils et al., (2018). The dark squares indicate the storage locations of items that are picked more often.

2.4 Simulating order picking performance

To study the effect of various policies in the domains of storage, batching, routing, zoning, or layout, conducting experiments, running simulations, or both is essential. In the majority of studies investigating warehouse efficiency, the preferred approach is to simulate the impact of changes in a model, as you can see in table 4. To be able to conduct a simulation, a model is necessary to measure the parameter(s) of interest, in this case at least the travel distance (Caron et al., 1998). Furthermore, the model should be able to test the impact of changing parameters due to changing storage policies, zone layouts, or batching policies (Chen et al., 2010). Petersen & Aase (2004) take into account the parameters average order size, warehouse shape, and the location of the pick-up drop-off point, resulting in a more accurate measurement of the effect of storage, batching and routing policies. Tsai et al., (2008) conducts a set of simulations, each with different order characteristics and warehouse environments, studying the impact of batch picking policies on travel distance. In order to take a combined approach on the closely related picking problems, a factorial design could be used to simulate the effect. This would measure the effect of each factor combination, finding the most optimal one. To effectively analyze the closely related problems in picking processes, employing a factorial design in simulation studies can show the impact of various factor combinations

(Petersen & Aase, 2004). This approach measures the outcome of each factor combination and identifies the most optimal one. An alternative to this is to measure the effect of each factor individually against the baseline, which would be the current state of warehouse policies. In both scenarios, the simulation process begins by defining the parameters. Next, it entails recording the travel distances and concludes with a comparison of the varying performances (Chan & Chan, 2011).

Table 4

Methods of studies that study order picking efficiency

Research method	Number of studies	Studies
Simulation model	8	(Liu, 1999;Chan, 2011; Koster et al., 1999; Tsai et al., 2008; Caron et al., 1998; Petersen, 2002; Petersen & Aase, 2004; Dukic & Oluic, 2007)
Other type of model (approximation, analytical, cost, or mathematical)	5	(Yu & de Koster, 2009; Parikh & Meller, 2010; Parikh & Meller, 2008; Koster et al., 2007; Aboelfotoh et al., 2019)
Experiment	1	(Henn, 2012)

3. Methodology

3.1 Research design

The approach used in this study to answer the research questions has both deductive and inductive characteristics. On one hand, observations are made and the research is formed around those observations. Observations are made by the researcher in the warehouse that is subject of the case study and experts are interviewed. On the other hand, theory from literature is used to formulate efficiency improvement approaches. Because interviews are needed in the preliminary research and quantitative data is needed for further analysis, this research fits a mixed method approach. This method of combining qualitative and quantitative research components is used to reach breadth and depth of understanding of the research topic (Johnson et al., 2007)

3.1.1 Qualitative data collection in interviews

The baseline that is used for the order picking efficiency model is based on the current state of the warehouse operations and policies. Semi-structured interviews were conducted to gain a deeper insight into the existing operations and to understand the considerations influencing the current state. Next to that, insights were derived from these interviews on possible changes that can be implemented in the warehouse that could improve order picking efficiency. The expertise from employees is needed to determine feasibility of the options suggested by literature. Employees possess firsthand knowledge of the specific operational context, challenges, and constraints within the organization. While literature may provide generalized recommendations, it lacks the nuance required to account for unique factors in the organization. Table 5 below shows the company experts that were interviewed. These were all semi-structured interviews, revolving around the following topics: the current state of warehouse operations, factors impacting productivity, and the feasibility of policies.

Table 5

Interview respondents

Expert	Position
Expert 1	Operations Director
Expert 2	Head of Logistics
Expert 3	Team leader
Expert 4	Logistics employee
Expert 5	Logistics employee

3.1.2 Qualitative data from literature review

To gather information on the measurement, the improvement strategies for order picking and the research method, literature reviews were conducted. First, the metric for measuring order picking efficiency was determined based on other literature. Next, a review of literature on order picking enhancement techniques was conducted to develop strategies for improvement. This was supplemented with insights gathered from interviews with company experts. The combination of findings from literature and interviews resulted in a set of improvement policies that are evaluated on efficiency improvement based on the created simulation model. And finally, the research methods employed in the studies in the beforementioned literature reviews were analyzed to gain insights on the most suitable method to evaluate the improvement policies.

The literature review is conducted using the website Web of Science. For both subjects shown in table 5 below, searches were done using specific keywords. Search results were sorted based on the number of citations (highest first). The studies that matched the requirement as listed in table 5, the references were stored in Mendeley.

Table 6

Literature reviews

Literature review	Keywords (including, but not limited to)	Requirements
Order picking efficiency indicators	Warehouse AND Efficiency Logistics AND Efficiency Warehouse AND productivity Warehouse AND metrics	Studies studying the order picking performance, evaluated on a specific metric.
Order picking problem categories	Warehouse AND efficiency AND improving Warehouse AND productivity Productivity AND measures AND logistics	Studies studying two or more categories of order picking problems.
Research method (simulation, experiment, etc.)	N/A	The studies form the above two literature reviews were used.

3.1.3 Quantitative data for simulation model

As discussed in Chapter 2.4, a simulation model is the most suitable methods to analyze the impact order picking policies in a warehouse. A simulation model will be created based on the warehouse data, that can give the travel distance as output, based on an order cluster as input. Based on the storage locations of the items in the order, the model will follow the given parameters and calculate the travel distance to pick this order. The data that will be used is sourced from the operating system of the warehouse that is subject of the case study. In this system, data is collected by the terminals that order pickers to scan each item that is picked. Next to that, the warehouse has exact measurements of warehouse sections and distances between storage locations available. Using the current state of the warehouse as the baseline, the model will have parameters that determine the distance an order picker will travel based on a certain cluster, or number of order lines. To test certain policies, inputs of the model can be changed, which could impact the order picking performance. An example of input that can be changed is a different storage assignment for each product. With items stored in different locations, order picker will travel to different locations to pick the same order, which could result in a shorter or longer travel distance. The main requirements for the simulation model are that it could directly leverage the company's proprietary data and can be applied across a broad range of policies. To address the specific needs of the case company, a custom-made simulation mode has been developed instead of using an off-the shelf solution. This method was chosen because it seamlessly integrates with the company's databases, allowing for a highly tailored analysis of warehouse and order picking efficiency based on historical data. Furthermore, all necessary software was already available in-house, so no extra licensing was required. Well-known alternative simulation tools are FlexSim, Simio, and AnyLogic, which offer robust modeling capabilities and are widely recognized for their effectiveness in various industries. However, these off-the-shelf solutions often require adjustments to align with specific organizational data structures and may not offer the same level of customization or integration with existing systems as a custom solution. The chosen approach not only ensures greater accuracy and relevance of the simulation results but also enhances the scalability and adaptability of the model to future changes within the company's operations. Chapter Five delves into more detail on the simulation model.

4.Case Study

4.1 Case introduction

In this study, a warehouse (called XYZ warehouse) storing educational products is studied as a case. The case is used to create a custom model to test the effect of order picking policies on efficiency and to evaluate the proposed changes. The XYZ warehouse consist of two floors with products assigned to floors based on their size and weight. Heavier and larger products are stored on the first floor for easy access, while items on the second floor are picked and transported using bins. These bins are transported on conveyors belts. Figure 3 shows the bins on the conveyor belt.

Figure 3

Bins in a storage location on the conveyor belt

This study only takes the second floor into account, for several reasons:

1. The order picking process starts on the second floor and is therefore not dependent on an order flow from another section. This is the case for the order picking process on the first floor.

2. The zoning problem is not relevant for the first floor, as the number of zones cannot be changed due to layout reasons.
3. The data available on order picking on the first floor is not clean enough for analysis. Order picking policies could be tested using experiments here, but this does contribute to a framework, which is the goal for this study.

Any mention of warehouse XYZ specifically refers to the second floor. In warehouse XYZ all order picking is done through low-level, picker-to-parts order picking. Batching or clustering is done through a sort-while-pick system where bins are placed on a cluster cart with a capacity of eight bins where the order picker sorts the items per order while picking. For efficiency reasons, orders are clustered for picking based on manual selection by a small team of logistics employees. This is based on some simple heuristics, but no automated system is in place, which is further discussed in 4.2.2. One bin could be one order, but for a larger order it could be that one order consists of several bins. Because the order picker is equipped with a terminal, it requires minimal effort to make sure the picked items end up in the correct bins.

Figure 4

Cluster cart with bins

At the starting point, the order picker scans the cluster that is first in line and places all bins on the cluster cart. The pick list appears on an order pickers terminal, which will show the location of the next item that needs to be picked. An example of a location identifier is 2D10B3. Table 4 below shows what this key means. When the order picker scans an item, the terminal will give the ID of the bin in which the items must be placed. Instead of picking the contents for each bin, one after another, the terminal navigates the order picker based on the optimal route for the cluster. The routing is determined by the sort code, which is further discussed in 4.3.3.

Table 7

Example of location identifier

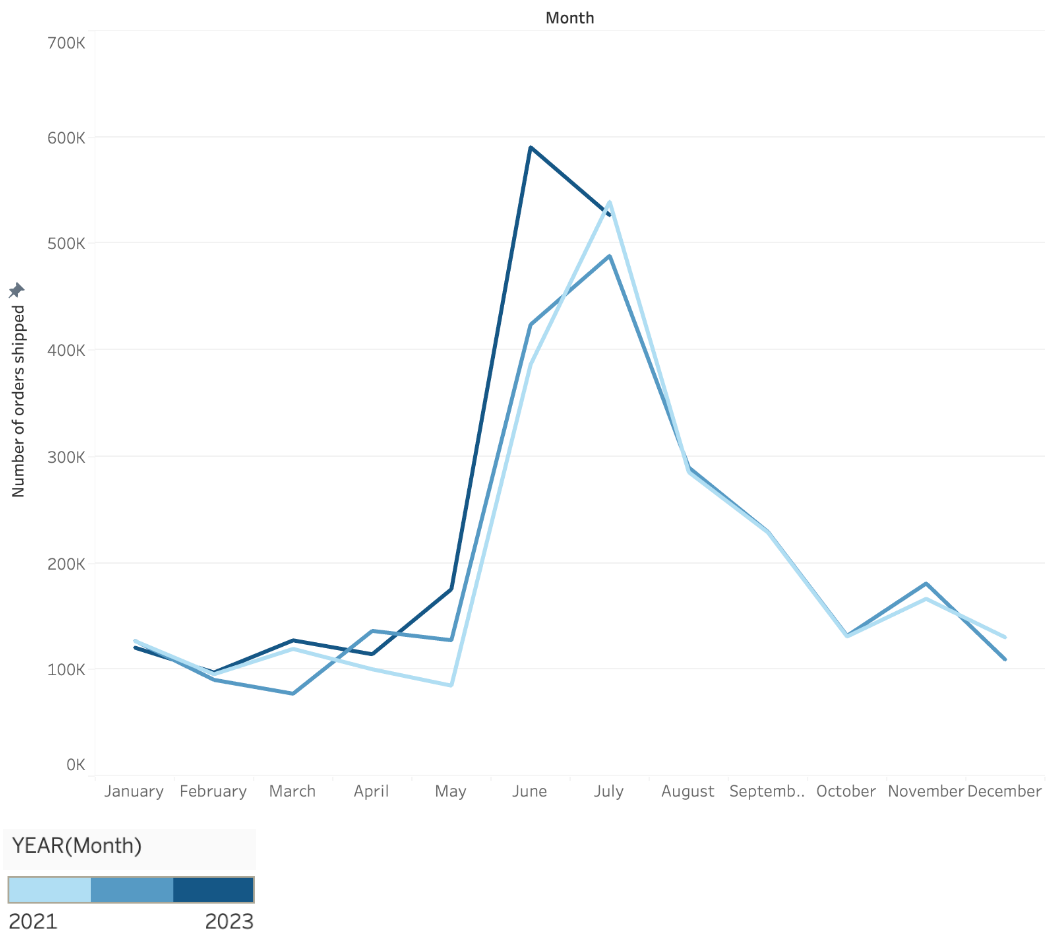
Section ID	Aisle ID	Rack ID	Location in Rack
2	D	10	B3

4.2 Seasonality

The nature of the products make that the demand is highly seasonal, with a spike in the months leading up to the summer. This results in a high volume of orders that need to be processed in the high season, compared to a lower number of orders in the off season. As mentioned in the literature review, the order volume can influence the performance of policies such as storage assignment. Therefore, this should be considered when simulating order data. Figure 5 below shows the difference in order output the warehouse has during those high season months over the last three years.

Figure 5

Number of orders shipped per month



Next to the increasing volume, the order composition of orders also changes during those months. The average number of order lines on an order increase from 5 to 11.3 and the average number of items per order lines increase from 5.3 to 8.1. The key to managing the increased workload during the high season is effective workforce management. During these peak periods, a large number of temporary workers are employed and quickly trained to meet the demand. Apart from that, the warehouse processes remain the same throughout the whole year.

4.3 Current state

The current state of the warehouse is further described through the five order picking problem categories that were identified in the literature: storage, batching, zoning, routing, and layout.

4.3.1 Storage

With a recent move to a new location, the storage assignment was completely revised. Items were reallocated based on historical volume data and heuristics such as product families. Given the dynamic nature of the company's product assortment, the storage assignment has been an ongoing process since then. As mentioned earlier, this research focuses on a specific section of the warehouse where items are picked in bins for transportation inside the warehouse. This results in items that do not fit the bins, based on the size and weight, being excluded from this section. Apart from these excluded items, the storage assignment is based on the order/picking volume of an item and product families. A team of warehouse employees monitors this and makes adjustment when deemed necessary. There is no structured, data-driven approach in place.

4.3.2 Batching

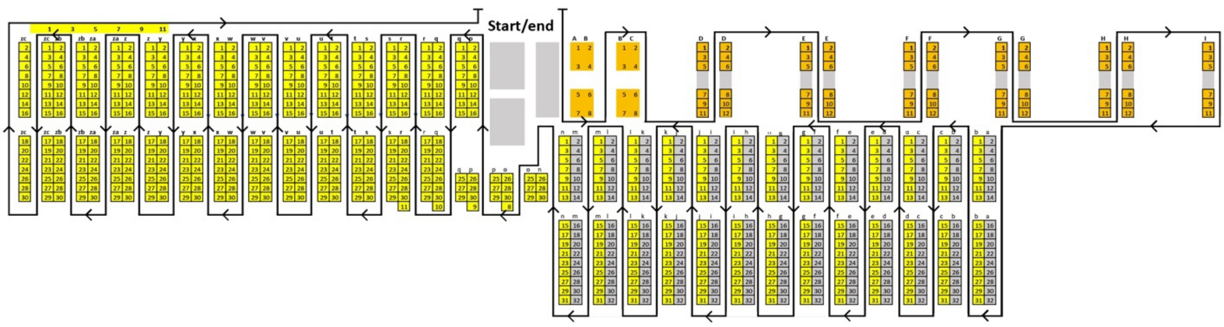
The terminology used at warehouse XYZ for picking multiple orders at the same time is called clustering, which is the term that will be used form now on. Orders are clustered for order picking, to improve the efficiency of the order picker, who is now able to pick up to eight orders at the same time. The order picker does not need to return to the drop-off point after completing each order, which results in efficiency gains. When an order is received, the system divides the order lines that need to be picked on the second floor over several 'works' (Dutch: werken), based on the volume and weight of the products in the order. Each work is a bin, and these bins have a max capacity of 12.0 kilograms and 0.027 CBM. For each item the dimensions and weight are stored in the system, enabling the system to automatically assign order lines to works or bins. As orders come in during the day, the number of works in the backlog builds up, divided into several categories. A warehouse employee monitors the number of works in each category. Once there are sufficient orders in a category, works are added to a cluster based on the start location of the work. Works are added to a cluster until the maximum of eight works on a cluster is met, or there are no works left. The average number of works in a cluster lies around six. The point of release is determined by a warehouse employee, who considers the number of works in the backlog, the amount of work needed in the warehouse, and the work category. When released, all clusters in the backlog are made available for picking. Groups of clusters that are released for picking are called 'waves', which are released several times a day, depending on the number of orders coming in.

4.3.3 Routing

The current routing in the warehouse is based on the s-shaped routing, as discussed in Chapter 2.3.3. Figure 6 below illustrates the path an order picker would follow if at least one item was picked from each rack. By arranging order lines in a specific order based on the storage location, the terminal directs the order picker to the next location. The sequence of the order lines is determined in the system based on the sort code, which is a list of all locations in the sequence of the routing. In practice, not every cluster has order lines in each rack, which means the order picker may sometimes take the quickest path to the next location instead of adhering to the prescribed route.

Figure 6

Warehouse map with current routing



4.3.4 Zoning

The warehouse consists of a single zone, as shown in Figure 6, with one route traveling through the entire warehouse. According to company experts, dividing the warehouse into zones has been under discussion for quite some time. It should be noted that the warehouse section under investigation can already be regarded as a zone within a larger warehouse.

4.3.5 Layout

In this one zone, the warehouse can be divided in three main sections, making it asymmetrical. It has three horizontal aisles and 33 vertical aisles, with the vertical aisles not being the same aisles for each block. In total there are 132 racks with a varying number of shelfs. Figure 7 shows an example of a rack and figure 6 the warehouse map. The starting point is located at the top middle of the map, just above the grey squares, where order pickers collect their cluster carts and load them with bins. The endpoint is in the same area, where order pickers deposit the completed bins onto the conveyor belt positioned at the top middle of the map.

Figure 7

Rack in warehouse XYZ

4.4 Order picking efficiency improvement approaches

Based on the current state of the warehouse policies, the insights derived from company experts and the literature review on order picking efficiency improvement, improvement policies are selected. The criteria are that the policy (1) is proven successful according to literature, (2) shows potential according to company experts, and (3) its effect can be simulated using a simulation model.

Scenario 1: storage assignment following class-based (ABC) storage

Although the current state of storage assignment is based on item volumes and other heuristics, warehouse experts agree there is no structured data-driven approach to this. Consequently, item's locations are updated occasionally, when for example the volume stands out or new items are added to the assortment. According to theory, the storage assignment problem can be approached by analyzing the items order volume and use ABC analysis to create zones. The number of order lines over a specific period will be used to allocate the SKUs to a new location. In the simulation model the two factor levels are the baseline (current storage assignment) and the class-based storage assignment.

First, an analysis is conducted on the active SKUs and available locations. Approximately 20% of SKUs are assigned to Zone A, 30% to Zone B, and 50% to Zone C. Notably, the 20% of SKUs in Zone A account for nearly 80% of the total items picked over the last twelve months. Table 8 below shows the division in of SKUs over the zones and the items picked in each zone. Based on the capacity of the warehouse racks, it is determined which racks fall into which zone. The number of locations varies from six to forty. Figure 8 below shows the A zone in green, the B zone in orange, and the C zone in red.

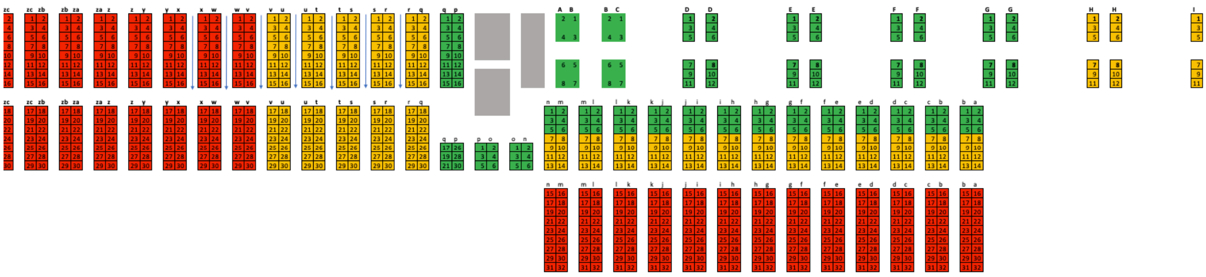
Table 8

ABC classification with items picked over the last 12 months

	SKUs	% of locations	Items picked	% of total items
Zone A	2386	20,1%	1,076,522	77,6%
Zone B	3560	30,0%	247,252	17,8%
Zone C	5924	49,9%	64,270	4,6%

Figure 8

ABC classification on warehouse map



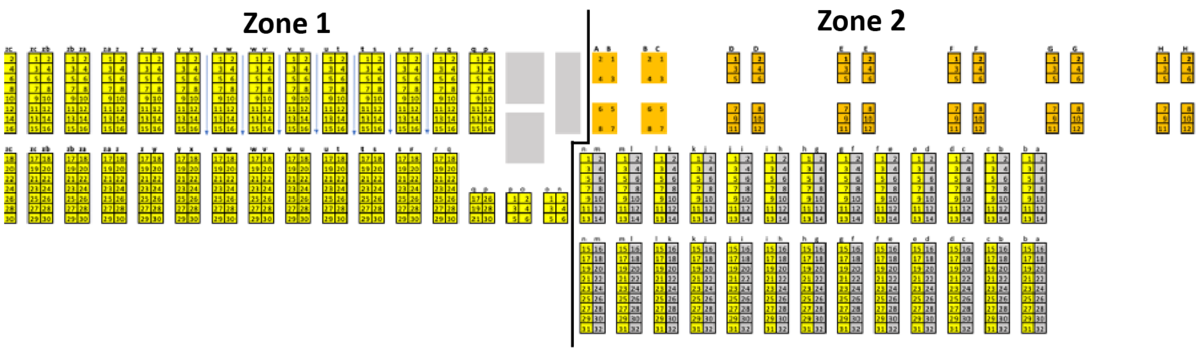
Next, the SKUs with the highest number of items are assigned to locations in zone A, starting with locations the closest to the start and end point. Subsequently, the SKUs are assigned to locations in zones B and C. As a result, all items are assigned to a new location following the class-based storage principle. Appendix II displays a snippet of the input utilized for the model.

Scenario 2: divide warehouse in two zones

For this change the warehouse layout should be taken into account, as well as the technical possibilities. According to company experts, dividing the one zone into two zones is possible and therefore worth simulating what possible efficiency gains could be. Depending on the outcome of this simulation, a scenario with three or more zones could also be tested. When dividing the area into two zones, the average travel distance of one cluster is expected to be lower. However, this requires a business-case approach, since adding a zone would result in more time needed to consolidate orders after picking. Furthermore, where one bin could be used for a work with items all over the warehouse, this would now be split into two bins, meaning extra handling. Another factor to consider is the difference in performance between the high and off season. Petersen (2002) found that average order size is a factor that impacts the optimal number of zones. The simulation model compares two factor levels, being the baseline (one zone) and two zones.

Figure 9

Warehouse map divided in two zones

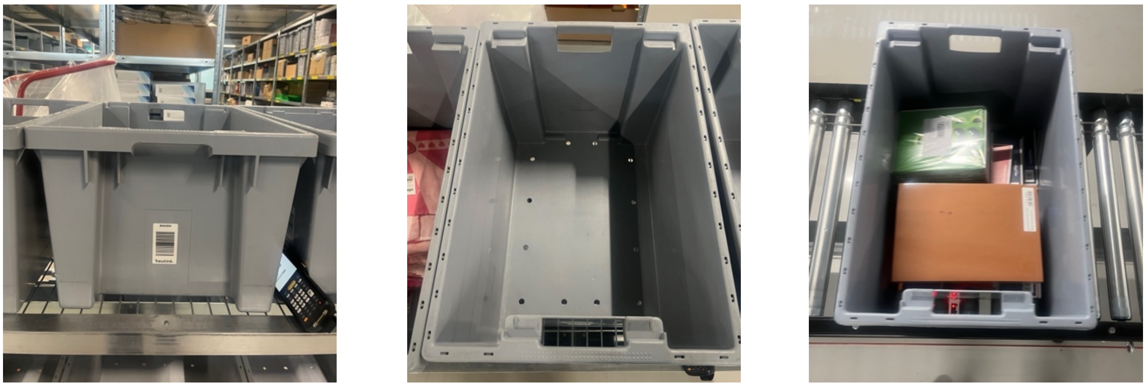


Scenario 3: introducing an (extra) smaller bin

Following the interviews that were conducted with company experts, another improvement suggestion came up, that does not fit one of the categories derived from literature. Chen et al. (2010) includes it as policy that impacts order picking performance but assumes that warehouse items all have the same size and does not consider the effect on the bin size and clustering. As described in the case introduction, the items are picked in bins for transport purposes. For small orders that include only a few lines with small items, there is often significant space remaining in the bin. Company experts proposed the option of introducing small bins with 50% of the capacity of the current bin. This could result in (1) efficiency gains as more bins can be placed on cluster carts, enabling bigger clusters and (2) less storage space needed in between processes because of less empty space is being stored. This requires a similar business case approach to the zoning problem because the efficiency gains need to be significant enough to justify an investment or the efficiency losses elsewhere in the process. The model simulation compares two factor levels: the baseline (current bin) and a smaller bin.

Figure 10

Current bin from front and top, both filled and empty



Analysis revealed that approximately 40% of the existing bins could be replaced with smaller bins, determined by the volume and weight of their contents. Table 9 below shows the max volume that fits a bin and the max weight the bin can have. In this scenario, the introduction of smaller bins is proposed alongside retaining the current bin.

Table 9

Bin capacity and max weight

	Capacity (CBM)	Max weight (KG)
Large bin	0.027	12.0
Small bin	0.0135	8.0

When comparing the three described scenarios with the policy categories from literature, policies for batching, routing, and layout are absent. The primary, overarching consideration has been whether simulating a policy offers practical added value for the case company. The absence of a batching scenario is because the current approach relies on manual heuristics that have proven to be effective. Moreover, the existing warehouse management system does not accommodate the implementation of complex cluster algorithms. For the routing policy, it holds that the current route is in general deemed a simple and efficient. Past attempt to introduce alternative routings have failed due to the limited tools to direct orders pickers. In practice, order pickers tend to find their own most efficient route and stick to old habits. This does not imply that altering routing policies couldn't prove effective, but it does suggest that simulation outcomes are potentially non-representative. Regarding layout, there are no improvement suggestions that could be tested using the simulation model. The reasons for this are that (1) the layout is highly dependent on the warehouse structure and therefore not easy to change, (2) layout problems should be considered when designing a warehouse from scratch, as changing the layout is expensive, and (3) the main suggestions made from literature the use of cross-aisles, which is already implemented (Battini et al., 2015; de Koster et al., 2007). Warehouse experts concurred with this conclusion, affirming changes to the warehouse layout are not realistic.

5.Simulation

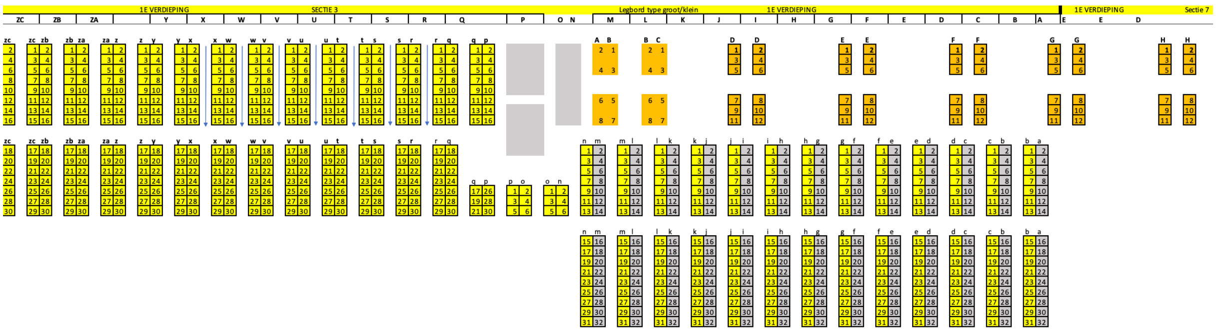
As described in Chapter Two, simulation is a common method to measure the efficiency of improvement policies in a warehouse. The goal of the simulation is to evaluate the proposed improvement policies, whether these have a significant impact on the efficiency. This requires a simulation model that can simulate the order picking performance of an order picker, based on order data. The model uses actual, historic order data from the case company.

5.1 Model structure

The starting point of the simulation model is the layout of the warehouse, which is a constant factor since no layout variations will be simulated. Based on a warehouse map in MS Excel, coordinates can be allocated to each warehouse location. The coordinates derive from the rows and columns of the sheet, which are then converted into X and Y values. Figure 11 below shows the warehouse map. Order data from the ERP system MS AX gives order lines for a specified time frame, with a storage location for each line. By referencing the storage location of each storage line, coordinates can be assigned, thereby providing a specific location within the model for each order line. The difference between location A and B is the travel distance.

Figure 11

Warehouse map



To sequence the order lines correctly for the calculation of the travel distance and for further simulation, MS SQL Server is utilized. Leveraging order data and coordinate inputs, a series of SQL queries constructs a model to generate travel distance as output. When calculating the travel distance between location A and B, the model keeps into accounts the racks and navigates through the aisles. Further information on how the travel distance will be calculated will be discussed in subsection 5.2.

Table 10

SQL pseudocode to calculate the distance between locations

```
For each set of storage locations 'loc1' en 'loc2':
        - calculate distance between isles:
            [distance Y isle] = absolute value of (w.y - loc1.y) + absolute
value of (w.y - loc2.y)
            [distance X isle] = absolute value of (w.x - loc1.x)
            [distance Y isle min] = minimum of (absolute value of (w.y - loc1.y)
+ absolute value of (w.y - loc2.y)) over (partitie per a.recid)

        - Calculate the distance between storage locations within an isle:
[distance Y] = if the first two characters of b.location differ from the first
two characters of a.location:
                    then 0
                else:
                    absolute value of (loc1.y - loc2.y)
[distance X] = if the first two characters of b.location differ from the first
two characters of a.location:
                    then 0
                else:
                    absolute value of (loc1.x - loc2.x)
```

Table 10 shows a snippet of the code of queries used for the simulation model. With this model as base, scenarios can be simulated by changing the input parameters and store these in the model as scenarios. Table 11 below shows a snippet of pseudocode how the different scenarios are selected to conduct the simulation. This is all done in a non-production environment, so edits to parameters are not implemented in the ERP system. All the input parameters are described in Chapter 5.2. Figure 12 shows the complete model structure.

Table 11

SQL pseudocode to select scenario for simulation

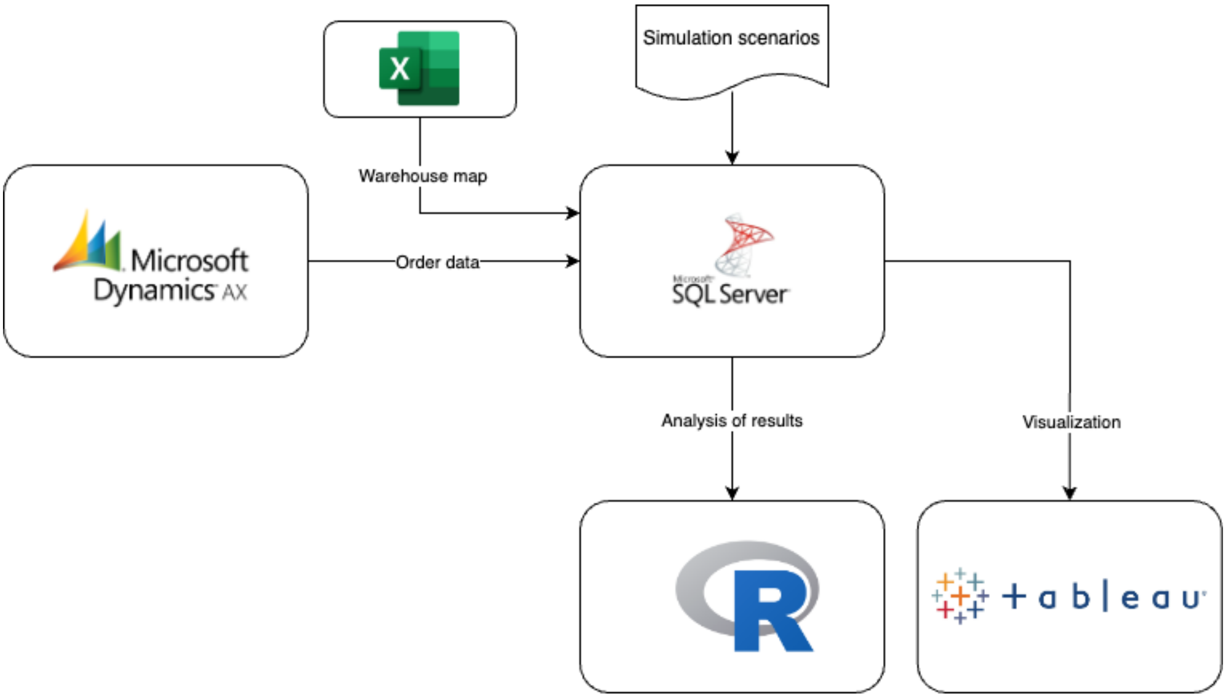
```
If  @scenario_sections equals 1 then
    set @scenario_sections_name = 'split sections'
else if @scenario_sections_name equals 2 then
    set @scenario_sections_name = 'current sections 2-3'
endif

if  @scenario_sorteercode equals 1 then
    set @scenario_sorteercode_naam = 'sorting_code_1
else if @scenario_sorteercode equals 2 then
```

```
    set @scenario_sorteercode_naam = 'sorting_code_2'
endif
```

Figure 12

Simulation model structure



5.2 Input parameters

In addition to the coordinates of the warehouse location and the order date, the model incorporates various other input parameters. Some of these parameters are needed for simulating specific scenarios, such as reallocating order lines to clusters or bins when necessary.

Storage location coordinates

As described in Chapter 5.1, a warehouse map is created in MS Excel with the proportions of the warehouse layout. Each rack and each isle subsection have X and Y coordinates, based on the columns and rows of the map. For example, location 3W23 has the coordinates (21, 19) and location 2E10 has the coordinates (71, 12). The subsection of isles also has coordinates, that are needed to calculate the route the order picker is travelling, as this cannot be a straight line from location A to B. This distance is calculated along the gridlines, traveling the X distance and the Y distance, also known as the Manhattan distance.

Order data

Datasets with actual historic datasets are used to simulate the scenarios. For a simulation the input is a full day of orders. An order file consists of several levels:

- Waves: A wave is a buffer of works that is released to be picked once it reaches a certain level, or work is required in the warehouse
- Clusters: A cluster is a batch of works that is combined to be picked by an order picker in one go using a cluster cart
- Works: A work is a set of order lines that is ordered on the same customer order. Once a work does not fit in one bin, it is split up in two or more works, each with a unique work ID. Each work also has a unique bin ID, once it has been picked in a bin.
- Order lines: An item or a number of the same items that needs to be picked

Next to this, each order line has information like the storage location, the weight of the item(s) in the order line, the volume of the item(s) in the order line, etc.

Storage location of SKUs

The order data contains both the product SKU and the product location where the product is stored. However, one of the scenarios tests a different storage assignment, meaning the storage location of each SKU will be different. A file with the new storage locations will be used for the travel distance calculation.

Sort code

The sort code is the sequence the terminal will display the items that need to be picked in, and thus to a certain extent the route that the order picker will travel. The model calculates the fastest route to the next location.

No. of zones & zone division

Splitting the warehouse into two zones is one of the scenario's that will be simulated. In the scenario with two zones, parameters such as the clusters and the storage assignment will be different.

Table 12 below contains some other notable input parameters that are not discussed above.

Table 12

Input parameters

Input parameters	Description
Max capacity bins	For a normal bin this is 0.027 CBM. The combined volumes of items in a bin cannot exceed this.
Max weight bins	For a normal bin this is 12 KG. The combined weight of items in a bin cannot exceed this.
Max capacity cluster cart	The number of bins that can be placed on a cluster cart. For the normal cluster cart this is eight.

5.3 Assumptions

The assumptions form the framework upon which the model operates, influencing its results and real-world applicability. The assumptions below, provide clarity on its scope and limitations, and enable a nuanced interpretation of the simulation outcomes.

- A picker-to-product system is assumed for the order picking process.
- Products stored in the same rack have the same storage location. When picking multiple items from different storage locations from the same rack, no additional distance is covered. With a width of 130 cm, all locations on the rack are accessible without the need for movement.
- Each order picker stops and start at the same location. When dropping of bins after completing the picking process, the picker can place the bins on a roller conveyor belt. In reality the exact drop off point could vary a few meters, but in the model this in one location.
- Running out of inventory in the warehouse is not considered.

- A dedicated storage system is considered, where each storage locations stores on SKU and each SKU is only stored at one location.

5.4 Sensitivity analysis

To ensure the robustness of the simulation, variation in key parameters is assessed. By varying these parameters within defined ranges biases are avoided. As described in chapter 4.2, as a result of the nature of the products stored in the warehouse of the case company, there is a high variety in the number of order lines that is being processed in the high season compared to the off season. Roughly 60% of the total order lines is shipped in the high season, which is the period June to September. In the high season the average order composition is different, with more average items per order line. Also, because more works are being processed, the expectation is that clusters can be more efficient, due to the pool of works being larger. To avoid biases caused by the seasonality effect, ten different order files are used, five order files in the high season and five order files in the off season. Table 13 below shows the ten order files. Because there also is a variation in average order lines processed on a day, depending on the day in the week, this is also considered.

Table 13

Order files for simulation

Order batch	Season
20-06-2023	High season
30-06-2023	High season
04-07-2023	High season
12-07-2023	High season
20-07-2023	High season
15-02-2024	Off season
22-02-2024	Off season
28-02-2024	Off season
05-03-2024	Off season
13-03-2024	Off season

6.Results and analysis

This chapter presents the results of the simulations conducted for each scenario. Each scenario's results are analyzed in detail, evaluating the significance of the observed effects. Additionally, this chapter examines other influencing factors such as seasonality, which might impact the results. Following this analysis, the findings can be used to prepare the business cases in Chapter Seven.

6.1 Data preparation

As described in Chapter Five, the simulations are conducted based on order batches that contain orders processed on one day. To ensure reliable results, the order files are cleaned before running the simulation. Specific order categories, such that are processed outside the normal order stream are excluded. An example of such order category is the Single SKU (SSKU) category, that is for orders with only one order line. Additionally, outliers such as products with temporary locations that have numerous order lines are not included in the results. Occasionally, a new item with many order lines is temporarily placed in an unregistered location that is not visible in the model. Order files displaying unusual patterns due to such incidents, which cannot be rectified by excluding subsets of data, are replaced with order files from other dates.

6.2 Scenario 1

Scenario 1 simulates an alternative storage assignment based on ABC-classification, where items are assigned to a location based on the number of order lines this item is in over a period. As table 14 shows, this new storage assignment does not perform better on efficiency, with an increased travel distance for each order batch. With an average increase of 28.7% the difference between the current state and the scenario is significant (p-value: 0.0026).

Table 14

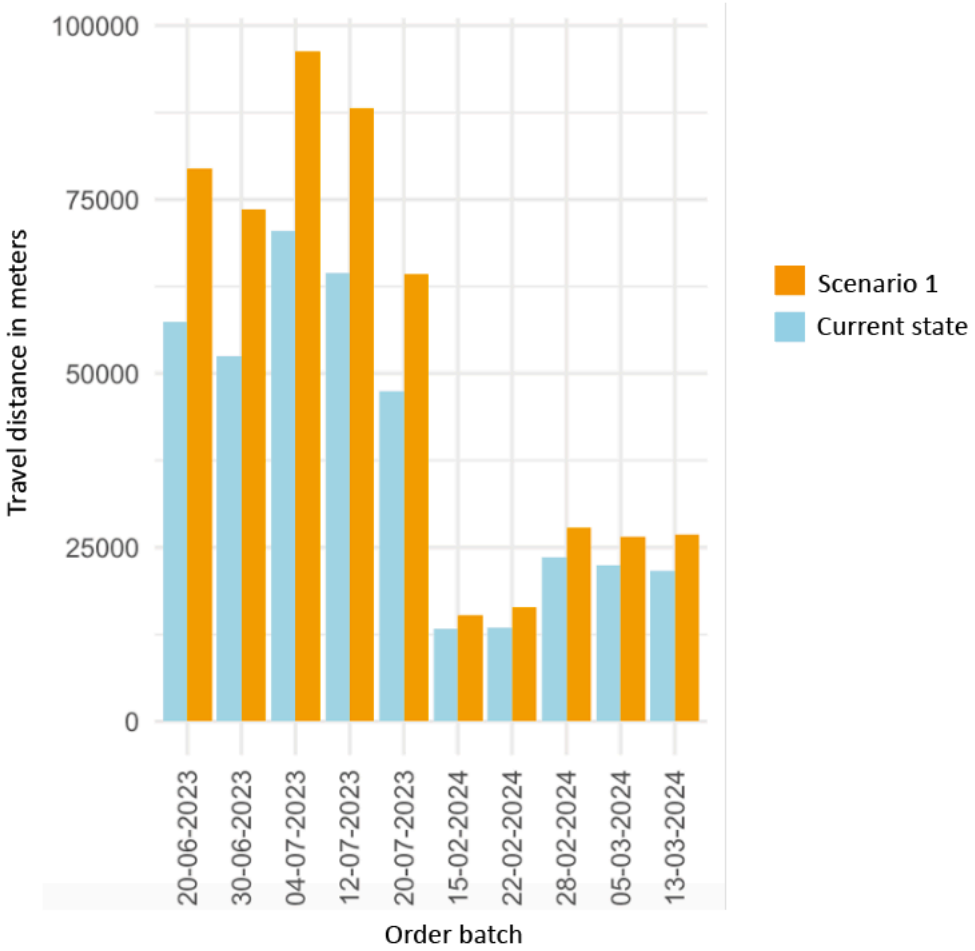
Difference in travel distance for scenario 1

Date	Order Lines	Distance Current State	Distance Scenario	Difference %
20-06-2023	17,431	57,417	79,402	38,3%

30-06-2023	15,242	52,520	73,628	40,2%
04-07-2023	22,068	70,395	96,228	36,7%
12-07-2023	20,211	64,351	88,038	36,8%
20-07-2023	13,777	47,443	64,263	35,5%
15-02-2024	1,799	13,219	15,324	15,9%
22-02-2024	2,093	13,374	16,425	22,9%
28-02-2024	3,847	23,522	27,880	18,5%
05-03-2024	3,612	22,438	26,592	18,5%
13-03-2024	3,668	21,692	26,901	24,0%

Figure 13

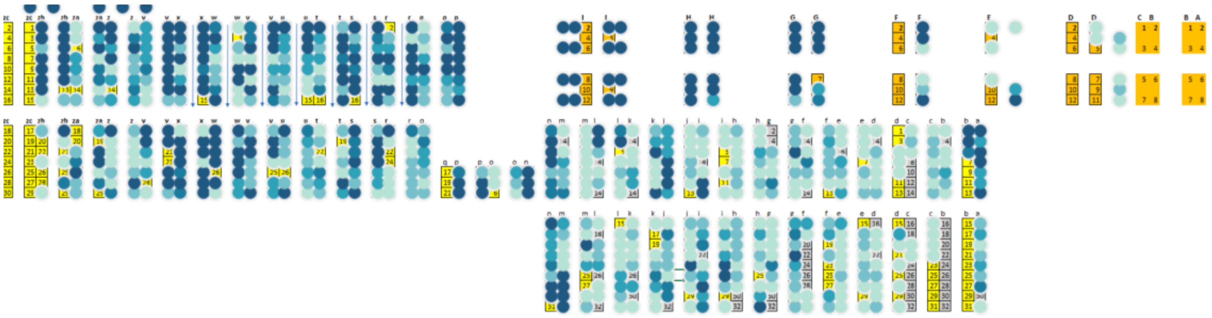
Bar chart of the travel distance of the current state and scenario 1



The reason for this negative effect seems to be that the heuristics used by the warehouse team, which rely on their experience, are effectively suited to the product offerings of the case company. Where fast-moving product are placed close to the in- and outbound point in the current state, just like the scenario, 'product families' are also considered. Based on years of experience, certain product groups are identified which often appear on the same orders, which are assigned to locations in the same racks, or isles. Figures 14 and 15 below show the spread of order lines for the current state and the scenario for the same order batch. Figure 14 shows that many items are picked on the left side of the warehouse. This is not particularly close to the in- and outbound point, but it indicates that a specific type of order is stored together, which enables efficient picking. Although the scenario shows an even spread around the picking route, it does not match the efficiency of the current storage assignment.

Figure 14

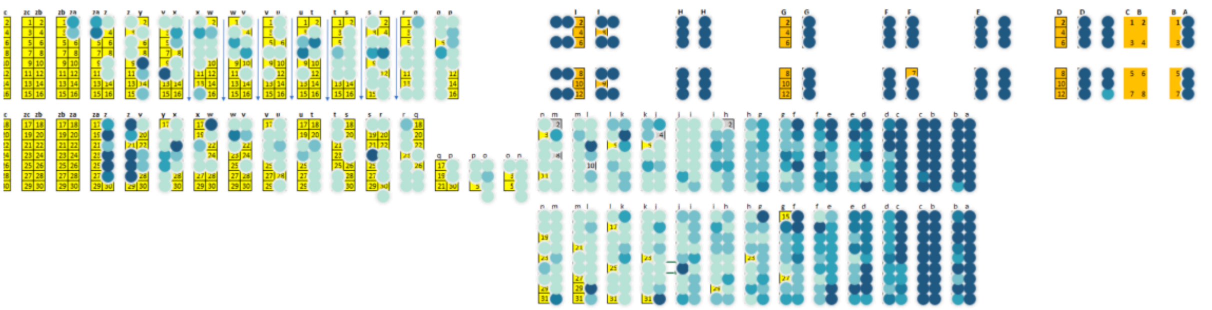
Spread of order lines current state



Note. Dark blue indicating a high number of order lines picked form this storage rack

Figure 15

Spread of order lines scenario 1



Note. Dark blue indicating a high number of order lines picked form this storage rack

To investigate whether the effect of the implemented policies differed between high season and off season, additional tests were conducted. High season includes the order batches from the dates in June and July, and off season are the other months in 2024. This difference is significant, with 37.5% increase in high season and 20.0% in off season, see table 15 (p-value: 0.008). The stronger effect in high season could be explained by the already mentioned placement of products in groups, which is even more effective during this time when these types of products are ordered more frequently.

Table 15

Difference high- and off season scenario 1

	Distance current state (avg)	Distance scenario (avg)	Difference %
High season	58,425	80,312	37.5%
Off season	18,849	22,624	20.0%

In conclusion, scenario 1 did not enhance efficiency and actually resulted in a significant increase in travel distance for order picking, particularly during high season. The current storage policy performs better, suiting the product assortment. Further investigation is needed to explore storage policies that can improve efficiency. Since the effect of this scenario on efficiency is negative, it will not be developed further into a business case in Chapter Seven.

6.3 Scenario 2

In scenario 2 the effect of the division of the warehouse in 2 zones is simulated. Table 16 below shows the results and compared the travel distance of each order batch, showing a decrease for each date. The implementation of this policy resulted in an average reduction of 15.8% distance travelled, which is statistically significant (p-value: 0.0002).

Table 16

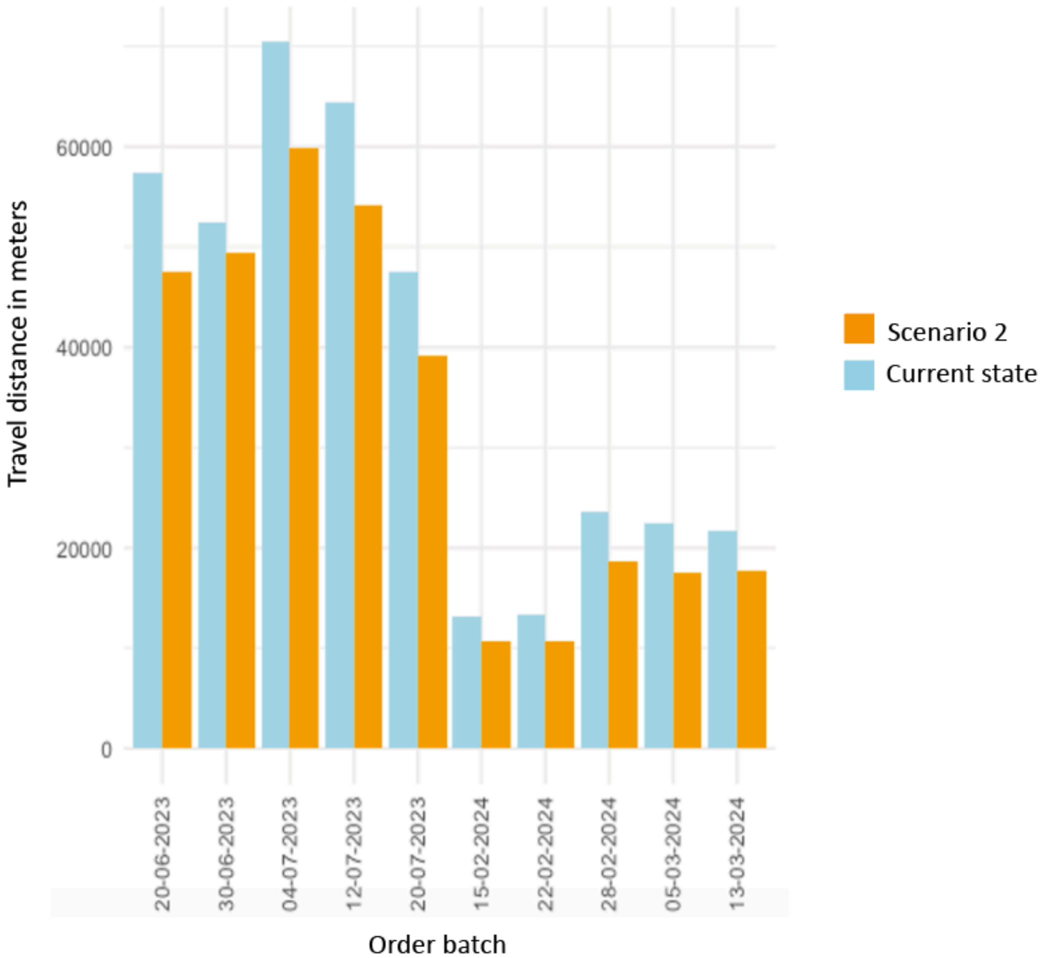
Difference in travel distance for scenario 2

Date	Order Lines	Distance Current State	Distance Scenario	Difference %
20-06-2023	17,431	57,417	47,486	-17.3%
30-06-2023	15,242	52,520	49,398	-5.9%
04-07-2023	22,068	70,395	59,924	-14.9%

12-07-2023	20,211	64,351	54,166	-15.8%
20-07-2023	13,777	47,443	39,140	-17.5%
15-02-2024	1,799	13,219	10,785	-18.4%
22-02-2024	2,093	13,374	10,698	-20.0%
28-02-2024	3,847	23,522	18,638	-20.8%
05-03-2024	3,612	22,438	17,539	-21.8%
13-03-2024	3,668	21,692	17,634	-18.7%

Figure 16

Bar chart of the travel distance of the current state and scenario 2



With the division of the warehouse into two zones, it was anticipated that the number of bins in use would increase since each bin could only be filled with items located within its respective zone. This expectation is confirmed, with an observed increase of 15.4% in the number of bins used. Corresponding to this increase in bins, the number of clusters also increased, with an average increase of 19.3%. This rise in clusters, coupled with a reduction in travel distance, led to a significant decrease in the average distance traveled per cluster, dropping from 139 meters to 94 meters. With the increase in bins for the same quantity of items, the fill rate of the bins drops with 14.2% on average.

Table 17

Difference in cluster and bin utilization for scenario 2

Date	Clusters Current State	Clusters Scenario	Difference %	Bins Current State	Bins Scenario	Difference %
20-06-2023	467	550	17.8%	3,512	3,949	12.4%
30-06-2023	433	502	15.9%	3,211	3,573	11.3%
04-07-2023	549	643	17.1%	4,159	4,666	12.2%
12-07-2023	494	588	19.0%	3,698	4,179	13.0%
20-07-2023	372	436	17.2%	2,828	3,186	12.7%
15-02-2024	84	114	35.7%	544	662	21.7%
22-02-2024	103	127	23.3%	728	845	16.1%
28-02-2024	147	181	23.1%	1,087	1,301	19.7%
05-03-2024	141	176	24.8%	1,026	1,215	18.4%
13-03-2024	144	177	22.9%	1,084	1,272	17.3%

The percentages for the dates in high season show lower values that low season, so a test is performed to determine whether this difference is significant. The p-value of the paired t-test suggests there is no significant difference between the seasons (p-value: 0.075). However, the value is close to the threshold, indicating potential practical significance.

Table 18

Differences high- and off season scenario 2

	Distance current state (avg)	Distance scenario (avg)	Difference %
High season	58,425	50,023	-14.4%
Off season	18,849	15,059	-20.1%

In conclusion, the results of the simulation of scenario 2 demonstrate that the simulated policy significantly improves the warehouse efficiency, by reducing the travel distance. At the same time, the number of bins rises which requires additional handling capacity. Although there is no strong statistical evidence to suggest that the effect of the policy differs between high and off season, it potentially has practical significance.

6.4 scenario 3

In scenario 3 the effect of the introduction of a small bin, with half of the capacity and volume of a normal bin, is simulated. Table 19 below shows the results of the simulation with the travel distance of both the current state and the scenario for each order batch. The use of the smaller bin resulted in an average reduction of 11.9% in travel time, which is a significant effect (p-value: 0.001).

Table 19

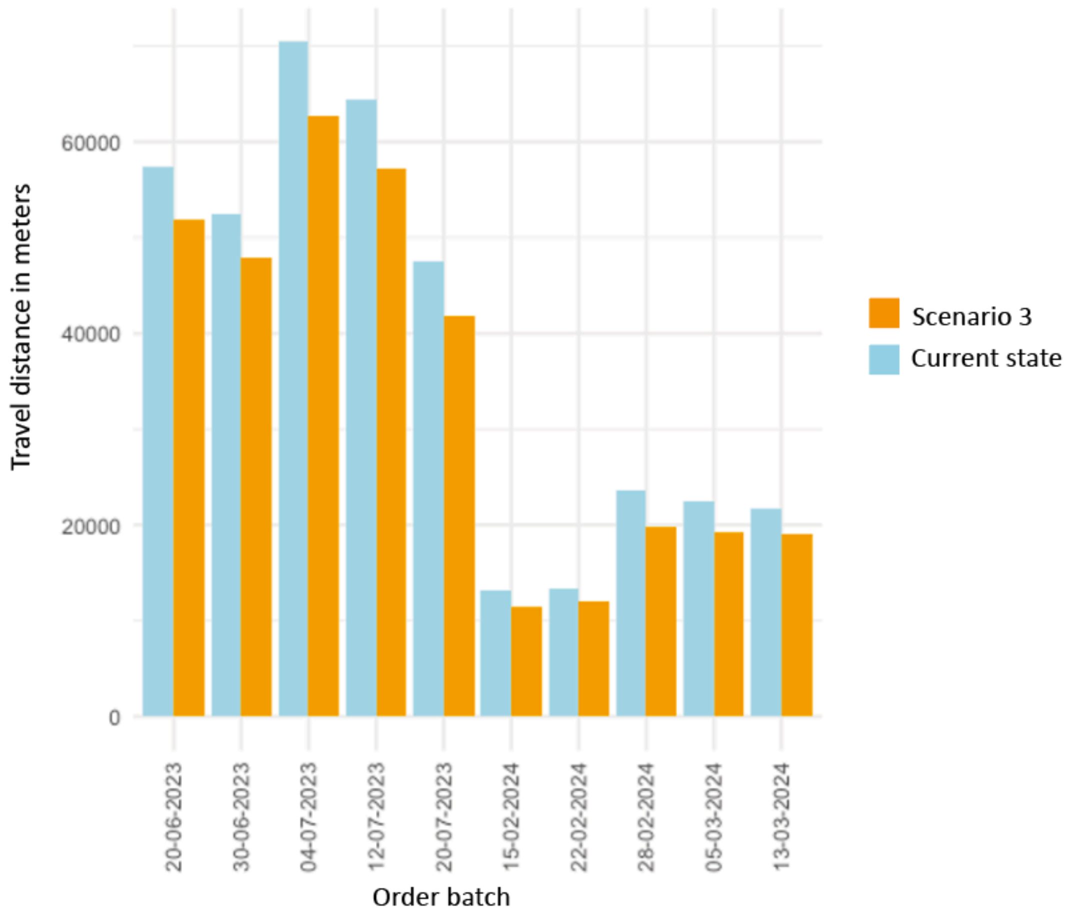
Difference in travel distance for scenario 3

Date	Order Lines	Distance Current State	Distance Scenario	Difference %
20-06-2023	17,431	57,417	51,845	-9.7%
30-06-2023	15,242	52,520	47,826	-8.9%
04-07-2023	22,068	70,395	62,698	-10.9%
12-07-2023	20,211	64,351	57,237	-11.1%
20-07-2023	13,777	47,443	41,777	-11.9%
15-02-2024	1,799	13,219	11,392	-13.8%
22-02-2024	2,093	13,374	11,988	-10.4%

28-02-2024	3,847	23,522	19,889	-15.4%
05-03-2024	3,612	22,438	19,215	-14.4%
13-03-2024	3,668	21,692	18,970	-12.5%

Figure 17

Bar chart of the travel distance of the current state and scenario 3



The use of smaller bins has increased the capacity of the cluster carts, which is the sole reason for the decrease in travel distance in this scenario. Table 20 indicates an average decrease in the number of clusters by 26.6%, while maintaining the same number of bins. Although the average travel distance per cluster increased to 167 meters from the current 139 meters, the significant reduction in the number of clusters results in an overall decrease in total travel distance.

Table 20

Difference in cluster and bin utilization for scenario 3

Date	Clusters Current State	Clusters Scenario	Difference	No. of bins	% of bins that are small bins
20-06-2023	467	354	-24.1%	3,512	62.2%
30-06-2023	433	325	-24.9%	3,211	64.7%
04-07-2023	549	405	-26.2%	4,159	64.9%
12-07-2023	494	365	-26.1%	3,698	64.8%
20-07-2023	372	282	-24.2%	2,828	60.9%
15-02-2024	84	66	-21.4%	544	70.2%
22-02-2024	103	70	-32.0%	728	75.1%
28-02-2024	147	102	-30.6%	1,087	73.2%
05-03-2024	141	99	-29.8%	1,026	73.9%
13-03-2024	144	106	-26.4%	1,084	65.7%

With an 10.5% decrease in travel distance in high season and a 13.6% decrease in off season, there is a significant difference in effect (p-value: 0.021). This difference can be explained by the higher percentage of small bins that can be utilized in the off season. On average, 71.6% of the bins used in off season can be small bins, while in the high season this is only 63.5%. A different order composition is the cause of this difference, with many more items per bin in the high season. In the off season there are more small orders, resulting in more works with low volume and weight that can fit a small bin. Figure 21 shows the significant difference in items per order with a high season average of 36.5 items against a low-season average of 15.2 items per bin.

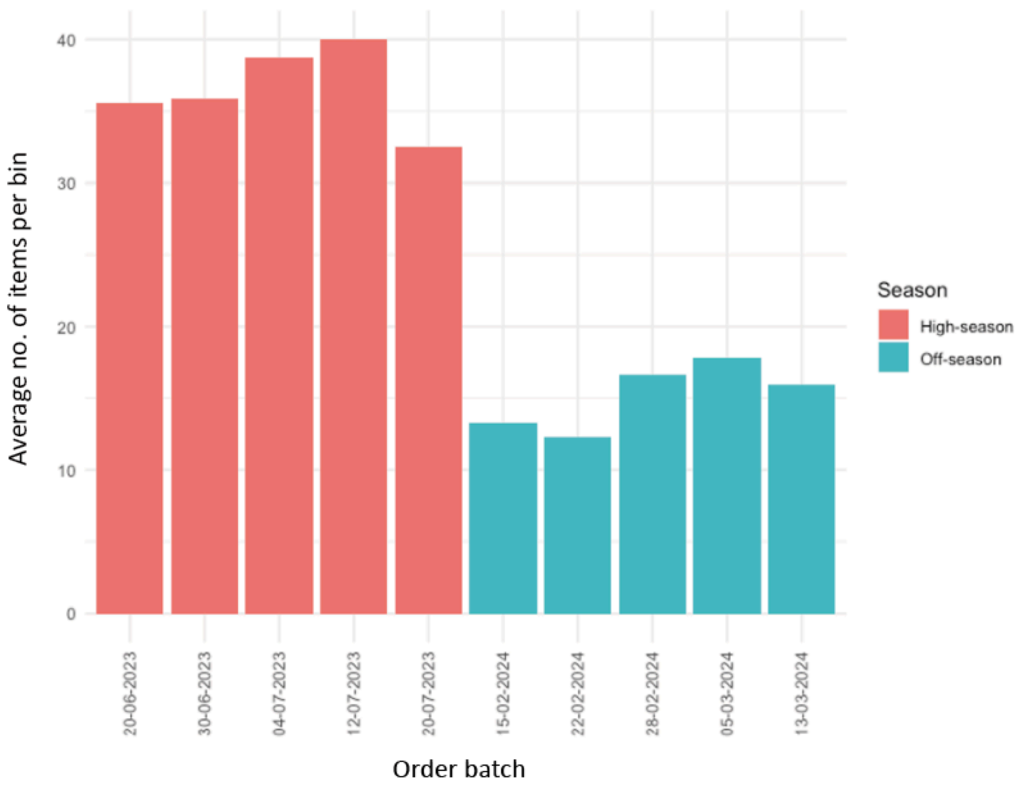
Table 21

Differences high- and off season scenario 3

	Distance current state (avg)	Distance scenario (avg)	Difference %	% of bins that are small bins	Average items per bin
High season	58,425	52,276	-10.5%	63.5%	36.5
Off season	18,849	16,291	-13.6%	71.6%	15.2

Figure 18

Quantity per bin in high- and off season



In conclusion, the introduction of smaller bins significantly reduces travel distances in by increasing cluster cart capacity, reducing the number of clusters needed. This efficiency is particularly pronounced in the off season, with a notable 13.6% travel distance reduction due to a different order composition. Therefore, it is worth further investigating the feasibility of implementing smaller bins.

6.5 Scenario 4

Given the significant and positive effect of scenario 2 and 3, the combined policies were also simulated. The combined effect is an average decrease of 27.5% in travel distance (p-value: 0.0002). The average difference in low season is slightly higher compared to high season, -30.5% compared to -26.6%.

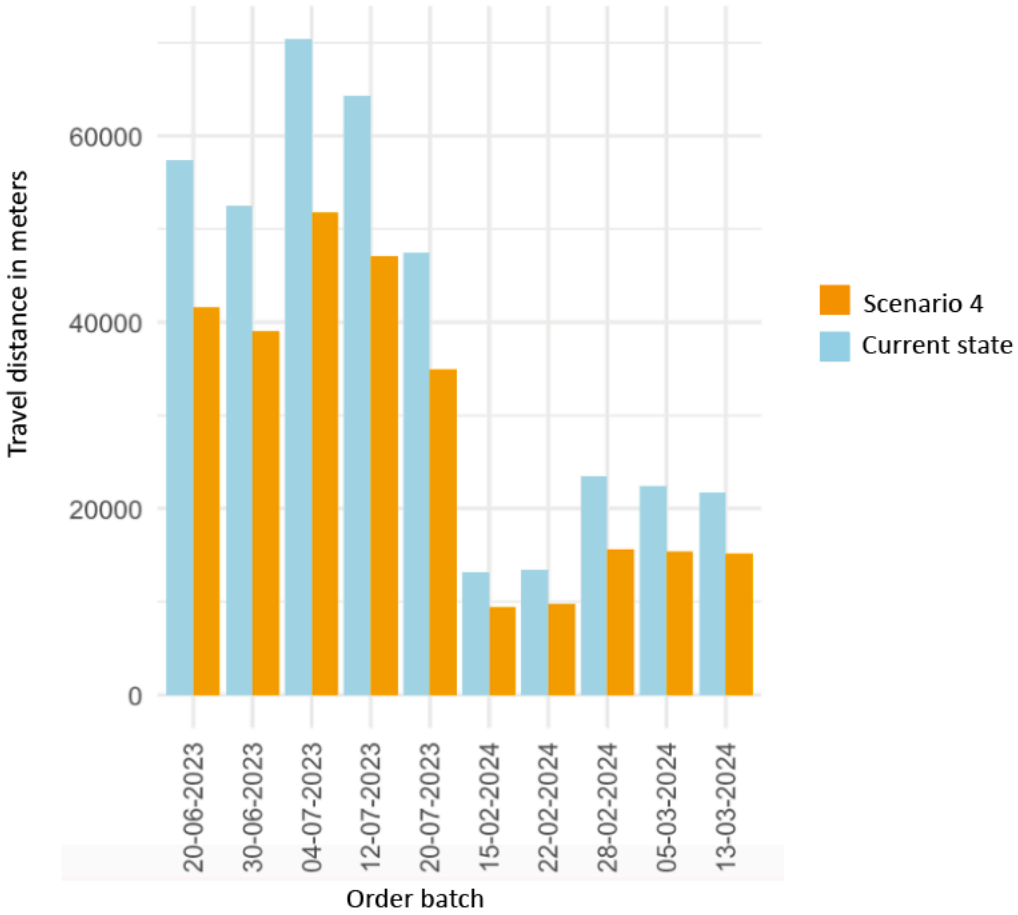
Table 22

Difference in travel distance for scenario 4

Date	Order Lines	Distance Current State	Distance Scenario	Difference %
20-06-2023	17,431	57,417	41,617	-27.5%
30-06-2023	15,242	52,520	38,995	-25.8%
04-07-2023	22,068	70,395	51,779	-26.4%
12-07-2023	20,211	64,351	47,130	-26.8%
20-07-2023	13,777	47,443	34,927	-26.4%
15-02-2024	1,799	13,219	9,420	-28.7%
22-02-2024	2,093	13,374	9,787	-26.8%
28-02-2024	3,847	23,522	15,651	-33.5%
05-03-2024	3,612	22,438	15,406	-31.3%
13-03-2024	3,668	21,692	15,220	-29.8%

Figure 19

Bar chart of the travel distance of the current state and scenario 4



Where scenario 2 sees an increase in clusters because of the increase in bins, scenario 3 sees a decrease in clusters because more bins can be assigned to one cluster. This results in a decrease in cluster for this scenario, but less strong than scenario 2. The number of bins is the same as scenario 2.

Table 23

Difference in cluster and bin utilization for scenario 4

Date	Clusters Current State	Clusters Scenario	Difference %	Bins Current State	Bins Scenario	Difference %
20-06-2023	467	396	-15.2%	3,512	3,951	12.5%
30-06-2023	433	376	-13.2%	3,211	3,631	13.1%
04-07-2023	549	459	-16.4%	4,159	4,677	12.5%

12-07-2023	494	427	-13.6%	3,698	4,291	13.4%
20-07-2023	372	318	-14.5%	2,828	3,198	13.1%
15-02-2024	84	87	-3.6%	544	662	21.7%
22-02-2024	103	90	-12.6%	728	845	16.1%
28-02-2024	147	120	-18.4%	1,087	1,301	19.7%
05-03-2024	141	120	-14.9%	1,026	1,215	18.4%
13-03-2024	144	126	-12.5%	1,084	1,274	17.5%

In conclusion, this scenario demonstrates the greatest potential for efficiency improvement with the highest reduction in travel distance. The combination of smaller bins and two zones optimizes the use of bins and clusters.

7.Business Cases

This chapter presents three business cases, based on the results from the scenario simulations discussed in Chapter Six. Scenario 1 is not further discussed, since it showed no improvement in efficiency, ruling out a positive outcome for a business case. Business case 1 is based on the results of scenario 2, where the warehouse is divided into zones. Business case 2 is based on the results of scenario 3, where a small bin is introduced to the warehouse process. Business case 3 is based on the scenario that combines scenario 2 and 3.

Business case 1: Divide warehouse into zones

Based on the results from Chapter Six, splitting the warehouse into two distinct zones can significantly improve order-picking efficiency. However, it is essential to consider potential challenges, such as increased bin usage and potential bottle necks. In the business cases the benefit of the efficiency improvement is measured in cost savings.

Benefits

The significant decrease in travel distance shows an efficiency improvement, however, according to van Gils et al. (2018b), 50% of the time spent on order picking can be attributed to traveling from location to location and the other 50% to searching, setup and picking. This is a reasonable assumption for a picker-to-parts system like the one used at the case company. Therefore, the efficiency improvement is calculated on 50% on the hours logged on order picking. Additionally, the analysis considers the difference between high and off seasons. This difference is significant because, first, in the high season the travel distance improvement is lower as shown in Chapter Six. Second, the hours per day spent on order picking is higher, because of the increase in order volume being processed daily (see figure 5). And third, the cost per hour is lower in high season, compared to off season.

Table 24

Efficiency improvement scenario 2 in hours

	Average order picking hours per day	Part of order picking that is travel time (50%)	Efficiency improvement	Efficiency improvement in hours
High season	450	225	14.4%	32.4
Off season	140	70	20.1%	14.1

The average order picking hours per day in table 23 is based on the average of the number of hours logged on order picking in the specific sections. The cost per hour in high season is higher because the company hires temporary, young holiday workers during this period. These workers have a relatively lower hourly wage compared to employees with permanent contracts. In the off-season, the company also employs workers through an employment agency, who are more expensive. Where an hour in high season costs €15 on average, this is €20 in off season. Consequently, these agency-employed hours are the first to be reduced. With the savings in hours per day and the cost per hour, the daily savings can be calculated, which can then be used to determine the annual savings. This calculation considers seven weeks of high season and forty weeks of off season. The total savings estimate in a year adds up to €73,410, of which the breakdown is in table 25 below.

Table 25

Yearly savings scenario 2 in euros

	Saving in hours per day	Cost per hour (€)	Savings per day (€)	Savings per year (€)
High season	32.4	€15	€486	€17,010
Off season	14.1	€20	€282	€56,400

Considerations & mitigation strategies

A reduction in travel distance is not the only consequence of splitting the warehouse into two zones. It also significantly increases the number of bins used for order picking. In the off season, the average number of additional bins is 165, an 18.5% increase compared to the current state. In the high season, the increase is 12.3%, resulting in an average increase of 429 bins. While this change does not impact the order picking process itself, it does affect subsequent stages of the order processing line.

Firstly, the additional bins lead to increased handling at the sorting and consolidation point, where bins are transported once picking is finished. At this stage, all bins are taken from the roller conveyor and temporarily stored in racks, so more time is required when extra bins are received. According to estimates by company experts stationed at this point, every 50 extra bins result in an additional 12 minutes of work. Secondly, the packing area also experiences increased workload due to the additional bins. Similar to the sorting and consolidation point, the extra bins extend the throughput time needed to process and pack all orders. Since items are distributed across more bins, more bins need to be handled, stored, and returned. An estimate from company experts stationed here, is that every 50 bins is an additional 7 minutes of work. At both stages there are two employees present, meaning the 50 extra bins add respectively 24 and 14 minutes of work. Table 26 shows the average hours a day these extra bins add, with table 27 showing the extra costs these extra hours add up to.

Table 26

Extra hours at sorting & consolidation and packing stage

		Average extra bins per day	Additional time per 50 added bins (minutes)	Average time per day added (minutes)	Average time per day added (hours)
Sorting & consolidating	High season	429	24	206	3.4
	Off season	165	24	79	1.3
Packing	High season	429	14	120	2.0
	Off season	165	14	46	0.8

Table 27

Extra cost scenario 2 in euro's

	Extra hours per day	Cost per hour (€)	Cost per day (€)	Cost per year (€)
High season	5.4	€15	€81	€2,835
Off season	2.1	€20	€42	€8,400

Finally, the increase in bins may create a potential bottleneck in the order processing workflow at the sorting and consolidation point. Figure 20 below shows the bins placed in the racks at this stage. The combined capacity of all racks is 672 bins. In the high season, the number of bins processed in one day can exceed 4,000, creating a bottleneck during peak times. With this scenario, the number of bins increases by an average of 12.3%, resulting in more than 400 additional bins that need to be processed. Since the consolidation and sorting point is already overflowing during peak times in the current state, it is expected that these additional bins will further Intensify this effect. The number of bins in storage not only depends on the influx from the warehouse section that is being analyzed, but also on the items that are picked in other sections, which are consolidated here. Therefore, the estimated number of bins at specific times cannot be calculated. However, this scenario is likely to create a bottleneck at the sorting and consolidation point if the capacity is not expanded. The location offers the possibility to expand with additional racks, of which the cost of material and labor is estimated at a total of €3,000. It should be noted that even with this increased capacity, there is no guarantee this will not be a bottleneck during peak periods.

Figure 20

Sorting and consolidation point

Cost-benefit analysis

Dividing the warehouse into two distinct zones reveals a notable increase in order-picking efficiency, resulting in substantial annual savings. The projected savings add up to €73,410 in cost of hours, with €17,010 saved in the high season and €56,400 in the off-season. However, the efficiency gain is counterbalanced by increased handling times and costs due to additional bins, adding €11,235 to annual costs and diluting the net savings to €62,175. Moreover, the increased bin usage could intensify existing bottlenecks at the sorting and consolidation point during peak times, necessitating capacity expansion to fully realize the benefits of the new zoning strategy. This expansion would require a one-time investment in extra racks and a reallocation of space in the warehouse, estimated at €3,000.

Business case 2: Implement small bins
The results in Chapter Six show a significant decrease in travel distance for this scenario, showing an improvement of order picking efficiency. Next to these gains, potential challenges and investments should be considered.

Benefits
Similar to business case 1, the efficiency is allocated to 50% of the hours that are logged on order picking. Also here, the difference between high- and off season turned out to be significant. The analysis shows the cost savings calculation for both seasons separately.

Table 28

Efficiency improvement scenario 3 in hours

	Average order picking hours per day	Part of order picking that is travel time (50%)	Efficiency improvement	Efficiency improvement in hours
High season	450	225	10.5%	23.6
Off season	140	70	13.6%	9.5

Refer to business case 1 for the explanation on the hours and hourly rates used for the calculation in table 28. The savings in hours translates to a total annual savings in cost of €50,565, which is specified in table 29 below. Another area where savings are achieved is in storage space, thanks to the reduced volume. By making adjustments to the sorting and consolidation area, more bins can be stored within the same space. Especially in combination with business case one, where this area creates a bottleneck due to the increase in bins, this could be a crucial benefit, which is further analyzed in business case three.

Table 29

Yearly savings scenario 3 in euros

	Saving in hours per day	Cost per hour (€)	Savings per day (€)	Savings per year (€)
High season	23.9	€15	€359	€12,565
Off season	9.5	€20	€190	€38,000

Considerations & mitigation strategies

Since switching from a normal-sized bin to a smaller bin only occurs when the bin's contents permit it, this will not result in an increase in the number of bins. Therefore, this does not impact the hours spend on handling, sorting, and consolidating. However, introducing a small bin entails an investment in the bins themselves and potentially in aligning the process for compatibility.

First, there is the investment in the new, small bins. These can be purchased from the same supplier that the company uses for its regular bins. The new bin has the same length and width but is half the height, thereby halving its capacity. Considering the fluctuating use of bins during high- and off season, both periods should be considered when determining the quantity of bins to purchase. Table 30 below shows the calculated quantity required, based on the percentages of bins replaceable with small bins as detailed in Chapter Six: 63.5% for the high season and 71.6% for the off season. This is based on the volume of items in the system, which is added up based on the items that are in one bin. In practice, according to company experts, it happens that items that should fit into a bin according to the system, may not fit due to their shape or weight. This results in more large bins being used than predicted by the system. Therefore, an error margin of five percent points is in place. Table 30 shows the final percentage of small bins that are needed.

Table 30

Number of small bins needed

	Bins per day needed	% small bin.	Small bins needed	Small bins needed (rounded)
High season	4500	58.6%	2637	2,700
Off season	3000	66.6%	1998	2,000

To ensure sufficient bins are available throughout the whole year, 2,700 bins are needed. To prepare for future order growth and unexpected peaks, it is advisable have an additional 10% buffer, which is also the case now with the current bin. With a cost per unit of €8, the total purchase value of 2,970 bins is €23,760.

Secondly, the warehouse system and workflow need to be compatible with this new bin size. The current system is designed for a single size, so both the software and hardware used for bin processing should be assessed for compatibility. Table 31 below lines out all considerations and the mitigations or solutions. The direct costs associated with these potential adjustments are minimal since they can be managed in-house, but this requires further investigation.

Table 31

Compatibility considerations for the small bin

Problem	Description	Mitigation or Solution
Scanning of the bin on the roller conveyor	Each bin has a barcode that is scanned at a scanning point on the roller conveyor. The new bins are shorter, with the barcode located lower on the bin.	Scanning points are adjusted.
Different sizes of bins on the roller conveyor	Bins are advanced on the roller conveyor as one bin pushes another. Issues may arise when a small bin pushes a larger bin, and vice versa.	According to experts, this will not pose any problems.

Capability of system and software	The system is not designed to make a distinction in bin sizes to e.g. make clusters.	According to experts, necessary changes can be made.
Cluster carts	Cluster carts as shown in figure 4 can only fit 8 bins, regardless the size.	The cluster carts can be modified to a capacity carrying 12 small bins.
Finding bins on clusters carts	Due to the increased number of bins on cluster carts, it is more difficult to find the correct bin for the picked items.	Solution in software need to be explored.
Storage racks capacity	The capacity of the sorting and consolidation point fits the same number of bins regardless the size.	Either the capacity of the storage racks can be increased, or bins can be placed on each other.

Cost-benefit analysis

The major benefit is a significant decrease in travel distance and time for order picking, resulting in improved efficiency. During the high season, the efficiency improvement translates to 23.6 hours saved per day, and 9.5 hours during the off-season. Annually, this results in cost savings of €12,565 in high season and €38,000 in off season, adding up to €50,565 (see table 29). Another benefit is the improved storage space utilization. With smaller bins, more items can be stored in the same area, alleviating bottlenecks, which shows even higher potential in combination with business case 1. On the other hand, this implementation involves an initial investment. The purchase of 2,970 small bins, each costing €8, totals €23,760. Additionally, warehouse systems and workflows need modifications to accommodate the new bin size. Overall, the long-term savings and operational efficiencies outweigh the initial investments, making this a profitable improvement.

Business case 3: Divide warehouse in zones & implement small bins

The results of scenario 4, which simulates the combined policies of scenarios 2 and 3, show the greatest impact on efficiency. Where the increase in bins is a crucial consideration for scenario 2, scenario 3 present a solution with reducing the storage space needed per bin.

Benefits
Using the same calculations as in the previous business cases, the savings in hours and euros can be found in tables 32 and 33 below. Total yearly savings amount to €117,065.

Table 32

Efficiency improvement scenario 4 in hours

	Average order picking hours per day	Part of order picking that is travel time (50%)	Efficiency improvement	Efficiency improvement in hours
High season	450	225	26.6%	59.9
Off season	140	70	30.5%	21.4

Table 33

Savings scenario 4 in euros

	Saving in hours per day	Cost per hour (€)	Savings per day (€)	Savings per year (€)
High season	59.9	€15	€899	€31,465
Off season	21.4	€20	€428	€85,600

Considerations & mitigation strategies
With a smaller bin, the issue of the sorting and consolidation point as a bottleneck is mitigated. Due to their smaller size, parts of the racks can be adjusted for the small bins by approximately 25%. Since the new bins are lower, shelves can be added to racks, increasing the capacity per rack by 50%, making it exclusively for small bins. These smaller shelves would not fit a normal bin, so this adjustment should be applied to approximately 50% of the racks. During high season, 58.6% of the bins are small bins, and this allows us to maintain a buffer, as small bins will fit in a normal spot, but not vice versa. If the capacity of 50% of the racks will be increased with 50%, the total bin capacity increases with 25%. With the current capacity being 672 bins, the new capacity will be 840: 420 for all bins, 420 for small bins only. The cost components are a combination of the previous scenarios, of which the background is further explained in business case one and two. The yearly extra labor cost as a result of the increase in bins is estimated at €11,234. Due to the division of zones causing an average increase in bins of 15.4%,

the number of small bins that need to be purchased is also increased by this percentage. 2,970 bins plus 15.4% results in 3,428. The total purchase value of the bins would be 3,428 x €8 which is €27,424.

Cost-benefit analysis
In conclusion, this scenario presents the most improvement on efficiency, resulting in a yearly cost saving of €117,065. The additional labor cost due to the increased number of bins is estimated at €11,235 annually. The one-time cost for purchasing 3,428 small bins is €27,424. Therefore, the initial investment will be quickly offset by the annual savings, leading to a net positive financial impact.

Table 34

Overview savings business cases

	Cost savings (yearly)	Cost added (yearly)	One-time investment	Net savings after one year
Business case 1	€73,410	€11,235	€3,000	€59,175
Business case 2	€50,565	€0	€23,760	€26,805
Business case 3	€117,065	€11,235	€27,424	€78,406

8.Conclusion & discussion

8.1 Main findings

The main findings of this study are derived from both a literature review and a custom-made simulation model tailored to the company's specific warehouse operations. The literature review highlights travel distance as the metric for order picking efficiency. While literature brings alternative options forward, travel distance is used in most studies since it is objective and consistent. A variety of improvement policies are suggested by literature, in the categories storage assignment, batching, routing, zoning, and layout. From these categories a selection of improvement policies was made with the help of company experts, of policies that showed potential and are realistic to implement. The selected improvement policies are a new storage assignment using ABC-classification based order lines, splitting the warehouse into two zones, and the utilization of a small bin in the order picking process. Literature also emphasizes the suitability of simulation models in measuring the effectiveness of these improvement policies. To validate the theoretical findings supported by warehouse management expertise, a custom-made simulation model was developed, integrated with the company's databases. This integration enabled a highly customized analysis of warehouse and order picking efficiency based on historical data. The scenario simulations provided insights on the performance of the efficiency improvement policies. Firstly, the suggested storage assignment method did not yield any improvement in efficiency, but instead, it shows an increase in travel distance. On the other hand, splitting the warehouse into zones demonstrated a significant improvement in efficiency and revealed substantial cost-saving potential. Similarly, the introduction of small bins also showed notable improvements in efficiency and potential cost savings. Since the previously mentioned scenarios performed well, a combination of splitting the warehouse into two zones and utilizing small bins was also simulated. This combined scenario demonstrated the greatest reduction in travel distance and yielded the highest cost savings.

8.2 Conclusions

The purpose of this research is to answer the following research question: How can order picking policies be evaluated on efficiency using a simulation model to support decision making in warehouse management? This is addressed by formulating four sub questions, which are answered through the findings from the literature and the scenario simulation.

1. ***What metric(s) should be used to measure order picking efficiency in a simulation model?***

Measuring efficiency in this context involves assessing the amount of time required to pick items—the less time needed, the more efficient the process. However, using order picking time as a metric necessitates assumptions about the picking speed, which can vary among workers and across different warehouse sections (Koster et al., 2007). To avoid these assumptions, the dominant metric used in literature is travel distance. This metric is preferred over alternatives such as travel time, order throughput time, or order retrieval time. Traveling is the most time-consuming and, consequently, the costliest component of order picking, making it the focus areas for warehouse process improvement (Aboelfotoh et al., 2019; Koster et al., 2007; van Gils, et al., 2018b). Research that studied picking setups where picking time is a variable observed variations between throughput time and travel distance (Chan et al., 2011). However, for the case company being studied, this is not the case. The time spent picking items at a location is the same for all simulated policies. A simulation model can calculate the travel distance of orders based on storage locations, making it a suitable performance metric, that is in line with literature. The business cases show that decisions on order picking policies also influence variables other than travel distance, such as the number of bins. These might not directly measure the order picking efficiency, but they do have an impact on subsequent stages of the warehouse operations.

2. ***What methods to improve order picking efficiency exist, according to literature?***

In literature five key areas impacting order picking efficiency are identified: storage assignment, batching, routing, zoning, and layout, which are discussed in Chapter Two. Each of these categories has been studied, with various methods suggested to enhance efficiency. Effective strategies for storage assignment include ABC-classifications based on order volume or turnover (Chan et al., 2011). Depending on the nature of products, SKUs can also be placed in groups based on complementarity or compatibility (Liu, 1999). In the current state of the case company, these heuristics are implemented, placing SKUs in groups of similar products, or that often appear on the same order. As an alternative, a simulation was conducted where products were assigned to locations solely based on order volume. This storage assignment showed a decrease in efficiency, contrary to studies presenting this as the most effective method. It emphasizes the effectiveness of considering the complementarity of SKUs in storage assignments. Although batching methods like the seed selection rule, Iterated Local Search, and other algorithms have proven effective for specific cases, no batching method was simulated in this study (Aboelfotoh et al., 2019; Koster et al., 1999; Henn, 2012). This is due to the reliance on effective manual heuristics and the limitations of the current warehouse management system, which does not support complex clustering algorithms. Literature suggests a variety of routing policies, including the currently applied s-shape routing, of which no one best-performing is suggested (Koster et al., 2007; van Gils, et al., 2018b). The performance of a route depends on variables like the storage assignment or the zoning (van Gils, et al., 2018b). However, introduced alternatives in the past have failed due to being unable to direct the order pickers and the order pickers' tendencies to stick to familiar routes. While changing routing policies could be effective, simulation outcomes may not accurately reflect real-world behavior, which is why no alternative routing policies were simulated. Regarding warehouse zoning, literature generally agrees that splitting a warehouse into zones effectively improves efficiency (van Gils et al., 2018b; Yu & de Koster, 2009). The optimal zone configuration depends on factors such as layout and product categories (Petersen, 2002; van Gils et al., 2017). For the case company, experts helped determine the number of zones, resulting in a two-zone split. The results aligned with literature, showing an improvement in efficiency. While several layout improvement suggestions were proposed, warehouse experts confirmed that they could not be feasibly implemented in practice. The use of sub-aisles has been shown to be an effective layout method, but this is already employed by the case company (Battini et al., 2015; Koster et al., 2007). In conclusion, the literature brings forward improvement methods across various areas, among which zoning, and a storage assignment method show potential for the business case. The improvement methods suggested in the literature are complemented by an additional method proposed by the case company: the use of a small bin.

3. ***How can the suggested order picking improvement methods be evaluated in a simulation model?***

These selected improvement methods are formulated into scenarios and simulated using the model described in Chapter Five. By adjusting parameters in the model, each scenario can be simulated, with the travel distance for a specific order batch as the output. Simulating these scenarios based on multiple order files ensures robust and reliable results, also allowing for the analysis of seasonality effects and the impact on the number of bins and clusters. First the parameters for each scenario where determined. Examples of this are the new storage locations for scenario 1, that are used as input for the model, or the new capacity threshold of the small bin. For each simulation run, the appropriate parameters need to be selected. Then, the simulation is run ten times for each scenario using the same order files for each scenario. As a result, all scenario results can be compared against the same baseline. Chapter Seven analyzes the effects of the scenarios based on the travel distance metric. All three scenarios show a significant impact, with only Scenario 1 having a negative effect. To further evaluate the performance of these scenarios for the case company, business cases are developed.

4. ***How can the simulation model support warehouse managers in decision making?***

To support decision-making, the effects measured in the simulation results need to be translated into business implications. Chapter Seven discusses three business cases for the scenarios that show potential based on the simulation results. A cost-benefit analysis presents the potential cost savings and considerations for each scenario. For the business case of splitting the warehouse into two zones, the analysis considers cost savings, additional handling costs due to an increase in bins, and the required capacity expansion, resulting in an estimated net outcome of €59,175 after one year. For the business case involving the introduction of a small bin, the analysis accounts for cost savings, investment costs, and compatibility considerations, yielding an estimated net outcome of €26,805 after one year. Finally, a business cased is presented for combination of methods of business case one and two, with a net result of €87,406 after one year. Based on this, warehouse management can make informed decisions on the proposed methods.

8.3 Theoretical implications

This study validates the use of a simulation model as a robust method for evaluating effectiveness of order picking policies, aligning with existing literature(Chan & Chan, 2011; Petersen & Aase, 2004; Tsai et al., 2008; van Gils et al., 2018b). The custom-made simulation model developed for this study highlights the importance of tailoring a simulation model to a specific organizational context. In this context, this study presents a model that not only measures travel distance as a performance metric for each simulation but also incorporates additional variables that can influence decision-making. This approach contributes to existing literature, where models typically focus solely on efficiency metrics like travel distance or throughput time (Chan & Chan, 2011; Chen et al., 2010; Tsai et al., 2008). The number of clusters or the number of bins utilized are examples of such additional variables, of which the impact is demonstrated in the business cases. Furthermore, by integrating the model with the company's database, accurate and recent data can be effectively leveraged for analysis. This suggests that future theoretical work should focus on versatile, integrated simulation frameworks so accurate, up-to-date data can be utilized for decision-making. By using the actual warehouse map and historic order files, factors like seasonality are more accurately simulated compared to using data samples or fabricated data. This robustness is strengthened by the high number of simulation runs with representative datasets (n=10).

One of the policy changes of which the effect is simulated and assessed is that of utilizing a smaller bin in the order picking process. With this policy change, this research identifies a previously overlooked area for potential improvement. While picking cart capacity is mentioned as a factor impacting order picking efficiency, it does not fit one of the dominant improvement areas in existing literature (Chen et al., 2010). This study not only reaffirms its impact on efficiency but also demonstrates how changing picking cart capacity affects order processing, such as the clustering process and storage. For warehouses with a picker-to-parts system, this is crucial to consider and should therefore be added as an area of improvement. The ABC classification method based on the number of picks or other indicators proved very efficient in specific warehouses (Chan & Chan, 2011). However, this study emphasizes that factors like product categories, product type, and fluctuating demand should be considered when assigning storage locations, advocating a hybrid approach. In particular the seasonality of demand, with product groups having a high number of order lines in specific seasons, asks for more dynamic locations management. This approach could include grouping principles like compatibility and complementarity based on data and expertise (Liu, 1999). Furthermore, this study highlights the positive effect of using zones in warehouses, consistent with current literature (van Gils et al., 2018; Yu & de Koster, 2009).

8.4 Practical implications

This study presents several practical implications for warehouse management, particularly in improving order picking efficiency through the use of a simulation model and data-driven decision-making. As warehousing is a major cost driver in supply chains, and order picking is the costliest activity within warehouses, enhancing efficiency can result in significant cost savings (Koster et al., 2007; Dukic & Oluic, 2007). The simulation model developed for the case company can support warehouse management in making decision on which policies to implement. The business implications arising from suggested improvement policies are presented in the business cases in Chapter Seven. More general, this study offers practical insights into how a company can leverage its available data to enhance decision-making processes. By for example utilizing warehouse parameters and historical order data, which are all available within the company, this research demonstrates an effective application of data in decision-making. As many companies aim to become more data-driven and struggle with the how (Bean & Davenport, 2019; Gupta & George, 2016), this study presents a valuable example of how to achieve this effectively.

To confirm the validity of the results that are intended for decision-making, actual efficiency performance numbers of the implemented two-zone policy (scenario two) are compared with the simulation results. The realized efficiency performance, as detailed in attachments IV and V, aligns with the simulation results. Actual measurement in the warehouse of the case company in off season showed an efficiency improvement of 21.6%, compared to a 20.1% improvement in the simulation. The increase in bins showed a more divergent, but beneficial effect, namely an 10.0% increase compared to a 18.5% increase in the simulation. Especially the efficiency improvement demonstrates the accuracy of the simulation model, making it suitable for warehouse management for decision-making.

8.5 Limitations & future research

This research is conducted in the specific context of case company XYZ. Where general implications regarding the use of simulation models for order picking efficiency are presented, the results and conclusions drawn from the simulation are influenced by the unique characteristics of the case company. These include the market the company is operating in, the layout of the warehouse, the type of products, etc. This limits the generalizability for other companies. Furthermore, this study does not consider human factors like adherence to picking procedures or order picking experience. All assumption that are in the model that could influence the real-world applicability of the results are listed in chapter 5.3.

Future research could include further developing the model, making it able to simulate an even wider set of policies. Since the simulated storage assignment scenario showed ineffective, alternative storage assignment methods could be explored, combining the expertise of warehouse management and SKU analysis to determine an optimal assignment. The current state of the case company's storage assignment performs well, so the principles used to assign locations cannot be ignored. To optimize this process, a data mining-based algorithm that extracts and analyzes the associations between different products could be explored (Pang & Chan, 2017). A method that examines the correlations among items picked in an order could also be effective for this type of stock, considering not only individual items but groups of items are required (Zhang et al., 2019). Additionally, given the seasonality of the demand, dynamic storage could be explored, where SKUs don't have a dedicated storage location. Research on clustering methods can be included for this case company, exploring advanced methods. While the current setup does not support this, it may be possible in the future. The same holds for strategically managing peak periods by changing policies in high- and off season. The results indicate that policy performance varies across these periods, suggesting the need for a dynamic approach to determine which policies to implement at different times.

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Appendix I: Information in order file (columns)

Information in order file (columns):

Cluster

Dataareaid

Einde werkregel

Gebruiker

Gebruiker naam

Inventdimid

Locatie

Locatie_sleutel

Magazijn

Modifieddatetime

Nummerplaat-id

Cluster

Sectie Sleutel

Start werkregel

Werk-id

Werkgroep-id

Werkklasse-id

Werkordertype

Werkstatus

Werktype

Zending

Gewicht

Index

Partition

Qtywork

Recid

Volume

Appendix II: Classed based storage assignment model input snippet
Class based storage assignment model input snippet:

location	zone	code
2A01A1	A	015003
2A01A2	A	081061
2A01A3	A	061065
2A01B1	A	165020
2A01B2	A	081060
2A01B3	A	075004
2A03A1	A	165021
2A03A2	A	080058
2A03A3	A	081070
2A03B1	A	061240
2A03B2	A	165022
2A03B3	A	165023
2A05A1	A	080333
2A05A2	A	080029
2A05A3	A	025055
2A05B1	A	080184
2A05B2	A	080023
2A05B3	A	061006
2A07A1	A	061004
2A07A2	A	061012
2A07A3	A	165050
2A07B1	A	752506
2A07B2	A	080182
2A07B3	A	080063
2B01A1	A	061014
2B01A2	A	061010
2B01A3	A	139002
2B01B1	A	061007
2B01B2	A	061002

2B01B3	A	061001
2B02A1	A	061008
2B02A2	A	084013
2B02A3	A	061005
2B02B1	A	061016

Appendix III: T-test results scenarios

Paired t-test scenario 1

data: datascenario1$currentstate and datascenario1$scenario1

t = -4.1244, df = 9, p-value = 0.002581

alternative hypothesis: true mean difference is not equal to 0

95 percent confidence interval: -19868.394 - -5793.406

sample estimates:mean difference -12830.9

Paired t-test scenario 2

data: data$currentstate and data$scenario3

t = 5.8891, df = 9, p-value = 0.0002322

alternative hypothesis: true mean difference is not equal to 0

95 percent confidence interval: 3754.544 - 8438.056

sample estimates: mean difference 6096.3

Paired t-test scenario 3

data: data$currentstate and data$scenario4

t = 6.3902, df = 9, p-value = 0.0001267

alternative hypothesis: true mean difference is not equal to 0

95 percent confidence interval: 2812.273 - 5894.527

sample estimates: mean difference 4353.4

Paired t-test Scenario 4

data: combinedscenario$cs and combinedscenario$scenario

t = 6.0346, df = 9, p-value = 0.0001941

alternative hypothesis: true mean difference is not equal to 0

95 percent confidence interval: 6653.862 - 14633.938

sample estimates: mean difference 10643.9

Appendix IV: Realized efficiency data order picking scenario 2

Date	Average order lines picked per hour	Hours needed for 1000 orderlines	Policy
27-feb	34	29,4	one zone
28-feb	41	24,4	one zone
29-feb	38	26,3	one zone
01-mrt	32	31,3	one zone
04-mrt	43	23,3	one zone
05-mrt	43	23,3	one zone
06-mrt	38	26,3	one zone
07-mrt	39	25,6	one zone
08-mrt	35	28,6	one zone
11-mrt	43	23,3	one zone
12-mrt	38	26,3	one zone
13-mrt	43	23,3	one zone
14-mrt	38	26,3	one zone
15-mrt	34	29,4	one zone
18-mrt	35	28,6	one zone
19-mrt	28	35,7	one zone
20-mrt	41	24,4	one zone
21-mrt	29	34,5	one zone
22-mrt	37	27,0	one zone
26-mrt	46	21,8	two zones
27-mrt	44	23,0	two zones
28-mrt	45	22,2	two zones
29-mrt	98	10,2	two zones
02-apr	72	13,9	two zones
03-apr	42	24,0	two zones
04-apr	43	23,2	two zones
05-apr	54	18,6	two zones
06-apr	37	27,3	two zones
08-apr	46	21,9	two zones
09-apr	43	23,1	two zones
10-apr	39	25,8	two zones
11-apr	41	24,4	two zones
12-apr	51	19,6	two zones

Appendix V: Realized data bin utilization scenario 2

Date	Average order lines per bin	Bins per 1000 order lines	Policy
27-feb	3,35	298,51	one zone
28-feb	3,35	298,26	one zone
29-feb	3,30	302,67	one zone
01-mrt	3,12	320,83	one zone
04-mrt	2,93	341,10	one zone
05-mrt	3,30	303,35	one zone
06-mrt	3,21	311,26	one zone
07-mrt	3,23	309,17	one zone
08-mrt	3,02	331,02	one zone
11-mrt	2,94	340,52	one zone
12-mrt	3,09	323,94	one zone
13-mrt	3,14	318,19	one zone
14-mrt	3,21	311,39	one zone
15-mrt	3,05	327,55	one zone
18-mrt	3,09	323,15	one zone
19-mrt	3,11	321,21	one zone
20-mrt	3,04	328,70	one zone
21-mrt	3,15	317,02	one zone
22-mrt	2,87	348,83	one zone
26-mrt	2,58	388,34	two zones
27-mrt	2,48	402,73	two zones
28-mrt	2,90	345,22	two zones
29-mrt	2,74	365,41	two zones
02-apr	2,77	360,95	two zones
03-apr	2,88	347,51	two zones
04-apr	3,06	326,80	two zones
05-apr	2,87	347,89	two zones
06-apr	3,71	269,80	two zones
08-apr	2,74	364,32	two zones
09-apr	3,01	332,45	two zones
10-apr	2,67	374,36	two zones
11-apr	2,85	350,85	two zones

Appendix VI: SQL Code Snippet

SQL Code Snippet

```
if OBJECT_ID('tempdb..#tmp_hulptabel_zending_sectie') is not null drop table
#tmp_hulptabel_zending_sectie

select a.*,ROW_NUMBER() over (order by zending) as index_zending  into
#tmp_hulptabel_zending_sectie

from

(select distinct zending,

Sectie_scenario as sectie

,count(*) over (partition by zending,sectie_scenario) as [aantal regels] from
#tmp_update ) as a

--select * from #tmp_hulptabel_zending_sectie --where zending = 'Z2206080'
--order by zending

if OBJECT_ID('tempdb..#tmp_bakken') is not null drop table #tmp_bakken

        Create table #tmp_bakken
        (Zending nvarchar(15), Sectie nvarchar(10) ,[index] int, gewicht
float,som_gewicht float, volume float, som_volume float, bak int, indicator int,
        locatie nvarchar(10), Locatie_sleutel nvarchar(4), zone nvarchar(2),
sorteercode int, [wave-id] nvarchar(12), [wave naam] nvarchar(30), recid bigint,
        qtywork float, volume_per_qty float, gewicht_per_qty
float,volume_restant float, gewicht_restant float, qty_erbij float,
qty_erbij_volume float, qty_erbij_gewicht float ,qty_restant float
        )

truncate table #tmp_bakken

        Declare @volume float
        Declare @som_volume float
        Declare @gewicht  float
```

```
        Declare @som_gewicht  float
        Declare @index int = 1
        Declare @index_zending int = 1
        Declare @max_index int --= 17
        Declare @max_index_zending int = 100
        Declare @bak int = 1
        Declare @max_volume float = 0.0313-- 0.0313 --0.05
        Declare @max_gewicht float = 10
        Declare @Indicator int
        Declare @Indicator_splitsen int

        Declare @zending nvarchar(15)
        Declare @Sectie nvarchar(5)
        Declare @sorteercode int
        Declare @locatie nvarchar(10)
        Declare @locatie_sleutel nvarchar(4)
        Declare @zone nvarchar(2)
        --Declare @start_werkregel datetime = '2024-01-01 08:00:00'
        Declare @wave_id nvarchar(12)
        Declare @wave_naam nvarchar(30)
        Declare @recid bigint
        Declare @qtywork float
        Declare @volume_per_qty float
        Declare @gewicht_per_qty float
        Declare @volume_restant float = 0
        Declare @gewicht_restant float = 0
        Declare @qty_erbij_volume float
        Declare @qty_erbij_gewicht float
        Declare @qty_erbij float
        Declare @qty_restant float



        select @max_index_zending = max(a.index_zending) from
#tmp_hulptabel_zending_sectie a

        while (@index_zending<=@max_index_zending)
        begin
```

```
        select @zending=a.zending, @sectie=a.sectie,@max_index=a.[aantal regels]
from #tmp_hulptabel_zending_sectie a where a.index_zending=@index_zending
        --print(@zending+'-'+@sectie)

            while (@index is not null and @index <=@max_index)
                    Begin

                        select

                        @gewicht=a.Gewicht,
                        @volume=a.Volume,
                        @locatie=a.Locatie,
                        @locatie_sleutel=a.Locatie_sleutel,
                        @zone=left(a.locatie_sleutel,2),
                        @sorteercode=a.sorteercode,
                        @wave_id=a.[Wave-id],
                        @wave_naam=a.[Wave naam],
                        @recid = a.recid,

                        @qtywork = a.Qtywork,
                        @volume_per_qty = a.volume/a.qtywork,
                        @gewicht_per_qty = a.gewicht/a.qtywork

                        from #tmp_update a

                        where a.Zending=@zending and Sectie_scenario =@Sectie
and Index_scenario=@index

                        --set @som_gewicht = isnull(@som_gewicht,0) +
isnull(@gewicht,0)
                        --set @som_volume =  isnull(@som_volume,0) +
isnull(@volume,0)
                        --set @indicator = case when @som_gewicht>@max_gewicht
or @som_volume>@max_volume then 1 else 0 end
                        set @indicator = case when ( isnull(@som_gewicht,0) +
isnull(@gewicht,0))>@max_gewicht or (isnull(@som_volume,0) + isnull(@volume,0)
)>@max_volume then 1 else 0 end
                        set @volume_restant = case when @Indicator = 1 then
@max_volume- @som_volume end
```

```
                        set @gewicht_restant = case when @Indicator = 1 then
@max_gewicht- @som_gewicht end

                        Set @qty_erbij_volume = case when floor(@volume_restant
/ @volume_per_qty)<@qtywork then floor(@volume_restant / @volume_per_qty) else
@qtywork end
                        Set @qty_erbij_gewicht = case when
floor(@gewicht_restant / @gewicht_per_qty)<@qtywork then floor(@gewicht_restant
/ @gewicht_per_qty) else @qtywork end
                        set @qty_erbij = case when
@qty_erbij_gewicht<@qty_erbij_volume then @qty_erbij_gewicht else
@qty_erbij_volume end

                        set @Indicator_splitsen = case when @qty_erbij > 0 and
@qty_erbij< @qtywork then 1 else 0 end

                        set @volume = case when @Indicator_splitsen=1 then
@qty_erbij*@volume_per_qty else @volume end
                        set @gewicht = case when @Indicator_splitsen=1 then
@qty_erbij*@gewicht_per_qty else @gewicht end
                        Set @qty_restant = case when @Indicator_splitsen =1 then
@qtywork - @qty_erbij else 0 end
                        set @qtywork = case when  @Indicator_splitsen=1 then
@qty_erbij else @qtywork end

                        set @som_gewicht = isnull(@som_gewicht,0) +
isnull(@gewicht,0)
                        set @som_volume =  isnull(@som_volume,0) +
isnull(@volume,0)



                        --set @volume_restant = case when @Indicator = 1 then
@som_volume end

                        If @Indicator = 1 and @Indicator_splitsen=0

                        begin

                            set @som_volume = @volume
```

```
                                set @som_gewicht = @gewicht
                                set @bak = @bak + 1

                        end

                         --insert into #tmp_bakken select
@zending,@Sectie,@index,@gewicht,@som_gewicht,@volume,@som_volume,@bak,
@Indicator,
@locatie,@locatie_sleutel,@zone,@sorteercode,@wave_id,@wave_naam,@recid
                         insert into #tmp_bakken select
@zending,@Sectie,@index,@gewicht,@som_gewicht,@volume,@som_volume,@bak,
@Indicator,
@locatie,@locatie_sleutel,@zone,@sorteercode,@wave_id,@wave_naam,@recid,@qtywork
,@volume_per_qty,@gewicht_per_qty,@volume_restant,@gewicht_restant,@qty_erbij,@q
ty_erbij_volume,@qty_erbij_gewicht,@qty_restant
                         --Print convert(varchar,@index)+' test
'+convert(varchar,isnull(@som_gewicht,0))

                                If @Indicator = 1 and @Indicator_splitsen=1
                        begin
                        set @som_gewicht = 0
                        set @som_volume = 0

                        while @qty_restant > 0

                                begin

                                set @bak = @bak + 1
                                Set @volume_restant=@max_volume
                                Set @gewicht_restant=@max_gewicht

                                Set @qty_erbij_volume = case when
floor(@volume_restant / @volume_per_qty)<@qty_restant then floor(@volume_restant
/ @volume_per_qty) else @qty_restant end
                                Set @qty_erbij_gewicht = case when
floor(@gewicht_restant / @gewicht_per_qty)<@qty_restant then
floor(@gewicht_restant / @gewicht_per_qty) else @qty_restant end
```

```
                                set @qty_erbij = case when
@qty_erbij_gewicht<@qty_erbij_volume then @qty_erbij_gewicht else
@qty_erbij_volume end

                                set @volume = @qty_erbij*@volume_per_qty
                                set @gewicht = @qty_erbij*@gewicht_per_qty

                                set @som_gewicht = isnull(@som_gewicht,0) +
isnull(@gewicht,0)
                                set @som_volume =  isnull(@som_volume,0) +
isnull(@volume,0)
                                Set @qty_restant = @qty_restant - @qty_erbij
                                Set @qtywork=@qty_erbij

                                insert into #tmp_bakken select
@zending,@Sectie,@index,@gewicht,@som_gewicht,@volume,@som_volume,@bak,
@Indicator,
@locatie,@locatie_sleutel,@zone,@sorteercode,@wave_id,@wave_naam,@recid,@qtywork
,@volume_per_qty,@gewicht_per_qty,@volume_restant,@gewicht_restant,@qty_erbij,@q
ty_erbij_volume,@qty_erbij_gewicht,@qty_restant

                                end
                        end

                         set @index = @index + 1
                         --set
@start_werkregel=Dateadd(second,1,@start_werkregel)

                    end

                set @index_zending=@index_zending+1
                set @index=1
                set @bak=1
                set @som_gewicht=0
                set @som_volume=0

        end
```