Analysis of the performance of the order picking process in an e-fulfilment centre: seasonal influences on regular versus peak periods

An application to an e-commerce company

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TU Delft

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Analysis of the performance of the order picking process in an e-fulfilment centre: seasonal influences on regular versus peak periods

An application to an e-commerce company

By

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Preface

The aim of this master thesis is to gain insight into the seasonal impact of customer orders on the performance of the order picking process. This study is conducted on behalf of an e-commerce company in association with the Delft University of Technology. With this thesis, I conclude the master program *Transport, Infrastructure and Logistics* at the faculty of Civil Engineering and Geosciences at the Delft University of Technology.

I would like to express my gratitude to everyone who helped me during my master thesis. First of all, I would like to thank my graduation committee for their guidance and feedback. I would like to thank prof. dr. ir. Alexander Verbraeck, the chairman of my committee, for helping me out with the discrete event simulation tool Simio. I would like to thank ir. Mark Duinkerken and dr. Bart Wiegmans, the daily supervisors of my committee, for all advices, feedback and talks during the project. Finally, I would like to thank my external supervisor for her help with the case study related aspects and her support during the entire master thesis.

In really enjoyed my bachelor *Industrial Design Engineering*, my bridging year at *Civil Engineering* and my master *Transport, Infrastructure and Logistics* at the Delft University of Technology. The interest and the variety in obtained knowledge kept me motivated. I am glad I made the switch, and I am proud of what I have accomplished during this graduation process, a period of discovering interesting fields while overcoming setbacks and achieving goals. After this intensive process, I am happy that I can change my status as an intern to a consultant at a consultancy company.

Elise Gelder
Delft, 2018

Executive summary

The order picking process is often done manually by pickers. Because this process is done item by item, it is a labour-intensive process. According to Dukic & Oluic (2005), 50% of the total order picking time is spent on unproductive traveling. The operations that need to be performed in warehouses are highly dependent on the customer demand. The customer demand shows seasonal patterns spread over the year caused by so-called seasonal influences. An increase in customer orders results in more items that need to be handled in the Fulfilment Centre (FC). During peak periods, the amount of orders increases and the composition of orders often differs from the composition of orders on a regular day. The **objective** of this research was to investigate and identify the opportunities and possibilities regarding the order picking process to react to the seasonal impact that influences the productivity of order picking. The **main research question** of this thesis is formulated as follows:

''How can the performance of the order picking process be improved taking seasonal influences into account for regular and peak periods?"

Internet fulfilment warehouses are designed to exclusively process online retail orders and can be identified by extensive storage, very large number of storage locations, bins with commingled SKUs, immediate fulfilment, short picking routes with single unit picks and high transactions with total digital control. These characteristics lead to order preparation in consumer units, high number of items within one order, high number of order lines within one order, high variation in sizes and weights of products and a high variation in fragility constraints of products. The storage area is the working area in a FC where the items are stored. In this study the randomized storing concept is assumed, where all items are stored randomly from all suitable empty shelve locations with an equal probability. When the customer has placed an order, the order picking process can be performed in the storage area. Order picking can be described as *a warehouse process of retrieving products from storage in response to specific customer request and bringing them to an area dedicated for collecting the assembled customer orders.* Order picking can be performed in a variety of Order Picking Systems (OPS). This study focusses on the lower automatization level of pick-and-sort batch picking using a picker-to-parts system. Here, order picking is done by operators and picking and sorting are processed independently. The orders are picked parallel, which means that the orders are divided over batches, and one batch, consisting of multiple(partial) orders, is handled by one operator in one zone.

The order picking performance is measured by the total cycle time of order picking. The processing time can be simplified into four elements: travel time, search time, pick time, and set up time. According to literature, the travel time consumes the major proportion. For measuring the total throughput time of order picking, the processes are simplified into three steps with sub-steps as visualised in Figure 0.1. Other performance measures are costs, utilization of the totes, and the walking distance of the picker.

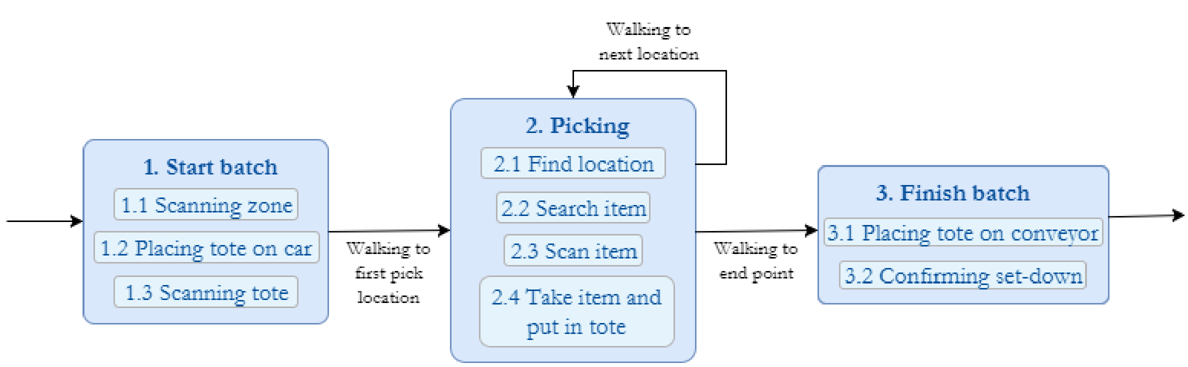

Figure 0.1: Overview of order picking processes

With the aim of improving the picking process, an insight of demand profiles in certain time series and order characteristics have been obtained. The most suitable method to perform the analysis is the decomposition model with multiplicative seasonal-adjustment. The model has decomposed the time series of historical data into trend, seasonality and noise. The decomposition was done for daily, weekly, and monthly patterns. The analysis gave insight into the behaviour of the number of orders and items, items per order, weight and volume per item, and the items per category. This analysis resulted into a clear distinction between regular and peak periods, used for setting up design alternatives (see Table 0.1).

Table 0.1: Overview seasonal influences analysis

	General	**Regular period**	**Peak period**
Number of orders	Improved efficiency in fulfilling mono-orders is necessary. Multi-orders form largest picking volume.	Number of orders is dependent on sales and releases.	More orders in peak periods lead to more picks in FC.
Number of items	Multi-orders cause higher number of items that need to be picked.	Number of items is dependent on sales and releases.	More multi-orders, amplified number of items during peak.
Items/order	More items/order in total leads to more picks.	Most of orders are mono-orders.	More items per order.
Weight/item	More items per batch can be picked when there is a decrease in weight/item	During regular period (May, June, July), higher weight/item, less items/batch, more travel time per item.	During peak lower weight/item, more items/batch, less travel time per item.
Volume/item	More items per batch can be picked when there is a decrease in volume/item	During regular period (May, June, July), higher volume/item, less items/batch, more travel time per item.	During peak lower volume/item, more items/batch, less travel time per item.

The alternatives are based on some primary interdependent policies proposed in the study of Wascher (2004): *storage policy, routing policy, zoning policy, and order consolidation policy*. The three design alternatives in this study are:

- class-based randomized storage,
- volume-based randomized storage, and
- zone decomposition.

The performance evaluation of the different alternatives was accomplished through the use of a verified and validated simulation model. These alternatives are tested for both regular and peak periods, compared to a base alternative which represents the current situation. The configuration variables are scenario-based picklists and the ratio of experienced versus inexperienced pickers. These are used in order to create the different scenarios while the KPIs serve as a measure of the success in meeting the requirements of the alternatives. The KPIs are cycle picking time and the variable order picking (labour) costs. Both KPIs need to be minimized for optimizing the order picking performance. The utilization of the tote and the travel distance are measured as well. The utilization of the tote needs to be maximized, while the travel distance is preferred as short as possible.

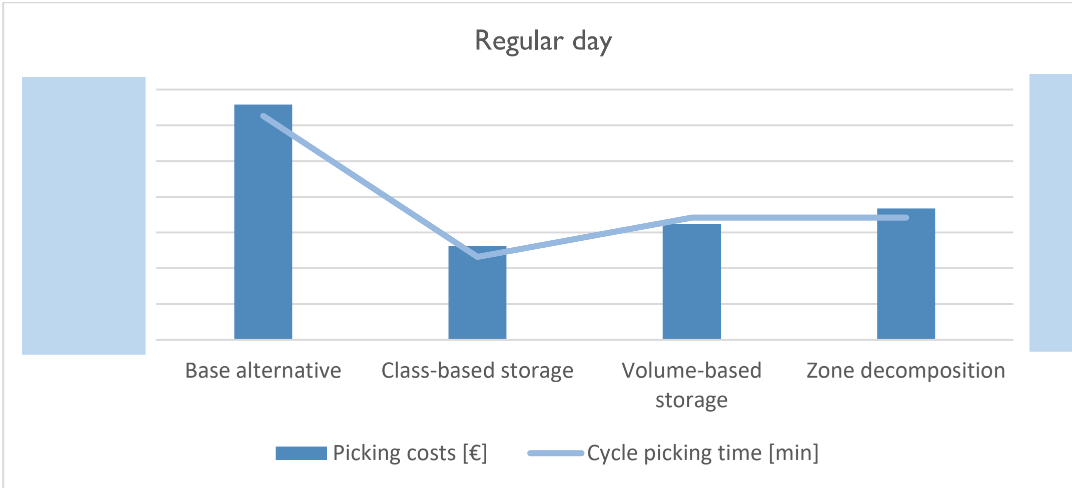

Figure 0.2: KPI overview on a regular day

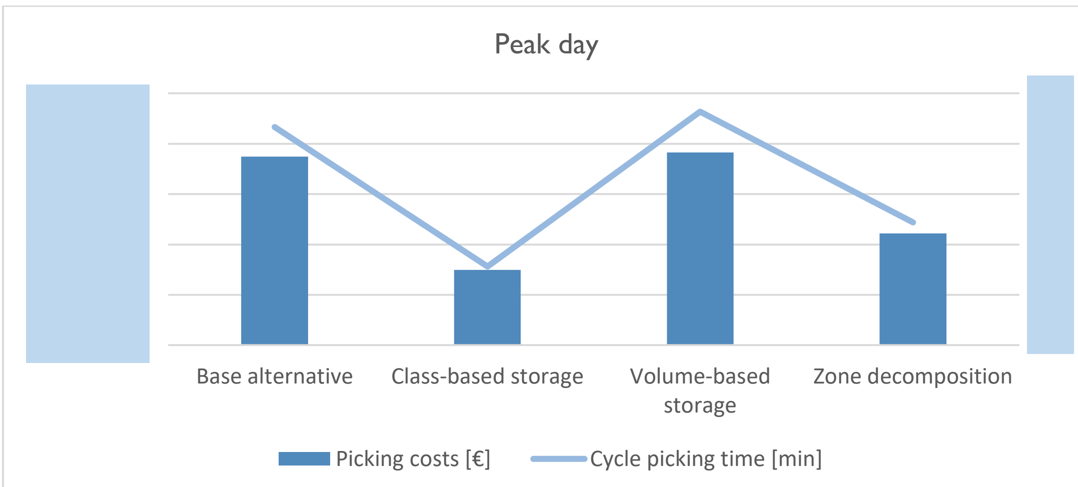

Figure 0.3: KPI overview on a peak day

As can be seen in Figure 0.2 and Figure 0.3, all three design alternatives seem to be promising for future order picking operations compared to the base alternative. The results of this study almost seem to be too good to be true. However, the results of this study show that major savings can be reached changing the order picking strategy in general. For companies, focusing on the reduction of travel distance of the operators can lead to more efficient processes in the fulfilment centre and in the end cause a decrease in labour costs. The three design alternatives proposed in this study all cause savings and faster fulfilment on yearly basis. This means that implementing the alternatives, less pickers are needed during the order picking process. On future's perspective, the fulfilment centre will be able to process all orders taking growth into account.

It is recommended for the company of the case study, to implement the class-based randomized storing policy. Implementing class-based randomized storage, both cycle picking time and travel distance decrease significantly, and therefore a major decrease in variable labour costs will occur. This can be seen in Figure 0.2 and Figure 0.3. On yearly basis, the order picking costs decrease with 12%. Overall, the variable labour costs off all processes within an e-commerce fulfilment centre, will decrease approximately by 1%. Looking at cycle time and travel distances, even higher savings can be obtained in future operation by deploying the zone decomposition dynamically during peak periods. This means that during peak periods, zones are dynamically divided into two sub-zones causing a decrease in travel distance between picks, leading to lower cycle picking times. In respect to the savings calculated for 2018, even higher savings can be obtained for the upcoming years, when the growth in customer orders is taken into account.

In future research, it is recommended that the order consolidation policy, together with the routing policy will be optimized as well. An even higher decrease in travel distances (and therefore cycle picking times) can be obtained implementing a suitable shortest path algorithm. This calculates the shortest path between the items that need to be picked. Another interesting improvement can be changing tote types and sizes for order picking to increase the tote utilization.

Keywords: order picking, e-fulfilment centre, seasonal influences, time series analysis, cycle picking time, case study, discrete event simulation

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Abbreviations

ADR	'Accord européen relatif au transport international de marchandises Dangereuses par Route'
B2C	Business to consumer
DC	Distribution centre
FC	Fulfilment centre
FCFS	First come, first serve
FMCG	Fast mover consumer goods
I/O	Input and output
IFW	Internet fulfilment warehouse
KPI	Key performance indicator
OBP	Order batching problem
OPS	Order picking system
SFC	Spacefilling Curves
SKU	Stock keeping unit
SMCG	Slow mover consumer goods
SMD	Sequential minimal distance
WCS	Warehouse control system
WMS	Warehouse management system

Chapter 1 Introduction

The business to consumer (B2C) e-commerce market keeps growing. In 2016 the Dutch online sales grew by 23% compared to 2015 (Thuij, 2017). This growth can be explained by the growing economy, an increase in the trust of consumers and disappearing retailers in the shopping districts. Internet retail is generally described as the online marketing and sale of products directly to the consumer (Onal, Zhang, & Das, 2017). The main disadvantage of online retailers, compared with traditional retailers, is immediacy: while the product can immediately be taken home after purchasing in a physical store, the customer must wait for the shipment to arrive in the case of e-commerce (Gong, Winands, & De Koster, 2010). As a result, the time available for processing and delivering an order is shortening. According to Lee & Whang (2001) order fulfilment, "the last mile of e-commerce", is among the most crucial elements of e-commerce, and "the most expensive and critical operation" for companies engaged in e-commerce. In internet retail, the main physical process is e-fulfilment, which typically involves a large fulfilment warehouse (Onal, Zhang, & Das, 2017).

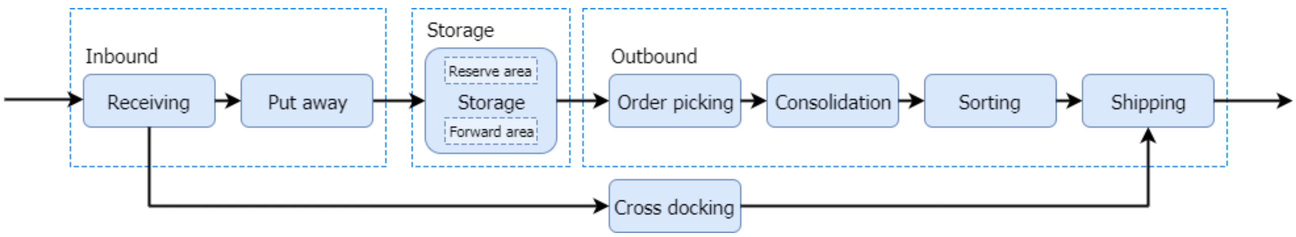

Figure 1.1: Warehouse processes (source: Rouwenhorst et al. (1999))

The flow of items through such a large fulfilment warehouse can be divided into several processes (see Figure 1.1). The processes are explained in detail in Appendix B3. The main difference between a warehouse in a distribution centre (DC) and a fulfilment centre (FC) is that the DC its customers are retail shops (or other businesses) and the FC its customer are the consumer and retail shops. This leads to differences in the presence of the order preparation in consumer units, the high number of items within one order, the high number of order lines within one order, the high variation of sizes and weights of products and the high variation in fragility constraints of products (Lee & Whang (2001)).

The process of order picking is the most labour-intensive and time-consuming warehouse operation, especially within manual warehouses (Giannikas, Lu, Robertson, & McFarlane, 2017). The costs of order picking are estimated to be as much as 55% of the warehousing costs (De Koster, Le-Duc, & Roodenbergen, 2007). This is a large part due to the fact that order picking requires the involvement of human order pickers, as automating order picking systems necessitates large investments (Henn, Koch, & Wascher, 2012). Because of this, order picking has in recent years become an area of increased interest for improving the productivity in warehouses (De Koster, Le-Duc, & Roodenbergen, 2007).

Order picking is a warehouse function dealing with the retrieval of items from their storage locations in order to satisfy a given demand specified by customer orders (Petersen & Schmenner, 1999) (Murray, 2017). The occurrence of it happens because incoming articles are received and stored in large volume unit loads while customer orders comprise small volumes of different articles. A prime objective is to shorten throughput times for order picking, and to guarantee the meeting of due times for shipment departures (Tarn et al. (2003)).

Within warehouses, the main goal is to keep the order fulfilment quality high, which means that accuracy of the processes is necessary. It is difficult to assure a high order fulfilment quality at peak moments. On busy days often more than 6 customer orders per second have to be processed and therefore a suitable order picking strategy becomes more and more important. The order picking process is done in the storage area. When orders are made by the customer, the warehouse management system (WMS) prepares the order picking process and makes a planning combining several orders. The orders are grouped in batches to be picked. The orders are completed in multiple totes. The operator stays in the same zone and each zone is picked by another operator.

1.1 Problem identification

The order picking process often is done manually by pickers. Because this process is done item by item, it is a labour-intensive process. According to Dukic & Oluic (2005), 50% of the total order picking time is spent on unproductive traveling. The operations that need to be performed in warehouses are highly dependent on the customer demand. A higher customer demand causes an increase in customer orders, and that results in more items that need to be handled in the FC. During peak periods, the amount of orders increases and the composition of orders often differs from the composition of orders on a regular day.

E-commerce companies have to deal with several seasonal influences a year, because of their wide assortment of products (think of garden articles in spring and Christmas presents in December). In these peak periods, the amount of items that need to be treated increases. Since the number of pickers can be changed depending on the amount of items that need to be picked, the performance of order picking is an important factor to keep the process efficient. With performance is meant the accomplishment of a given task measured against pre-set known standards of accuracy, completeness, cost, and speed (Performance, 2017).

1.2 Case study

In the problem identification an e-commerce company that has to deal with the seasonal influences is described. The company that is used as a case study in this research is a well-known web shops in the Netherlands. The company had an assortment of more than million products. A more comprehensive description of the company is given in Appendix B. The company has its own fulfilment centre for item fulfilment. Processes within the FC, are analysed, seasonal influences are treated with data of this company, and the company setting the boundaries of this study.

1.3 Scope of the research

In order to keep the project manageable, a scope is set to determine the boundaries of the research of this project. This study focusses on the performance of manual order picking within a fulfilment centre processing customer orders. The order picking strategy is assumed to be picker-to-part and parallel picking is performed. The layout of the warehouse is assumed to be divided into multiple zones, each zone existing of one I/O (input and output) point, two cross aisles (front- and back-cross aisle), a middle aisle and multiple picking aisles, based on the layout of the FC. The warehouse only processes products that fits within the totes used. One type of tote is used. The data from the December 2015 until June 2017 is used to analyse the current situation related to order picking and the seasonal influences on orders.

1.4 Research objective and questions

A warehouse has to deal with multiple seasonal influences spread over the year. In peak periods much more orders need to be processed in comparison to the rest of the year and the composition of the orders differs compared to the composition of regular orders. At the moment, there is not enough insight into the characteristics of orders during the peak itself, such as the amount of items within an order and the volume of the items. Therefore, it is not known how exactly to react to and how to keep the performance of order picking high during the peak periods.

The **objective** of this research is to investigate and identify the opportunities and possibilities regarding the order picking process to react to the seasonal impact that influences the productivity of order picking. This research fills the gap in literature as it captures the change in the composition of orders and the adapted handling of items during the order picking process in peak periods. The results of this study will be used to prove a solution on how to develop the performance of the order picking process for future peak periods.

In order to contribute to the research objective, several research questions will be answered. The **main research question** of this thesis is formulated as follows:

''How can the performance of the order picking process be improved taking seasonal influences into account for regular and peak periods?''

The **sub research questions** that are needed to answer the main question are stated below:

1. What different seasonal, monthly, and weekly influences can be differentiated, and when do they occur?
2. What are the characteristics of orders during peak periods compared to regular orders?
3. What are possible policies proposed in theories for improving the order picking performance?
4. What are design alternatives that can be generated in order to improve the performance of order picking during peak periods?
5. What alternative is most promising in the case of improving order picking during peak periods?

1.5 Research methodology

In order to answer the main research question, the sub questions need to be answered. Therefore, an appropriate systematic methodology has been set up. The research methodology which is used in this study is described below and visualised in Figure 1.2.

- **Problem identification and definition:** In the first phase of this study, the problem and objective were identified, together with the research scope. In addition, the main research question together with different sub research questions, that will be answered in this study, were formulated.

- **System description:** In the second part, a system description is given to get more insight into the system and all processes in an e-fulfilment centre regarding and influencing the order picking process. The boundaries of this research are set. The performance indicators interesting for this study are introduced.

- **Background analysis:** In the background analysis the seasonal patterns together with the characteristics of orders are identified. First, a method of decomposing time series is chosen, and then the data analysis is performed. The analysis leads to a better insight of the problem and the characteristics of regular versus peak periods are determined and compared.

- **Optimization theory:** For analysing the optimization theory, first key performance indicators and requirements are defined based on the results of the system boundaries and the background analysis. Then, a literature review is done for identifying the manual order picking processes and for analysing different theories and practices regarding improving the performance of the order picking process. After reviewing the theory of literature reviews, alternatives are identified. The alternatives can be tested based on the key performance indicators and requirements using a model.

- **Conceptual model and implementation:** For testing the alternatives based on the theories found in literature reviews, a conceptual model is elaborated based on the system description and boundaries of this study, together with some theories. Then, the model implementation is done by performing calculations and simulations.

- **Results:** A part of the model is calculated by using some equations. The rest is simulated in a discrete event simulation to test and evaluate the behaviour and achievements of the design alternatives. Based on these calculations and simulations, an evaluation of the design alternatives is made and further conclusions are drawn.

- **Conclusion, discussion, and recommendations:** The aim of the conclusion is to provide an answer to the main research question formulated in the problem identification of this study. The discussion reflects on possible estimations and assumptions made in the model and the influences of it on the results. At last, recommendations are given for the company and for further research.

1.6 Thesis outline

In Chapter 1, the problem and objective were identified and research questions were formulated. Chapter 2 will focus on the system and the description of it, and in Chapter 3 the background analysis is performed. Then, Chapter 4 discusses several optimization theories and alternatives are identified. In Chapter 5, a conceptual model is elaborated and implemented. In Chapter 6, the results of the modelled design are discussed. In the last chapter, Chapter 7, the conclusion, discussion, and recommendation are made.

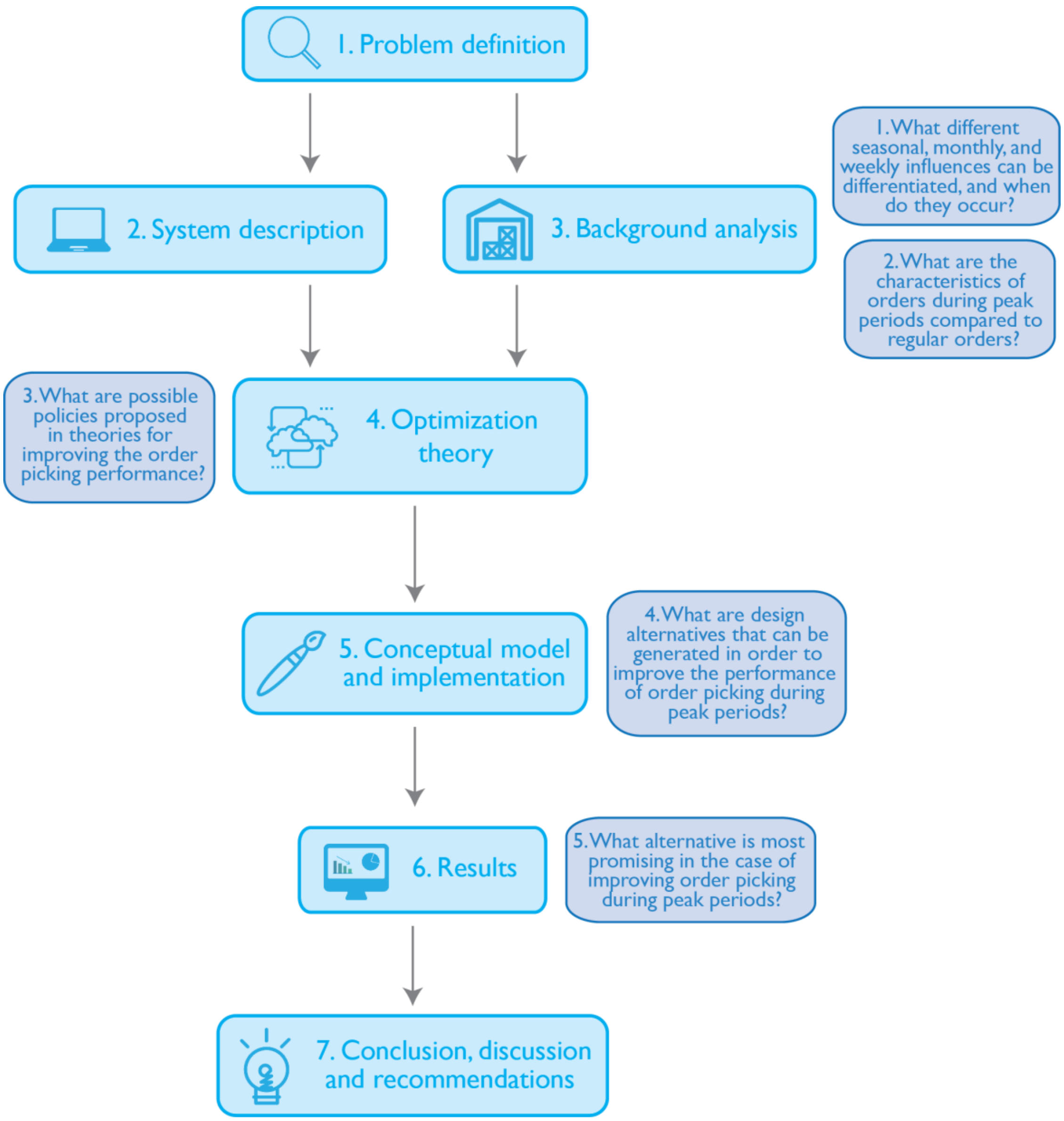

Figure 1.2: Visualization of the research methodology (source icons: flaticon)

Chapter 2 Order picking system for e-fulfilment

In this chapter first different order picking systems in e-commerce explained in literature are discussed. Based on these theories, the system of this study is defined.

2.1 The FC storage area for e-fulfilment

Internet fulfilment warehouses (IFW) are designed to exclusively process online retail orders. An observational study of Onal et al. (2017) reveals that IFW operating and design attributes are significantly different from traditional warehouses in their storage and fulfilment policies. Six differentiators can be identified: explosive storage, very large number of storage locations, bins with commingled SKUs, immediate fulfilment, short picking routes with single unit picks and high transactions with total digital control. This leads to differences in the presence of the order preparation in consumer units, the high number of items within one order, the high number of order lines within one order, the high variation in sizes and weights of products and the high variation in fragility constraints of products (Lee & Whang, 2001).

The storage area is one of the working areas in a fulfilment centre. Other working areas in an IFW that can be divided are the receiving area, packing area, and the shipping area. In the storage area, the items that need to be stocked (both short-term and long-term), need to be assigned to storage locations in the storage area. These items are waiting here to be picked when a customer orders a specific item. In literature, much is discussed about the storage of items. Different aspects can be explained. The first aspect is the design of the storage area. Next, the items that need to be stored can be explained. At last, the different storage concepts within the storage area are discussed.

2.1.1 Design of storage area

The design of a storage area is intended to capture the dimensions of the building of the fulfilment warehouse together with the layout of the storage area. According to Rouwenhortst et al. (1999), in a framework, the design of the storage area can be determined, based on dimensions of the storage systems, the number of material handling equipment, and the organizational design including dimensioning of picking zones and the selection of a storage concept. The review of Gu et al. (2007) organizes the layout design into the overall structure, sizing and dimensioning, department layout, equipment selection and operation strategies within the storage area. Both articles describe the main goals for the design of the storage area: "achieving high space utilization and facilitate efficient material handling". Bartholdi III & Hackman (2011) provide a comprehensive review of the science of warehouses including a categorisation of operations within the storage area, used equipment, and issues similar to the framework discussed in the article of Rouwenhorst et al. (1999). However, in this study the layout of the internet fulfilment warehouse is designed based on the organizational design, with the dimensioning of the picking zone together with the storage concept. The order picking strategy is described in detail later on. The storage area is divided into multiple zones with a randomized storage concept. Order pickers only pick items of one batch within one zone. Therefore, the zones are treated independently. As depicted in Figure 2.1, each zone has an I/O (input and output) point, two cross aisles (front- and back-cross aisle), a middle aisle and multiple picking aisles. A detailed overview of the building of the fulfilment centre together with the design of the storage area is given in Appendix B2.

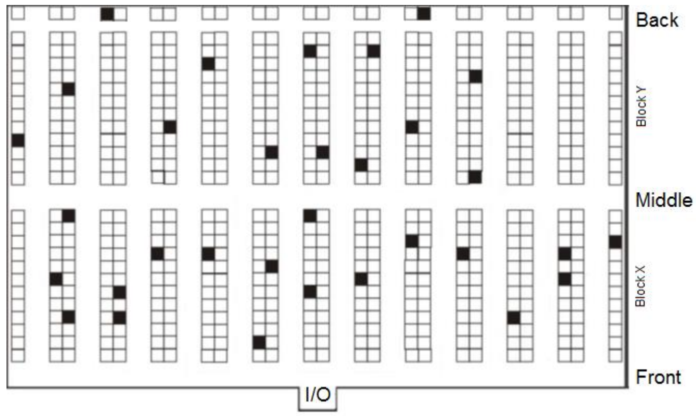

Figure 2.1: Layout storage area (Dukic & Opetuk, 2016)

2.1.2 Items in storage area

In a storage area, items are stored. The storage of items involves the placement of a set of items in a warehouse (Kofler et al. (2010)). In fulfilment warehouses, a lot of different items are processed. Therefore, the warehouse must be able to deal with different product weights, dimensions, varieties, and shapes to make it totally flexible (Brockman & Godin, 1997). The storage area may consist of two parts: the reserve area, where products are stored in the most economical way (as bulk storage), and the forward area, where products are stored on shelves for easy retrieval by an order picker Rouwenhorst et al. (1999). The part of storage area interesting in this study is the forward area. Manual order picking is done in the forward area, and therefore it has the focus from now on. The fulfilment warehouse of this study in which the storage area is assumed only processes products within a range of weight and volume (confidential information). Products with other dimensions or weight are processed in other fulfilment centres. The products have to fit within the tote used in the fulfilment centre.

2.1.3 Storage concept in storage area

The storage concept is the way the items are assigned to its storage location. There are multiple concepts to do so, the well-known concepts suggested by Wascher (2004) are dedicated storage, randomized storage, and closest open location. In a *dedicated storage* location, the items are stored in a fixed location for a long period of time (De Koster et al. (2007)). The use of fixed locations can help the pickers become familiar with the specific storage location of the items and over time can result in a reduction of order picking time (De Koster et al. (2007)). A disadvantage of dedicated storage is that a location is reserved even for products that are out of stock. For *randomized storage*, every incoming pallet is assigned a storage location in the warehouse that is selected randomly from all suitable empty locations with an equal probability (Petersen, 1997). Storing items randomly results in a higher space utilization (Chloe & Sharp, 1991). Another advantage is that with different order compositions, different shortest routes for picking can be obtained. According to De Koster et al. (2007), this policy only works in a computer-controlled environment. Different than in a randomized storage policy is the *closest open location storage*: a system where pickers are able to choose the storage location themselves (De Koster, Le-Duc, & Roodenbergen, 2007).

The storage concept that is assumed to be used in this study in the storage area stores items both dedicated and randomized on its storage locations dependent on product type. Products with explosion hazard are stored dedicated in a fireproof area, costly products are stored dedicated in a locked area, and the rest of the products are stored randomized. The storage area where the items are stored randomized are part of the scope of this study.

2.2 Processes in FC storage area for e-fulfilment

In Figure 1.1 all processes in a fulfilment centre are visualised. Three of these processes are performed in the storage area, as depicted in Figure 2.2 coloured blue. The processes performed in a fulfilment centre located in a storage area are the put away, storage, and order picking process.

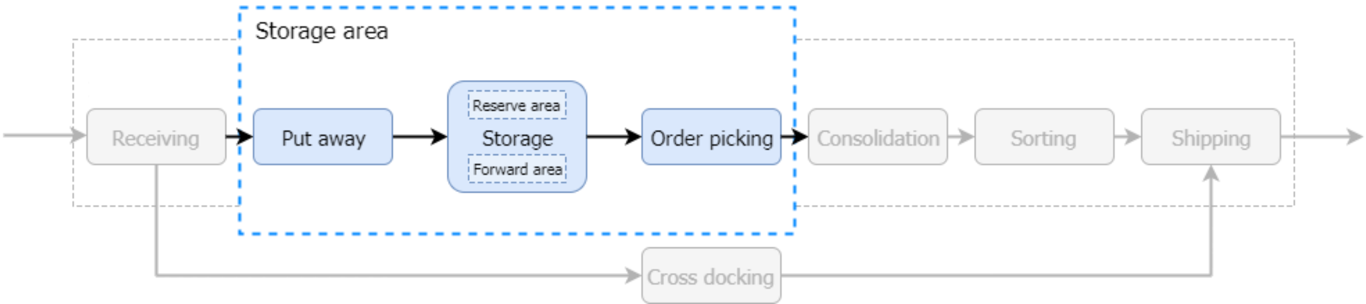

Figure 2.2: Processes in FC that take place in storage area

2.2.1 Put away process

In the put away process the items are placed in the storage locations within the storage area for easy retrieval by an order picker later on (Rouwenhorst, et al., 1999). Since the processes in the internet fulfilment centre are performed manually, the put away process is done manually as well. In this study, the zone and the spur where the tote arrives is determined by the system. First, the operator scans the tote and then the items one by one using a hand held scanner device. Due to the randomized storage concept explained earlier, it is the operator that determines the final storage location randomly. The storage location is saved in the WMS.

2.2.2 Storing process

In the process of storing items, there are different storage types. The storage type depends on the item characteristics, e.g. slow and fast moving goods. Fast Moving Consumer Goods (FMCG) are regarded by means of marketing goods commonly transacted and consumed in a short period of time (Nemtajela & Mbohwa, 2017). Slow moving consumer goods (SMCG) however, are goods with a longer shelf life. In this study such a distinction is made between consumer goods. Important item characteristics, such as flammability and fragility, play a role as well. The different storage types are:

- pallet storage, often used for FMCG and for bulk goods;
- shelve location storage, used for common goods;
- special storage location, in order to accommodate specific products.

The storage types that are taken into account in this study are the shelve location, used for common goods, and the special storage location, in order to accommodate specific products. Products with high value are stored separately, extra security included. Products with explosion hazard, are stored in a fire resistant space. In the pallet storage area order picking is not done fully manual. Instead of walking, the pickers drive in automated vehicles. Therefore, this area is not assumed here. The items are stored in racks. The racks exist of 6 pick levels, with another layout for each level due to the fact that items have different dimensions.

2.2.3 Order picking process

When the customer has placed an order, regardless of the item characteristics, the order picking process can be performed. This is the first step in the outbound process. Order picking refers to the retrieval of items from their storage locations, which can be done (partly) automated and manually (Rouwenhorst, et al., 1999). In this study, the operator first scans an empty tote available on the spur using a hand held scanner device. The device its display visually guides the operator towards the storage racks in which to pick the items.

According to Giannikas et al. (2017), the process of order picking, especially within manual warehouses, is the most labour-intensive and time-consuming warehouse operation. Because this process is the most time-consuming, this process is an interesting topic for optimizing the warehouse performance. The process is explained in detail in the next section.

2.3 Order picking in FC storage area for e-fulfilment

Since the order picking process is the focus of this study, theories about the system and the system of this study are discussed. First the difference in order picking systems is discussed. After setting up boundaries regarding the order picking system, the corresponding processes can be explained. At last, it is discussed how to measure the performance of these processes.

2.3.1 Order picking system

The order picking process in e-fulfilment is based on the orders the customers place on the website of the selling company. A customer order consists of order lines, which specifies the product and required quantity. Order picking is, therefore, a *warehouse process of retrieving products from storage in response to a specific customer request and bringing them to an area dedicated for collecting the assembled customer orders* (Henn, Koch & Wascher (2012)).

Order picking can be performed in a variety of *Order Picking Systems* (OPS). According to Dallari et al. (2009), the design of the OPS depends on a couple of warehouse elements, ranging from products (e.g. number, size, value), customer orders (e.g. number, size) and the design and layout of warehouse areas. The classification of order picking systems is based on five decisions made when designing (Figure 2.3): 1) who picks the items (operators or machines), 2) who moves in the picking area (pickers or goods), 3) are conveyors used to transport picked items, 4) what is the picking strategy, and 5) what order picking system is used.

According to the figure, the items can be picked by humans or by machines. If the items are picked by machines, the OPS is a fully automated system. When the picking is done by humans (read operators), the second decision that can be made is the picker or the goods that move within the storage area. Moving goods leads to a Parts-to-picker OPS. When it is the picker that moves, it is decided if a conveyor is used to connect picking zones. If this is the case, the picking can be done by order, which leads to the OPS Pick-to-box, or by item, which leads to the OPSs Pick-and-sort and parts-to-picker. When the picking is done per zone, per order or per item, a picker-to-parts system is used.

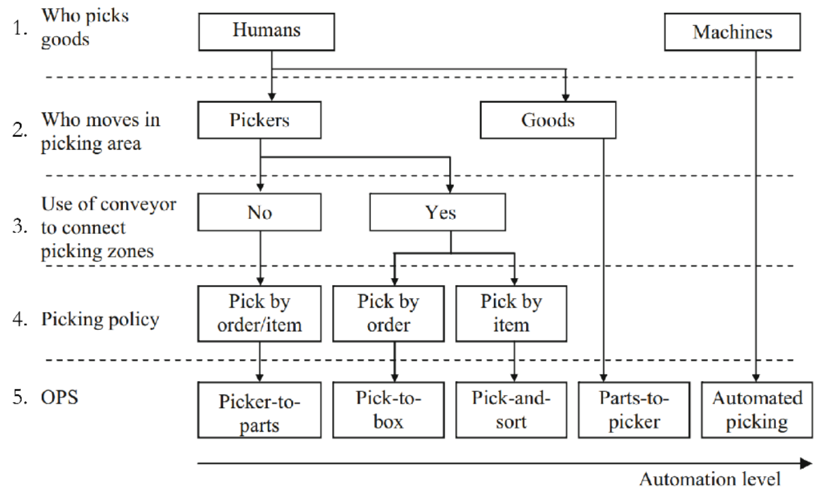

Figure 2.3: Classification of the order picking system (source: Dallari et al. (2009))

De Koster et al. (2007) made a distinction between *picker-to-parts* and *parts-to-picker* systems. The first one requires pickers to walk or drive along the aisles of the warehouse to pick items and is the most common system. Parts-to-picker systems use automated storage and retrieval systems that retrieve unit loads and bring them to a pick position where the picker can pick the right amount of items.

Two variants of picker-to-parts systems were identified by De Koster (2007) and Dallari et al. (2009): picking by article (batch picking) and picking by order (discrete picking). During *discrete picking*, for each order, all products are picked and a new order is picked yet when that order is finished. This is only profitable when mostly large orders have to be picked. During batch picking a higher efficiency may be achieved (Berg, 1999), because multiple orders are picked by an order picker at the same time. There are two ways of batch picking systems. In the *pick-and-sort* system, items are picked first and have to be sorted into single orders after picking. Then, items can be picked with a high pick rate, but the items need to be sorted separately (automated or manual). In the *sort-while-pick* batch picking system, items are picked and sorted simultaneously into customer orders. The items do not need to be sorted, but the pick rates increase.

This study focusses on the lower automation level of pick-and-sort batch picking using a picker-to-parts system. This order picking system is used by the company of this study. In the OPS described the order picking is done by operators and picking and sorting are processes independently of each other. The orders are picked parallel, which means that the customer orders are divided over batches, and one batch, consisting of multiple (partial) orders, is handled by one operator in one zone. The batches are made using a batching algorithm. The algorithm follows several priority rules for dividing the items of the orders in batches. A batch determines the number of items that are picked by one operator in one zone. The number of items have to fit in a tote, based on a number of items, maximal weight and maximal volume. The number of items in a batch are of high importance for measuring the order picking performance in a fulfilment centre. In a zone a particular route is travelled to pick a batch. When more items in a batch are picked, the process time per item decreases. The contents of a batch determine which items are picked simultaneously. This influences the process time as well.

2.3.2 Order picking process

The process of order picking starts with a customer who places an order, consisting of a number of order lines. The orders are batched before being sent to the order picking system. When the batch size reaches a certain number of items, the batch is released for picking to the order picking system with a pick bin assigned to it (Yu & De Koster, 2009). A pick-list is generated which contains information about the sequence in which items have to be picked. The order picker receives his picking list at the I/O-point and returns to it when picking in the zone finishes. In low-level order picking systems, items are picked from picking locations while travelling along the aisles (Dallari, Marchet, & Melacini, 2009).

The pick-list shows the batch that is generated based on the customer orders. There are different types of orders based on its characteristics and the processes that follow after the order picking process. In the company of this study, different order types are assigned to different batches. A distinction can be made between mono- and multi-orders. Mono-orders are orders consisting of only one item. Multi-orders contain two or more items. Mono- and multi-orders are divided over different batches, because mono-orders do not have to be sorted and can be packed directly after picking. However, this is not included in detail in this study, since this study only focusses on the order picking process. The batches generated can be picked by an operator in the storage area. The steps of the operator during the order picking process are depicted in Figure 2.4.

Figure 2.4: Steps in order picking process considered in study

The order picking performance is measured by the total cycle time of order picking. The cycle time is defined as the time lapse from scanning the zone until the picker has confirmed that the batch is finished. Henn et al. (2012) simplified the processing time of a picker-to-part picking tour to the following four elements:

- *travel time*, i.e. the time the picker spends travelling from the depot to the first pick location, between the pick locations and from the last pick location back to the depot;
- *search time*, i.e. the time the picker needs for searching locations and identifying articles;
- *pick time*, i.e. the time required for moving the items from the pick location onto the tote;
- *set up time*, i.e. the time consumed by administrative and setup tasks at the beginning and end of each tour.

As depicted in Figure 2.5, the travel time consumes the major proportion. The search and pick times can be assumed as constants and the set up time can often be neglected (Henn, Koch, & Wascher, 2012). Therefore, the travel time can be seen as the influencing factor of the total time of an order picking tour. Travel time can be divided into three components 1) the travel time from the I/O point, 2) the travel time across and in the aisles, and 3) the travel time to the I/O point.

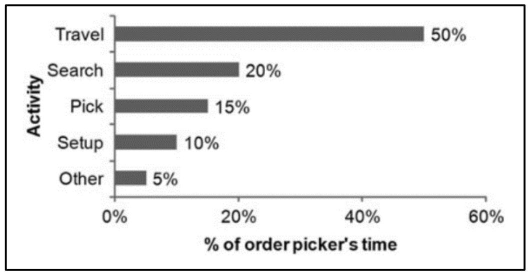

Figure 2.5: Typical composition of the order processing time (source: Tompkins et al. (2010))

2.3.3 Order picking performance

Knowing the amount of time it takes to pick an item and to complete a batch is essential for improving the performance of order picking. For measuring the total throughput time of order picking, the processes are simplified into three steps (start batch, picking, and finish batch) with sub-steps (see Figure 2.6).

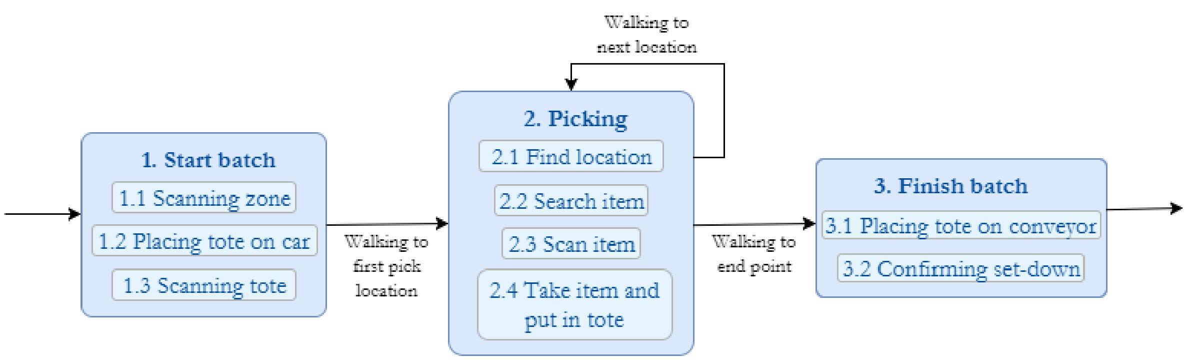

Figure 2.6: Simplified steps in order picking process

One approach to estimate cycle times concerns the use of Predetermined Motion Time Systems (PDMTS). The use of PDMTS, like MOTS (Zandin, 1990) requires to observe actual work and then disaggregate the cycle of a job into motions, specifying characteristics of each motion. Hence, separate measurements would be required for every combination of factions: height, location, product mass and volume. According to Larco et al. (2016), PDMTS makes fundamental assumptions that may not hold in a warehousing context. Notably, the expected time takes to execute a motion is assumed independent of other motions. As activities like searching and walking may interact, this assumption of motion independence may likely be violated. Alternatively, an often used method for estimating cycle times is linear regression. A large set of observations of the day-to-day operational data is needed. However, since the FC of this study does not have these data available, this method cannot be used. Another method that is often used for measuring cycle times of the order picking process is the motion and time method (Kijne, 1996). It is a method for establishing the picking productivity standards in which a complex task is broken into small, simple steps, the sequence of movements taken by the picker is performing those steps and the time taken for each movements are measured. This method is not applied because the order picking process cannot be measured in the fulfilment centre of the study's company yet. In this study there is lack of data. Therefore, it is chosen to compare several time parameters of manual picker-to-part systems described in literature with the estimated time per process of the company of this study. These parameters are shown in Table 2.1, based on the processes and sub-processes determined before. The parameters found in literature do differ from the estimates of the company, while some resemblances could be found. However, the values of the company of this study are used. Due to the fact that these are estimates, a range around these values are pursued. These are determined later on.

Table 2.1: Parameters of manual picker-to-parts systems in seconds

<table>
<tr><th></th><th>Pan & Wu (2012)</th><th>Chan & Chan (2011)</th><th>Van Nieuwehuyse & De Koster (2009)</th><th>Yu (2008)</th></tr>
<tr><td>Walk speed (m/s)</td><td>1</td><td>0.83</td><td>1</td><td>1</td></tr>
<tr><td>1. Start batch</td><td></td><td></td><td></td><td></td></tr>
<tr><td>1.1 Scan zone</td><td>5</td><td>3</td><td>3</td><td rowspan="3">20</td></tr>
<tr><td>1.2 Place tote on car</td><td></td><td></td><td>14</td></tr>
<tr><td>1.3 Scan tote</td><td></td><td>3</td><td>3</td></tr>
<tr><td>2. Picking</td><td></td><td></td><td></td><td></td></tr>
<tr><td>2.1 Find location</td><td rowspan="2">5</td><td rowspan="2">5</td><td rowspan="4">8</td><td rowspan="4">18</td></tr>
<tr><td>2.2 Search item</td></tr>
<tr><td>2.3 Scan item</td><td rowspan="2">10</td><td>3</td></tr>
<tr><td>2.4 Take item and put in tote</td><td>8</td></tr>
<tr><td>3. Finish batch</td><td></td><td></td><td></td><td></td></tr>
<tr><td>3.1 Place tote on conveyor</td><td></td><td></td><td>40</td><td>30</td></tr>
<tr><td>3.2 Confirm set-down</td><td></td><td>3</td><td></td><td></td></tr>
</table>

The throughput time is the total time of a picking tour. The time it takes for an order picker to pick all items of one batch consisting of averaged 10 articles is estimated by the company to take 610 seconds. However, flexibility is added to the order picking process by employing human operators (Grosse et al. (2015)) which influences the total time of a picking tour. These factors are not taken into account in detail, since the focus of this study is on the seasonal influence during peak periods. However, in peak periods more order pickers are needed to process the large quantities of orders. Many temporary workers are employed to catch up the increased number of items. These temporary workers are relatively inexperienced working in the fulfilment centre and with the travel routes. Not only during peak periods inexperienced pickers are working in the fulfilment centre. Order picking is often a temporary job, done by for example students and guest workers. Therefore, there is a constant change in employees. In this study, it is assumed that new employees are working in a test zone first, to learn the order picking steps and to get used to the work. However, still a difference in speed is observed between new and existing pickers. According to Gilbreth (2017) the operators can be classified into experienced and inexperienced operators. The times described before represent the experienced operator, the inexperienced operators picking tour takes 120% of that time.

An article of Krauth et al. (2005) that conducted a literature review in order to find the performance indicators for logistics service providers is used to find other performance measures. For measuring efficiency, the system and labour utilization together with order throughput time, and labour costs are proposed for warehousing problems. For an internal perspective reducing walking distance seems to be an important measure. The performance indicators are elaborated further on in Chapter 4.

2.4 Conclusion

In this chapter, the boundaries of the order picking system for e-fulfilment of this study are set. The working area of the order picking process is the storage area. The storage area of this study is divided into multiple subzones. Each subzone consists of one I/O point, two cross aisles and a middle aisle. The items are assumed to be stored according to the storage concept that is called randomized storage. For the order picking process that is analysed and of which the performance is improved, shelve location storage is assumed.

Order picking can be performed in a variety of order picking systems. This study focusses on the lower automation level of pick-and-sort batch picking using a picker-to-parts system. The orders are picked parallel, which means that the customer orders are divided over batches, and one batch, consisting of multiple (partial) orders, is handled by one operator in one zone. The batches are generated by a batching algorithm. The operators receive the batches translated into pick-lists which contains information about the sequence in which items have to be picked.

The order picking performance is measured by the total cycle time of order picking. The processing time can be simplified into four elements: travel time, search time, pick time and set up time. The travel time consumes the major proportion and therefore, this element is used for improving the order picking performance. The total throughput time of order picking can be determined based on the three steps (start batch, picking and finish batch) of the order picking process. In the next chapter the seasonal influences and order characteristics are determined for further analysis of the order picking process.

Chapter 3 Background analysis of seasonal patterns in customer orders

Now the order picking system is explained, the seasonal influences on this system can be analysed. This chapter describes a part of the background of this study by analysing the demand profiles by determining seasonal patterns in customer orders. Answers to the following sub-research questions are provided: ''What different seasonal, monthly, and weekly influences can be differentiated, and when do they occur?'' and ''What are the characteristics of orders during peak periods compared to regular periods?'' The output of this chapter consists of the composition of customer orders during peak periods compared to regular periods. These are used as an input for the order picking process optimization in the chapters that follow.

3.1 Customer orders and its behaviour and seasonal patterns

Since the order picking process is the retrieval of orders, customer orders are essential to perform the process. Order picking is a demand-driven organization with a possible high product variety and large variations in order sizes (Chen & Wu, 2005). Customer orders and their due dates are entirely exogenous, there is nothing we can do to control them (Hariharan & Zipkin, 1995). Therefore, often pictures of advance-ordering behaviour are painted to try to forecast and control the demand.

In e-commerce, the demand is highly variable and unpredictable, both in terms of volume and value, both short and long shelf-life occur, and out-of-stock items are replaced with new collection products instead of restocked (Pedrielli et al. (2016)). As a result of these characteristics, the management of orders and identifying a fitting order picking strategy to generate pick lists for the pickers to fulfil the orders becomes challenging. With the aim of improving the picking process, an approach which relies on the characteristics of the orders faced by a case study company is proposed. The improvement can be done after a good insight of demand profiles in certain time series and order characteristics are secured, and theories of performance optimization of order picking are obtained.

3.2 Time series analysis: state of the art

Many business and economic time series exhibit seasonal and trend variations. Seasonality is a periodic and recurrent pattern caused by factors such as weather, holidays, repeating promotions, as well as the behaviour of economic agents (Hylleberg, 1992). According to Zhang et al. (2005), seasonal variations are perhaps the most significant component in a seasonal time series, a stochastic trend is often accompanied with the seasonal variations and can have a significant impact on the demand curve. Accurate analysing of seasonal and trend time series is important for effective decisions in retail, marketing, production, inventory control, personnel, and many other business sectors (Markidakis & Wheelwright, 1987).

The seasonal influences, together with its time of occurring, are analysed and determined performing a data analysis. Analysing seasonal influences of customer orders requires a method: a time series analysis. Time series are described as a record of phenomenon irregularly varying with time (Kitagawa, 2010). The amount of customer orders varies with time and using the time series analysis patterns and position of patterns can be investigated. Performing the time series analysis can be done in three steps: data collection, data analysis based on a mathematical model, and then conclusions can be drawn. These steps are explained in the next paragraphs.

3.2.1 Data collection for time series analysis

The first step of the time series analysis is the collection of raw data. In this step needs to be determined which data is required to perform the analysis and to answer the sub-research questions mentioned before.

To determine what different seasonal, monthly, and weekly patterns can be identified in the historic data of customer orders, the amount of customer orders in a particular time span is required. There are different types of orders to distinguish: the moment the customers place an order, the moment the customer order is planned to be processed in the warehouse and the actual moment of processing in the warehouse of the customer order.

The type of order that is needed is dependent on the type of order that is needed to plan a batch in a warehouse. Therefore, the type that is required for analysing the data is the moment the order is planned to be processed.

The characteristics of orders during peak periods need to be analysed as well. The characteristics of customer orders that are able to be identified are the amount of items in an order, the product category of the items and the item volumes and weights. It is useful to compare the amount mono- and multi-orders and the amount of items in an order during peak periods compared to a regular period. The product category of the orders can be important as well because it is possible that the amount of customer orders increases during a seasonal pattern, but only for a particular product category. The product categories can be categorized in several levels. Information regarding order volumes and weight are necessary because it determines an important part of the workload of the systems and employees working in the warehouse.

3.2.2 Mathematical model time series analysis

3.2.2.1 Seasonal decomposition

Literature describes and compares different decomposition methods (Lovell (1963), Damsri et al. (2007), Suhartono & Subanar (2005), Zhang & Qi (2005) and Taylor & Letham (2017)), such as Winter's exponential smoothing, seasonal ARIMA model, neural network time series, decomposition method and time series regression. Traditional approaches to modelling seasonal time series are to remove the seasonal variations using a certain seasonal adjustment method and then the models are scaled back using the estimated seasonal effects for analysis purposes (Zhang & Qi, 2005).

In this study the decomposition model with seasonal-adjustment is used to analyse the time series. This model is used because it covers all components that are desired to be analysed. The other models are more complex, which is not necessary for calculating the seasonal influences. Decomposition of time series is a statistical method that deconstructs a time series into several components. The procedure determines the additive or multiplicative seasonal factors for periodic time series can be estimated using the ratio-to-moving averages method of seasonal decomposition. The ratio to moving average is the most widely used method for seasonal component estimation (Zhang & Qi, 2005).

The time series Y_t is decomposed in three components (trend, seasonality, noise). A model of this kind is called a structural time series model (Harvey & Peters, 1990). The seasonal factors are *multiplicative*, because the seasonal effects are mixed with non-seasonal effects (and therefore, the factors do not have a linear relation). The multiplicative decomposition model of Y_t can be written as

$$Y_t = T_t \cdot S_t \cdot \varepsilon_t \tag{3.1}$$

Where

- Y_t (time series): input raw data, representing the amount of orders, volume of items, weight of items etc. on a specific time interval t;
- T_t (trend): long-term progression and the pattern of change in the dependent variable on a specific time interval t (growth);
- S_t (seasonal): seasonality, repeated regular, predictable periodic fluctuations from the trend on a specific time interval t;
- ε_t (observation noise): irregular pattern on a specific time interval t which are not accommodated by the model;
- t (time): time interval in n days, where t = 1…n and $m+1 \leq t \leq n-m$;

For defining the trend, the moving averages method can be used. Constructing a moving average is a simple method for smoothing time series with noise (Kitagawa, 2010). For a moving average model, a period (p) must be specified e.g. monthly series usually have a seasonal period of 12. The realization of the trend component locally becomes a smooth function that resembles the polynomial (Kitagawa, 2010).

$$T_t = \frac{1}{pt+1} \sum_{j=-m}^{m} Y_t \tag{3.2}$$

Where

- pt = period of trend;
- m = range of moving average, where 2m=p.

The seasonal effect can be estimated by ratios (i_{trend}) between the original series to the moving averages of t_t. A seasonal moving average model expresses the current observation as a linear function of the current disturbance and one or more previous disturbances (Koopman & Hoogerheide, 2013). After calculating the ratio between original series and the seasonal moving average, the seasonal component can be realized (see Equation 3.5.

$$i_{trend} = {}^{y_t}/_{T_t} \tag{3.3}$$

$$i_{seasonal} = \frac{1}{ps+1} \sum_{-m}^{m} i_{trend} \tag{3.4}$$

$$S_t = Y_t \cdot i_{seasonal} \tag{3.5}$$

Where

- i_{trend} = ratio between original data and moving average (trend);
- $i_{seasonal}$ = ratio between original data and moving average (season);
- ps = period of seasonality;
- m = range of moving average, where 2m=p.

The last step of the decomposition is determining the irregular influences, ε. The irregular influences are the residuals, which can be obtained by using Equation 3.1.

3.2.2.2 Correlation and dispersion

A part of the order characteristics can be determined based on the seasonal decomposition, looking at the decomposed behaviour of customer orders separated in categories. Different patterns can be obtained. Another way to analyse the characteristics, is to calculate statistically the correlation and variance of the data. Here, the relation between the order pattern over the year and the patterns of the separate categories over the year can be determined.

The correlation and the importance of an effect can be measured using Cohen's d, Pearson's correlation coefficient *r* and the odds ratio (Field, 2009). The correlation coefficient measures the strength of relationship between two variables, based on the covariance. Pearson's correlation coefficient (Equation 3.6) is constrained to lie between ***0*** (no effect) and ***1*** (perfect effect). The correlation coefficient can also be negative, which represents the direction of the relationship.

$$r = \frac{cov_{xy}}{s_x s_y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{(N-1)s_x s_y} \tag{3.6}$$

Where

- r= correlation coefficient of Pearson
- $s_x s_y$= standard deviation of values of x and y
- x_i/y_i=value of ith value of x and y

- $\bar{x}/\bar{y}$= mean of values of x and y
- N= number of observations/data values

In this study the suggestion of Cohen (1988) about what constitutes a small or large effect is used:

- r = 0.10 (small effect): In this case the effect explains 1% of the total variance,
- r = 0.30 (medium effect): The effect accounts for 9% of the total variance,
- r = 0.50 (large effect): The effect accounts for 25% of the variance.

The dispersion of the data can be calculated and then be visualised using a boxplot. At the centre of a boxplot is the median, which is surrounded by a box the top and bottom of which are the limits within which the middle 50% of observations fall (the interquartile range) (Field, 2009). Sticking out of the top and bottom of the box are two whiskers which extend to the most and least extreme scores respectively. A boxplot is a useful technique for spotting and correcting outliers.

3.2.3 Conclusions of time series analysis

After the data collection and the data analysis, in which the trends and seasonal patterns are calculated and determined, and the order characteristics can be expressed, conclusions can be drawn. Together with the dates of Holidays and (sales) events (Appendix C), the seasonality can be explained.

3.3 Time series analysis: case study

The seasonal composition method that is applied in this research is applied to the case study. The research could be applied to any other similar (e-commerce) company. However, the customer order patterns and characteristics, the warehouse configuration and the constraints of the company of this study its warehouse are used for this research.

3.3.1 Data collection

Since there is no historic data of customer orders available from the new FC of the case-study company yet, there is no data to analyse. Nevertheless, the items processed within the scope of the FC have been processed in another warehouse before. During the retrieval of data, there has to be filtered on the FC that processes the products within the product scope.

Within the filtered FC, the data of the orders can be retrieved. The amount of orders is measured over a certain period of time. Different order statistics are measured, such as the actual time an order is placed, the planned process time, and the actual process time.

The statistic that is relevant for planning the order picking process is the planned process time. These orders are retrieved per day and are bound to a date. Based on these data the trends, seasonal patterns, Holidays and promotion periods can be allocated. Analysing the order's planned process time does capture some factors that are able to cause some unexpected fluctuations in the data, such as shifted service frames (shift in next day delivery, e.g. before 10 PM instead of 12 PM). It is possible that articles are not in stock at the moment a customer order is placed. Such orders have adjusted planned process times because these orders need to wait until the article is in stock again. Therefore, these will result in deviating trends in the data. Nevertheless, in this study is focussed on order picking and the item only can be picked when it is in stock.

The amount of items as a function of time are measured because to analyse the order characteristics, it is useful to determine the (average) amount of items in a customer order. An average is analysed, because of retrieving each item ordered over a year, results in a query-size that does not fit between the boundaries of the retrieval system. The items are categorized in categories and in different category levels. For this study, the items are divided into the levels[1] units and categories of the company. The reduction of orders into product types gives more insight into the order behaviour of customers. More insight of the purchase behaviour gives more certainty for the items that need to be processed in the fulfilment centre. The units and categories are used to determine relationships between a certain period, the amount of orders and the product type.

Table 3.1: Product categories

3.3.2 Data analysis

For the data analysis to determine the seasonal influences occurring over a year, at least one year of data must be retrieved. Reliable data is available from 01-12-2015. Therefore, performing the data analysis is done over a period from 01-12-2015 until 01-07-2017. This results in a time series dataset of 578 days, 82.57 weeks, 19 months, or 1.58 years. The period of seasonality is determined by this numbers. The relevant outcomes are treated; the total analysis can be found in Appendix C.

3.3.2.1 Seasonal decomposition

The first part of the time series data analysis consists of the seasonal decomposition part. There data can be decomposed over a period. Weekly and monthly periods are chosen to determine repeating patterns on a certain day in a week or in a month. The collected data can be divided into 27 situations as a function of time. Since for each situation both weekly and monthly periods were decomposed, there are 54 number of time series decomposed into trends, seasonal patterns, and irregular influences. The output of the analysis is shown in figures existing of four graphs. The time series situations calculated are:

- number of orders,
- number of items,
- items/order,
- weight/item,
- volume/item,
- items/unit,
- items/category.

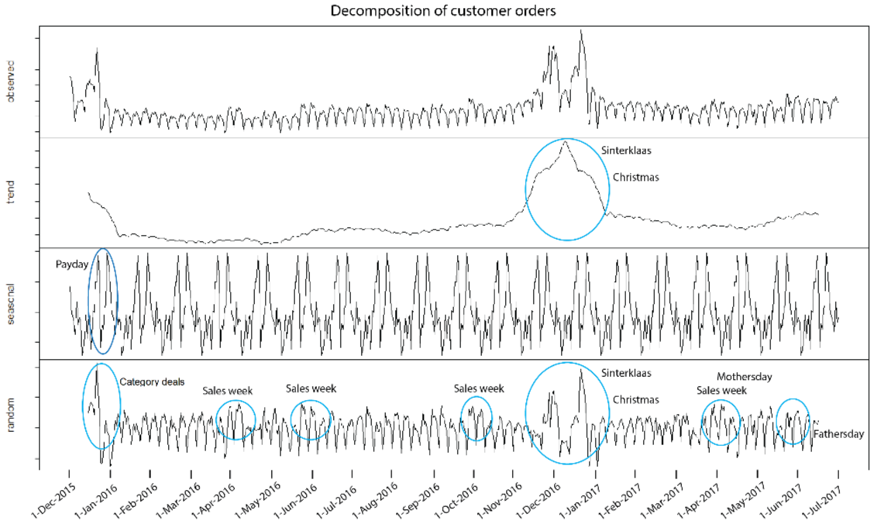

Figure 3.1: Monthly decomposition of orders in trend, seasonal and random influences

In Figure 3.1 the time series of orders per day are decomposed in both weekly and monthly periods. In the figure, the upper graph shows a plot of the time series of the raw data. Beneath, the raw data is decomposed into a trend, a monthly/weekly (seasonal) pattern, and the irregular influences. In the figure can be seen that the December peak can be seen as a trend. The amount of orders grows slowly from October until December. In the monthly pattern can be seen that two days a month, more orders are placed. This can be explained by the days that people receive their salary. In the irregular influences, the sales weeks and holidays can be distinguished.

In the original report, an extensive analysis was done for determining the hourly patterns over the week. The categories were analysed and the correlation and dispersion between them were determined. The ratio between mono-orders and multi-orders and its pattern were calculated. For the order picking process it is important to know as well what the weight and volume per order are. This influences the number of items that fit into one tote. This information was omitted for confidentiality reasons. Based on this information, a regular and a peak week were determined. The characteristics of these weeks are used in further sections in this report.

3.3.3 Conclusion

A time series analysis was performed. The ratio-to-moving-averages method turned out to be the best method to decompose the time series into trends, seasonal patterns, and irregular influences. The most important conclusions are summarized in Table 3.2.

Table 3.2: Conclusions time series analysis

The conclusions of the data analysis are strongly related to the impact on the order picking performance. In Table 3.3 the conclusions based on the data analysis regarding the order picking process are recited.

Table 3.3: Conclusions time series analysis regarding the order picking process

	General	Day	Week	Month
Number of orders	Improved efficiency in fulfilling mono-orders should be designed. Multi-orders form the largest picking volume.	Peak in number of orders lead to more picks. On Monday evening a large volume need to be picked in a short time span.	On Saturday less orders are placed, and therefore pre-processing can be done by batching orders that are sent on Sundays.	During sales, more orders are placed and thus more items need to be picked.
Number of items	Multi-orders cause a higher number of items that need to be picked.	-	-	-
Items/order	In peak weeks more items per order, and therefore higher pick volume.	-	On Saturdays more items/order and therefore more items need to be picked	In period X, sales weeks and on salary day more items/order which leads to more items to pick
Items/unit				
Items/category				
Weight/item	More items per batch can be picked when there is a decrease in weight/item.	-	-	In peak lower weight/item, more items/batch, less travel time per item. In period X the other way around.
Volume/item	More items per batch can be picked when there is a decrease in volume/item.	-	-	In peak lower weight/item, more items/batch, less travel time per item. In period Y the other way around.

When in peak periods the number of orders increases together with the number of multi-orders, the impact on number of items is amplified. The workload increases significantly for the order pickers in the fulfilment centre. The increase of the workload occurs especially during the peak period during the Holidays (October, November, and December). During this period, the weight per item and volume per item decrease, which means that batch sizes can be adjusted in such a way that more items can be picked in one zone. The same distance in the zone is travelled, which leads to less travel distance per item. Interesting parameters to play with for optimization of the order picking performance are thus the number of items, weight and volume per tote and the travel distances. This topic is discussed in detail in the next chapters.

Chapter 4 Theories optimization performance order picking

This chapter gives insight into order picking performance optimization. First, the key performance indicators and requirements are chosen. Then, based on the results of the time-series analysis, appropriate optimization aspects are exposed based on literature reviews. This part of the chapter answers the sub-research questions: ‟What are possible policies proposed in theories for improving the order picking performance?‟ and ‟What are possible solutions that can be generated in order to improve the performance of order picking during peak periods?” For testing the optimizing aspects, a model is necessary to measure any improvements. Suitable methods of modelling are investigated. Then, the model is set up, validated and elaborated.

4.1 Key performance indicators and requirements

The Key Performance Indicators (KPIs) and the functional requirements of the model are related to the order picking process and the performance measures explained in Chapter 2. Using the KPIs and requirements, the performance can be assessed and be compared. The KPIs allow for the comparison between the base alternative and the optimization alternatives. The requirements are the needs the alternatives must comply. In the following sections the KPIs and requirements are elaborated in detail.

4.1.1 Key performance indicators

The performance indicators have been determined for measuring the performance of the order picking system. An extensive list of indicators is determined based on literature and in harmony with the company of this study. All performance indicators are explained and considered in 0. From this list, a selection of indicators is made representing the Key Performance Indicators of this study. The important performance indicators are selected as well. The KPIs are used for measuring a difference in the order picking performance testing between the base alternative and the design alternatives. In Table 4.1, an overview is given of the KPIs together with the unit the KPI is expressed in, the objective of the KPI, and a detailed description of it. In Table 4.2, an overview of the remaining performance indicators interesting for testing the alternatives are showed.

Table 4.1: Key performance indicators

Criteria	Unit	Obj.	Detail
Costs per item	€/item	↓	Costs made per processed item during the order picking process
Cycle time picking (batch)	sec/batch	↓	Average time per batch

Table 4.2: Performance indicators

Criteria	Unit	Obj.	Detail
Utilization tote	%	↑	Ratio between the capacity of the tote and the number of items, volume or weight carried
Cycle time picking (item)	sec/item	↓	Average time for an item to be picked
Distance travelled	m/batch	↓	Distance travelled by operator per batch

To obtain the highest performance, a balance between the performance indicators should be provided. In this study, it is a boundary condition that all items ordered by customers need to be processed. Keeping this in mind, it is preferred for the costs to be minimized, while the utilization of the system must be maximized while preventing congestion. The cycle time of picking and the travel distance are preferred to be as low as possible, as explained earlier in Chapter 2.

4.1.2 Requirements

The system in which the key performance indicators must be tested, have to fulfil some needs. These needs are called the requirements. The two types of requirements that can be distinguished are constraints and objectives (Verbraeck, 2016). Constraints are the mandatory requirements the system must comply. The objectives are preferred requirements that need to optimize the system as much as possible. At the same time, these requirements can be functional or non-functional. Functional requirements are actions that a system has to take (constraints), while non-functional requirements are the qualities that a system has to have (objectives). The requirements for the order picking system are as follows:

- Functional requirements
    1. The alternatives shall be applicable to the order picking process
    2. Using the alternative all items in a batch must be picked
    3. The alternative must be applicable in the existing storage layout of the fulfilment centre
- Non-functional requirements
    1. The alternative should lower the costs per item during the order picking process
    2. The alternative should decrease the throughput time of the operator picking in the storage area in a fulfilment centre
    3. The alternative should increase the tote utilization

4.2 Theories order picking performance

While optimizing the performance of a lower mechanization level of pick-and-sort batch picking using a picker-to-parts system, the main focus is on reducing the total time needed for order picking. As explained in Chapter 2.3.1, the main influencing factor of the total time of an order picking tour is the travel time. It can be assumed that pickers travel at a constant speed, which results in minimization of the total travel distance (Gademann & Van de Velde, 2005) to minimize the total picking time.

For optimizing the performance of the order picking process, several aspects can be presented. When designing a new warehouse, the layout optimization is an important aspect. However, in this study, an existing warehouse is assumed. As discussed in the study of Wascher (2004) there are some primary interdependent order picking policies that can help optimize the performance. These policies are the *storage policy, routing policy, zoning policy, and order consolidation policy*. These are explained in detail in the following sections. In these sections, optimization proposals for this study are made.

4.2.1 Storage policy of order picking

The storage policy determines how to assign items to storage locations within the warehouse. The storage concept of this study is assumed to be randomized. The two policies that can be implemented without changing the layout of the storage area (which was stated in the scope of the study) are the full-turnover and the class-based storage.

In a *full-turnover storage*, items are distributed over the storage area based on sales rates. Items with the highest sales rated are located at the easiest accessible locations, usually near the depot. Slow moving products are located somewhere towards the back of the warehouse (De Koster, Le-Duc, & Roodenbergen, 2007). In *class-based storage* products are grouped into classes in such a way that the fastest moving class can be picked more easily. Classes are determined by some measure of demand frequency of the products (i.e. pick volume) (De Koster, Le-Duc, & Roodenbergen, 2007). Class-based storage can be done within-aisle and across-aisle as depicted in Figure 4.1. According to Yu et al. (1999), class-based storage requires significantly less picker travel than randomized storage. However, a random storage policy generally utilizes the entire picking area more evenly and reduces worker congestion. A combination of both class-based storage and randomized storage could lead to even less picker travel and at the same time a reduction of the worker congestion can be obtained.

Classifying storage can be done following as suggested in literature, namely based on fast moving and slow moving products. Another option is a classification of storage based on the volume of a product. Both options lead to optimization alternatives. Another possibility is to change the storage policy during peak periods.

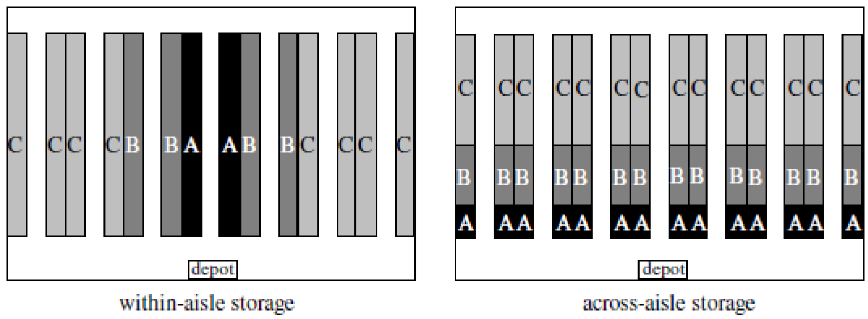

Figure 4.1: Illustration of two common ways to implement class-based storage (source: De Koster et al. (2007))

4.2.1.1 Class-based randomized storage

As described in literature, an interesting alternative for optimizing the order picking performance by minimizing travel distance is implementing class-based storage based on fast moving and slow moving products. While the items are grouped based on fast, medium, and slow moving products, the items still can be stored randomized within each class. The fast moving product, classified as class A, are stored near to each other following an across-aisle storage near to the I/O point. The slow moving products, class C, are stored at the end of the aisles because these products have to be picked the least often. The medium moving products, class B, are stored in between. The across-aisle storage policy is chosen instead of the within-aisle storage because of the layout of the storage area within the fulfilment centre of this study. The storage area contains a cross aisle and is divided into two areas. The end of the area leads to highest travel times, and therefore class C products are stored over there.

4.2.1.2 Volume-based randomized storage

Implementing a class-based storage based on volumes leads to sufficient filling of totes. The storage concept can be still randomized, which means that still all articles are divided over all zones. The difference in storage is, that at the beginning of the route of the operator, the items with largest volumes are stored. This can be obtained by dividing the items in for example 3 classes based on volume (small, medium, and large volume). Storing the items in such a way that the larger volumes are stored in the first part of the route the batch suggest, leads to a more efficient filling of the tote. When the largest item is picked the last, can lead to a situation the product does not fit in the tote anymore. Starting with the larger volumes and ending with the smaller items will lead to a situation where more items fit in a tote. Then, more items can be picked per tour which leads to smaller travel distances per item.

4.2.2 Routing policy of order picking

The customer orders that are batched into an order pick list, have to be grouped in such a sequence that the total length of all picker tours necessary to collect all items is minimized (Scholz & Wascher, 2017). In order to determine the length of a picker tour, it has to be decided in which sequence the storage locations of the respective items have to be visited. This gives rise to the *Picker Routing Problem* in which a picking order is given, and a tour of minimum length has to be determined that allows for picking all items included in the picking order. De Koster and Van der Poort (1998) have shown that time savings can be obtained using an optimal algorithm as compared to the case of heuristics that are used in practice.

According to De Koster et al. (1999), the advantage of heuristics is that they are much simpler to implement in practice and faster to compute than the optimal algorithms. In Figure 4.2 several heuristics of routing strategies (Return, S-Shape, and Largest Gap) are depicted (Petersen & Aase, 2004). The pick locations are symbolized as black rectangles. The depot is visualised and the front cross aisle is located at the side of the depot. In the *Return strategy* proceeding the picker enters each aisle in which an item has to be picked from the front cross aisle, walks up to the most distant pick location in this aisle and then returns to the front cross aisle. Proceeding the *S-Shape strategy* (also known as traversal strategy) (Hall, 1993), the picker successively traverses each aisle entirely if it contains at least one pick location. Correspondingly, the first aisle is entered from the front cross aisle, the second one from the rear cross aisles, etc. In the *Largest Gap strategy*, the storage area is divided into two section. A picker enters an aisle as far as the largest gap in an aisle (Petersen, 1997). The gap represents the separation between any two adjacent picks, or between the first pick and the front aisle, or between the last pick and the back aisle.

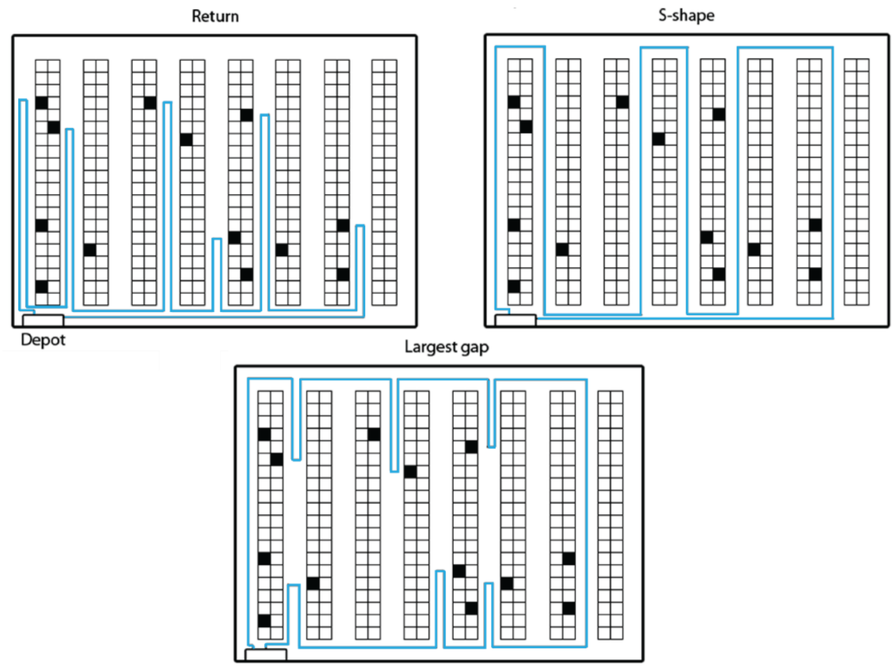

Figure 4.2: Routing strategies (source: (Petersen & Aase, 2004))

The routing policy could be an interesting aspect of optimizing the order picking performance because much travel time can be won implementing a routing strategy that decreases the travel distance and therefore the travel time as well. The fulfilment centre discussed in this study uses an S-Shape strategy for routing. Now, the order picker has the option to decide for himself whether a shorter route can be travelled through the aisles. It can be rewarding to implement another heuristic for routing that applies the shortest path approach for decreasing the total travel time of a picking tour that the picker should follow. However, in accordance with the company, it is decided to exclude this topic for optimizing the order picking performance.

4.2.3 Zoning policy of order picking

Yu and De Koster (2009) describe zoning as the problem of dividing the whole picking area into a number of smaller areas (zones) and assigning order pickers to pick requested items within the zone. The main objective of zoning is to achieve maximum utilization of the picking resources, by distributing the total picking workload equally among the defined zones. Batching and zoning are closely related issues. The analysis on zoning is classified into synchronized zoning and progressive zoning. During *progressive zoning,* each batch of orders is processed at a zone at a time. In progressive zoning, the batch of orders is passed from one zone to the next, which is why such systems are also called pick-and-pass systems. During s*ynchronized zoning,* all zone pickers work on the same batch of orders at the same time. The performance of synchronized zoning is assumed in this study. As described in the scope of the research, the warehouse of the study its FC is divided into multiple zones.

4.2.3.1 *Zone decomposition*

The background analysis showed that during peak periods more orders need to be processed. The number of orders in peak periods are multiple** times as much as the number of orders in a regular period. The analysis showed that the ratio of multi-orders compared to mono-orders increases during peak periods as well. This causes an amplified effect on the number of items that need to be picked by the order pickers. Therefore, in these periods more order pickers are needed for picking all these items. This means that more operators are working per zone. Mentioning the increase of operators per zone, a promising alternative for the optimization of the order picking process arises. By decomposing the existing zones in two sub-zones during peak periods, fewer operators per sub-zone are working. The chance of congested aisles is decreased. Each operator still picks the same amount of items, but then in a smaller zone. Implementing this temporary parameter in the algorithm, therefore, leads to less travel distance per operator and thus shorter travel times per batch. Half of the travel time can be obtained while picking twice as many items.

4.2.4 Order consolidation policy of order picking

Henn et al. (2012) define order consolidation as the transformation of customer orders (batching) into order pick lists (batches). Order batching is the process of grouping customer orders together and picking them on the same tour. Its main objective is to reduce the order picker's travel time per order (Xu et al. (2014)). With explaining order batching, the O*rder Batching Problem* (OBP) arises i.e. the grouping of a given set of customer orders into feasible picking orders such that the total length of all picker tours and the average throughput time of an arbitrary order is minimized. In order to calculate the length of a picker tour, the sequence has to be determined according to which the items contained in the picking order will be picked (Scholz & Wascher, 2017). This problem is solved by an algorithm. Several authors present hierarchical methods for batching the orders. These methods basically follow three steps: *1) a method of initiating batches, 2) a method of allocating orders to batches and 3) a stopping rule to determine when a batch has been completed* (Gibson & Sharp, 1992).

Chloe and Sharp (1991) investigated the two main criteria for batching: the proximity of pick locations and time windows. Proximity batching is the gathering of orders to a batch based on the proximity of their storage locations. In time window batching, the orders arrive during the same time interval called a time window and then are gathered as a batch. Yu and De Koster (2009) explain the existing trade-offs in the order picking process: if batch sizes increase, the flow rates to pick zones will decrease (fewer bins to zones), leading to lower utilization of the zones and hence reducing the potential waiting time of bins in front of each zone; on the other hand, a larger number of orders in a bin means longer service time at pick zones which tends to increase the mean order throughput time in the system. Also, a larger batch size implies longer queuing time for batch completion and longer processing time in the sorting process at the end of the pick-and-pass system. Therefore, finding an optimal batch size is important for the order picking system performance.

With respect to the availability of information concerning customer orders, order batching can be distinguished into *static (off-line) batching and dynamic (on-line) batching* (Henn et al. (2012) and Yu et al. (2009)). In static batching, it is assumed that the set of orders is self-contained and complete information about its composition is available before batching. In dynamic batching, the order information is not known before batching. The customer orders arrive at different points in time while the picking process is already being executed (Henn, Koch, & Wascher, 2012). The stochastic property of the order (i.e. order arrival process and a total number of order lines in a batch) is taken into consideration by Xu et al. (2014).

There are various order picking methods for static batch picking. The method that is used in this study is parallel picking. In parallel picking, a number of operators start with the same order, each picker works in his own zone (De Koster, Le-Duc, & Roodenbergen, 2007). The partial orders emerge in the consolidation process after the picking is done. In literature, several strategies of static order batching are discussed. The first is using a **heuristic algorithm**. Several heuristic algorithms exist to group orders into static batches. There are three conventional approaches to solve the OBP. These approaches are explained below: the priority rule-based algorithm, the seed algorithm, the saving algorithm, and a data mining approach. Metaheuristics have been used to solve the OBP as well, such as local search, tabu search, and population-based approaches (Henn, Koch, & Wascher, 2012). *Priority rule-based algorithms* consist of a two-step procedure. In the first step, priorities are assigned to the customer orders. In the second step, the customer orders are assigned, in accordance with these assigned priorities (Henn, Koch, & Wascher, 2012). Several priority rules are suggested in literature. The first-come, first serve (FCFS) rule assigns the priorities to the customer orders as they come in (Gibson & Sharp, 1992). No good quality solutions can be expected because a random sequence will be generated using FCFS. According to Bartholdi (1995), the space filling curves (SFC) rule batches the items that are close to one another in the storage system will generate theta values which are close in magnitude. The distance between two orders is a measure of the travel distance between the item locations of one order to those of another. Batches also can be constructed sequentially (Next-Fit Rule) or simultaneously (First-Fit Rule, Best-Fit Rule). As for the Next-Fit Rule, customer orders are added to a batch until the capacity of the picking device is exhausted, then a new batch is opened. According to the First-Fit Rule batches are numbered in the order in which they were opened. This means that the next customer order is allocated to a batch which possesses the smallest number and still provides sufficient capacity for the accommodation of the customer order (Ruben & Jabobs, 1999). The Best-Fit Rule assign an order to the batch with the least remaining capacity (Wascher, 2004).

Seed algorithms generate batches sequentially in two phases (Henn, Koch, & Wascher, 2012). First, a seed selection is made and then an order congruency is done. During the first phase, an order (seed) is chosen for a batch according to the seed selection rule. In the second phase, orders are added to the batch according to the accompanying-order selection rule (based on the distance from the seed) until the batch reaches its capacity constraint (see Figure 4.3). The generation of batches continues until all customer orders have been assigned. A large number of seed selection and accompanying-order selection rules exist, e.g. the Sequential Minimal Distance (SMD) (Gibson & Sharp, 1992). Distances between items have to be measured. These distances are measured with two different measures: the aisle distance measure (Gibson & Sharp, 1992) and travel time measure (Clarke & Wright, 1964). The study of Henn et al. (2012) investigated lists of examples of selecting orders based on seed selection rules, i.e. randomly, smallest/largest number of items, smallest/largest number of locations, and time savings.

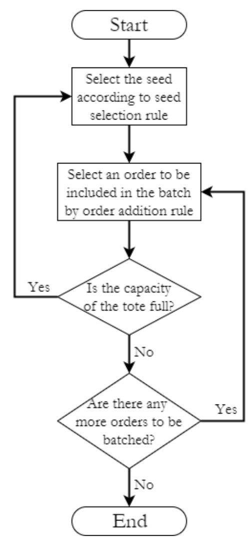

Figure 4.3: An order batching heuristic procedure (source: Pan & Liu (1995))

Saving algorithms are based on the famous vehicle routing problem of Clarke & Wright (1964). Saving algorithms are based on the time savings s_{ij} that can be obtained by combining two orders i and j in one route (with order pick time t_{ij}) as compared to the situation where both orders are collected individually (with order pick time $t_i + t_j$). Hence, $s_{ij} = t_i + t_j - t_{ij}$ The algorithm adds the customer orders to batches according to the largest saving without exceeding the capacity constraint of the tote (Henn, Koch, & Wascher, 2012). From this definition it appears that the routing algorithm applied may be of influence. Both the S-shape and Largest gap routing algorithms are used (De Koster, De Poort, & Van der Wolters, 1999).

Finally, Chen & Wu (2005) describe an order batching approach based on a *data mining approach* and integer programming. By means of an association rule, similarities of customer orders are determined. For each pair of orders, an order correlation measure is obtained. In a 0-1 integer programming approach orders are clustered into batches such that the sum of all support values to the batch medians, an order which serves as the basis for each batch, is maximized (Henn, Koch, & Wascher, 2012).

In static batching, customer orders are known at the beginning of the (short-term) planning period whereas in dynamic batching customer orders become available dynamically over time (Henn, 2012). A dynamic picking system is used to batch customer orders by using *real-time* order fulfilment strategy (Gong & de Koster, 2008). Orders arrive online and are picked in a batch, followed by later sorting per customer order. The picker travels the entire (or a part of the) warehouse and picks all outstanding order lines in one pick route. During a pick cycle, pick information is constantly updated by a pick device. Tarn et al. (2003) stated that compared with static picking, where the pick locations during a pick cycle are given and fixed, dynamic picking can shorten the response time and can thereby improve the customer service. There are two main dynamic batching strategies that are discussed in literature. *Fixed time window batching* is a strategy where a batch contains all orders that have arrived in a fixed time interval (Giannikas et al. (2017)). *Variable time window batching* is a strategy where a picker waits until a predetermined number of orders has been received and can be grouped in a batch (Giannikas et al. (2017)).

For the dynamic order batching approach where orders arrive real-time, complex algorithms are used. The possibility of using the dynamic order batching for optimizing the order picking performance is not part of this study because of the complexity of the topic and the lack of time. This topic however, is a promising strategy to analyse in the future for decreasing the pick time of one batch and the customer service and is explained further on in Chapter 7 in the recommendation section.

4.2.5 Conclusion

Results of the simulation experiment of Yu and De Koster (2009) show that batching has the largest impact on reducing total fulfilment time, particularly when small order sizes are common. On behalf of the agreements around this study, and in accordance with the company, it is chosen to optimize the performance of the order picking process by implementing design alternatives that influence the batch composition. However, more improvements could be done for optimizing the order picking performance. On algorithm level, some points of improvements could be done as well. These are explained in the discussion, for further research in the future.

Since all policies are primary interdependent, a combination of policies are used to define alternatives. Based on these policies three design alternatives were proposed for optimizing the order picking performance in a fulfilment centre:

- Volume-based randomized storage
- Class-based randomized storage
- Zone decomposition

In the following chapter, the model is specified for optimizing the performance of the order picking process testing the design alternatives compared to the base alternative.

Chapter 5 Model optimization performance order picking

In Chapter 4, three alternatives were proposed for optimizing the performance of the order picking process. The alternatives need to be tested to determine if optimization in the performance is achieved. The tests are done by first setting up a conceptual model that represents a simplification of the order picking system described in this study. Secondly, the alternatives are converted into scenarios that are tested in the model. Then, it is described how the model is implemented to practically perform the simulation. At last, the implemented model is verified and validated. The next chapter presents and provides the discussion of the model and its results.

5.1 Conceptual model

The model is specified according to the zone, described in Chapter 2, within the fulfilment centre described in this study. The model is depicted in Figure 5.1. For specification, if there is no specific data available (yet) on the processes, measurements are performed and if necessary information is asked from experts. The specification is a cyclic process with verification and validation until a satisfactory level of usability is reached in order to answer the research questions. In this paragraph the model specification will be described regarding the following aspects:

- Layout zone
- Input
- Model
    - Entities
    - Scenarios
    - Picklists
    - Processes
- Output

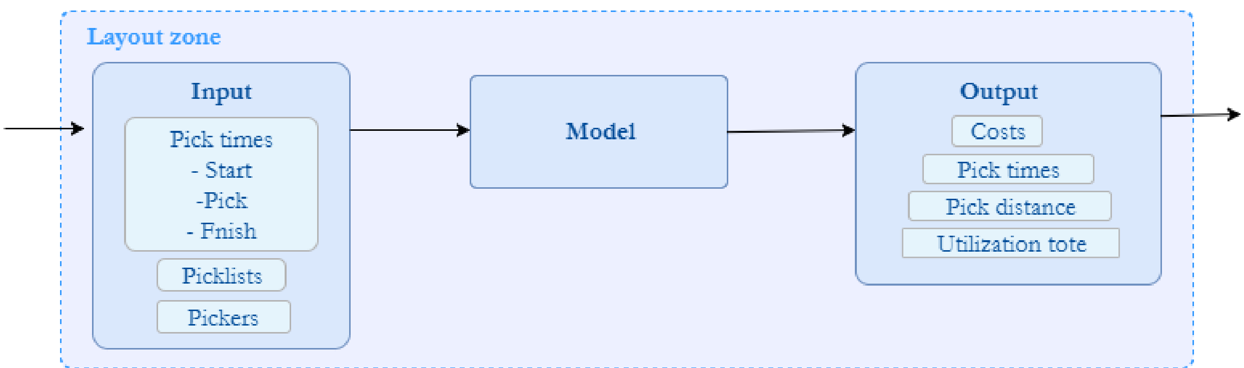

Figure 5.1: Conceptual model of the order picking process performance optimization

5.1.1 Layout zone

The layout of the zone in the fulfilment centre as described in Chapter 2 is used in the model as the so-called hardware. The zone is constructed with multiple aisles, two cross aisles, and a middle aisle. The I/O point is split into an input and an output point. In reality, the shelve locations are divided over multiple levels in the racks. In the model, the levels are taken into account indirectly by adding more variance in the pick time. This has consequences for the reliability of the pick times used in the study.

5.1.2 Input

As a model input, the system description given in Chapter 2 is combined with the results of the background analysis performed in Chapter 3. The inputs are the process times of the handlings during the order picking process, the picklists created by the batching algorithm and the order pickers. The order pickers are described as entities in the following section. The construction of the picklists is scenario dependent and therefore explained later on.

Another input of the model is the processing time of the steps in the order picking process. The processing times are already discussed in Chapter 2. The setup and scan time of a picker are assumed to be constant. The time to take an item from a storage location and put in a tote is dependent on the shelve location level and the picker.

5.1.3 Model

5.1.3.1 Entities

In this model study, the model entities represent the operators in the storage area performing the order picking process. The model entities are created based on the input and travel along the paths defined in the model on the events on which the performance of the system is measured. The average travel time of the entity through the zone is a key performance indicator. Different characteristics are assigned to the entities, based on the different scenarios.

One of the characteristics is the experience of the operator. As described before, there is a high increase of operators needed at short notice during the peak. The actions of the order picking process take longer for the new operators. In the system description in Chapter 2, it was stated that the pick time of inexperienced pickers is 120% of the time of experienced pickers. Because the rack levels were not included in the processing time estimated by the company, a safety degree of another 10% is applied. The difference in pick times of the (in)experienced picker together with the difference in shelve heights are translated into ranges of values depicted in Table 5.1. In a regular period particularly permanent employees are picking the items. Most employees are temporary, and therefore, the ratio between experienced and inexperienced pickers during a regular period are 2:1 and 6 pickers are working per zone. Due to the fact that during peak periods more order pickers are needed to process the large quantities of orders. Many temporary workers are employed to catch up the increased number of items. These temporary workers are relatively inexperienced working in the fulfilment centre and with the travel routes. Therefore, the ratio between experienced and inexperienced pickers during peak periods is respectively 1:3 and in total 12 pickers are working per zone.

	Start time [s]	**Pick time variance [s]**	**Finish time [s]**
Experienced picker	*15**	*10-20**	*35**
Inexperienced picker	*18**	*15-25**	*40**

Table 5.1: Experienced and inexperienced pickers

** Fictional in terms of confidentiality*

The travel time of the entities (operators) is determined based on the walking speed together with the travel route. The walking speed of the pickers is assumed to be constant. The routing logic determines the flow of the entities through the model from the input to the output. The routing is determined based on pick-lists that are batched based on the different scenarios. Another assumption that is made is that the picker directly goes to the next picking location after completing the picking in a specific aisle.

The variable costs that are taken into account are the labour costs of the operators. The labour costs of the operators are set to €***/hour for 2018 by the company of the case study. These costs are equal for both experienced and inexperienced pickers.

5.1.3.2 Scenarios

As determined in the background analysis of this study, orders in a regular period have different order characteristics than orders in a peak period. The amounts and volumes of the products differ and there is a shift in fast moving products. For the different periods, two different order lists are created based on the different order characteristics. For the simulation to test the different scenarios with the differences in stock locations of products within the alternatives, scenario-specific picklists need to be generated by the batching algorithm of the company. In 0 the method of creating picklists is described in detail. In this section, first, the differences between orders in regular and peak periods are described. Later on, the alternative-specific characteristics are clarified.

For creating the picklists, 300 unique articles are created. The articles are classified in 15 different weights and volumes divided over the volume classes depicted Appendix E1. For the orders in both regular and peak periods, the average volumes measured in Chapter 3 are used for determining the number of items of each volume class. Since more operators are picking in a zone during peak periods, the order list (sales) in peak periods contain more orders. Both order lists contain fast, medium and slow moving products based on a ratio determined in consultation with the company. The ratio of the product classes within the order lists based on the sales is shown in Table 5.3. Volume classes are not equal to the moving classes. Volume classes are based on volume groups, while moving classes are based on weight and volume, not on volume classes.

For the batching algorithm to create picklists, besides the article information, it is necessary to know the storage locations of the articles. The storage policy is alternative-dependent, and each alternative is regular- and peak-period tested. Therefore, the storage locations are different for all scenarios and all scenarios (Table 5.2) have different pick-lists. The determination of the storage locations is explained further on.

	Scenario	Name scenario
Alternative 1	Regular	Base alternative in a regular period
	Peak	Base alternative in a peak period
Alternative 2	Regular	Class-based randomized storage in a regular period
	Peak	Class-based randomized storage in a peak period
Alternative 3	Regular	Volume-based randomized storage in a regular period
	Peak	Volume-based randomized storage in a peak period
Alternative 4	Regular	Zone decomposition in a regular period
	Peak	Zone decomposition in a peak period

Table 5.2: Overview of scenarios

The *base scenarios* (alternative 1) represent the storage policy that is currently used in the fulfilment centre of the company. The base scenarios are simulated for measuring the optimization in the order picking performance between the current situation and the alternative situations during both regular and peak periods. The storage policy in the base scenarios is the randomized storage policy. Storage locations are randomly chosen over the total zone for all articles. The base scenario is tested in a regular period and in a peak period.

Alternative 2 represent the *class-based randomized storage alternative* in a regular and peak period respectively. The class-based storage policy is applied dividing the products in the three product classes (A, B, C) based on the ratio between fast, medium, and slow moving products determined earlier (see Table 5.3). The classified articles are stored in the separately classified subzones. The areas of the subzones are shown in Figure 5.2. The decision for the design of this layout is based on the walking distances. The slow moving products are stored in subzone C to reserve the largest walking distances for the least bought products. In subzone A, the fast moving products are stored in the nearest aisles to the I/O point and at the end of the first block, adjacent to the cross aisle. Since the products classified in class B are frequently ordered, subzone B is placed in the remaining areas between the subzones of A, and in the next block. A- and B-class products are ordered most and its subzones provides a decrease in walking distance. Only a few times a day the picker need to walk to the back of the zone (to subzone C). Within the subzones A, B, and C the products are stored randomized again.

Table 5.3: Class-based randomized storage ratios

	Percentage [%]	Number of orders in regular period [#]	Number of orders in peak period [#]
Class A: fast moving	*50**	*350**	*500**
Class B: medium moving	*35**	*260**	*310**
Class C: slow moving	*15**	*60**	*90**

** fictional values in terms of confidentiality*

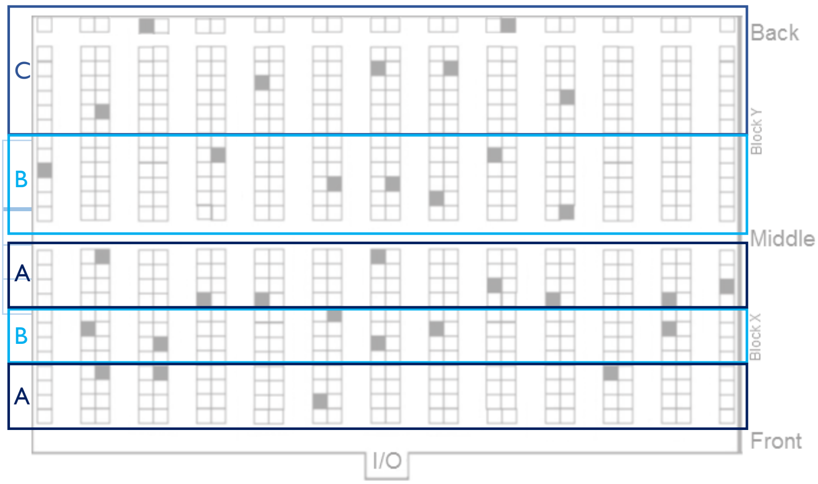

Figure 5.2: Warehouse layout with class-based randomized storage

The *volume-based randomized storage* policy alternative is tested in both a regular and a peak period. The zone is divided into three areas for applying the volume-based randomized storage policy which consists of three classes (class 1, 2, and 3) as depicted in Figure 5.3. The products are classified based on its volumes. Products within class 1 are between 0 and 1 litres, products within class 2 between 1 and 7 litres, and products within class 3 with 7 litres or more. The ratio is determined using the statistics of product volumes shown in Chapter 3. The zone is subdivided in a way that products are picked from products with high volumes to products with low volumes. The products on the picklist are sorted so the products of class 3 are picked first, then products stored in class 2, and at last the class 1 products. Since there are no products that need to be picked more often (such as fast moving products), the storage locations at the end of the pick aisles cannot be avoided for a certain

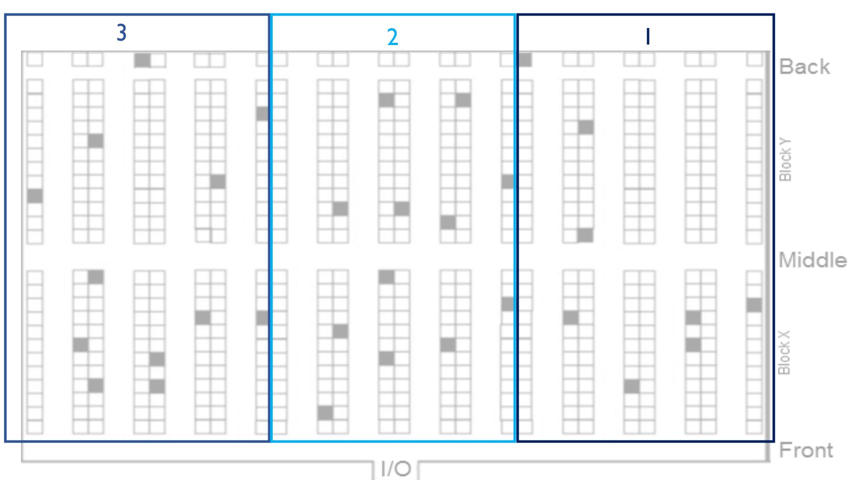

Figure 5.3: Warehouse layout with volume-based randomized storage

volume class. It has been decided to assign four aisles per zone per volume class. Within the subzones, the products of a specific volume class are stored according to the randomized storage policy again.

In the zone decomposition alternative, the zone is divided into two symmetric sub-zones with the same size to test both regular and peak periods (see Figure 5.4). Applying the *zone decomposition* on the zone, the zone is divided into two subzones, resulting in a decrease in travel time of pickers per picklist, especially during the peak. However, the alternative is tested for a regular period as well. The products are randomly divided over subzone 1 and subzone 2. Within both subzones, the products are stored according to the randomized storage policy.

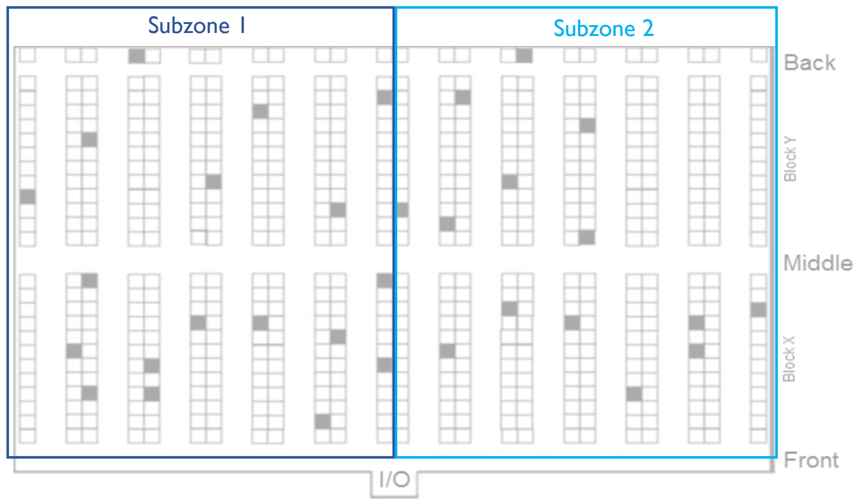

Figure 5.4: Warehouse layout with zone decomposition

5.1.3.3 Picklists

The picklists are scenario dependent. In 0, all steps performed for creating the picklists are explained in detail. A picklist is obtained by the batching algorithm. As an input, the algorithm needs a list of articles together with its characteristics, a list of available products and the storage location it is available on, and a list of customer orders. The output is a list of articles that are ready to be picked together with its storage locations. Since the batching algorithm needs a list of available products with its storage locations, the picklists are made scenario dependent.

5.1.3.4 Processes

The various process-times and characteristics to be implemented in the model are based on the processes of the order picking process and the processing times described in Chapter 2 (see Figure 5.5). The processes and the processing times are important features since those determine the flow rate of the entities. The flow rate affects significantly the order picking performance.

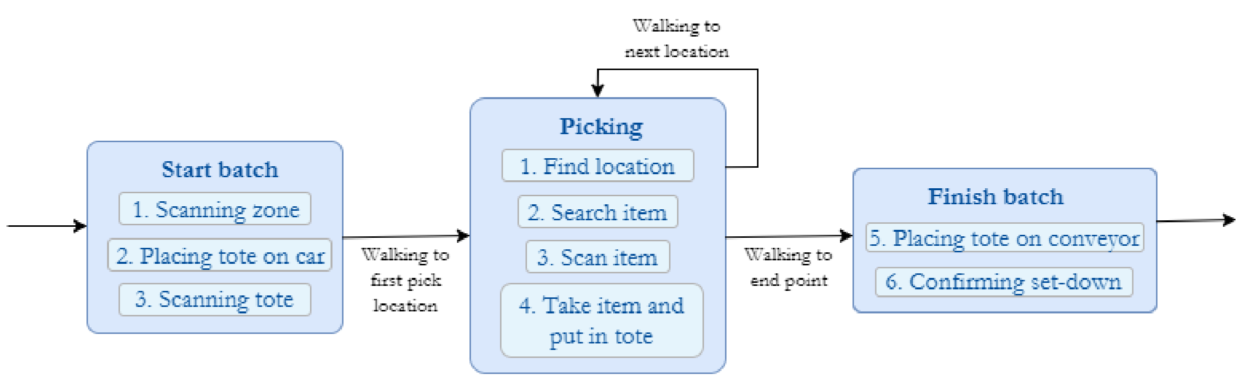

Figure 5.5: Order picking processes

Modelling the processes, there are some assumptions made:

1. Each item in a batch is independent of the other items within an order.
2. All the information about the batch to be picked is known in advance.
3. There is always an empty tote available
4. All items in a batch fit in one tote
5. All items batched are assumed to be available in the storage location

5.1.4 Output

The model is able to record the entities and their individual values at certain points in time. Because of the quantity of data available, specific indicators are checked to verify and validate the behaviour of the model. The purpose of the output of the model is to give insight into any performance optimizations of the scenarios. There are key performance indicators on which the performance of the system will be assessed for the different alternatives. The key performance indicators are the costs, the cycle time picking, walking distances, and the utilization of the tote.

5.2 Model implementation

The objective of evaluating the performance of the different alternatives proposed in this study can be accomplished through the use of an Excel calculation, together with a verified and validated simulation model. The tote utilization is determined calculating the use of the tote based on the number of items, weight and volume utility. The cycle time of picking is determined by performing a simulation The conceptual model as described in the previous paragraph can be implemented performing the simulation. Simulation is used often as an imitation of the operation of a real-world process or system over time and it is an indispensable tool for decision making and problem-solving (Schriber & Brunner, 2000). There are several strategies of simulation models, such as interval-based, event-based, activity scanning, and continuous simulations. However, this research uses discrete event simulation. According to Varga (2001), it can be defined as "a system where state changes (events) happen at discrete instances in time". This strategy is chosen, due to the fact that events are measured at certain time points. The time determines what happens. This is necessary to measure distance, costs, and items per amount of time. Further on in this paragraph, the use of discrete event simulation is defined and the verification and validation of the model follow.

5.2.1 Excel calculation

One of the outputs of the model is the tote utilization. The tote utilization can be calculated by using the picklists created by the batching algorithm. The picklists can be arranged and edited using the pivot table in Excel. Then, the average number of items, total weight and total volume per batch per scenario can be collected. By dividing these values by the maximum filling degrees of the totes, the percentage of the utilization of the totes can be obtained.

5.2.2 Discrete event simulation

Discrete event simulation is a tool that enables the user to compress time and study system performance characteristics. Fundamentally, a discrete-event simulation is one in which the state of a model changes only at a discrete, but possibly random, set of simulated time points, called event times (Schriber et al. (2012)). The conceptual model is implemented in the Simio simulation software. The order picking system of the FC of this research is built as explained in the model description. Due to the fact that there are internal processes on each built node and critical decisions made as a product of it, the model is explained in detail in 02. The simulation time is set to two hours. A warm-up time of 1 hour is used, so the performance measurements start when the order picking process is already running.

5.3 Validations

After building the model it is vital to understand if it is correct against the specifications (Sargent, Verification and validation of simulation models, 2005). Validation is performed in a modelling cycle in conjunction with the specification and verification of the model. This can be seen in the modelling cycle of Sargent (2009) in Figure 5.6. The problem entity is the system (real or proposed) to be modelled; the conceptual model is the mathematical representation of the problem entity developed for this study, and the computerized model is the conceptual model implemented on a computer. The conceptual model is developed through an analysis and modelling phase, the computerized model is developed through a computer programming and implementation phase, and inferences about the problem entity are obtained by conducting computer experiments on the computerized model in the experimentation phase. Often, it is too costly and time-consuming to determine that a model is absolutely valid over the complete domain of its intended applicability. Instead, tests and evaluations are conducted until sufficient confidence is obtained that a model can be considered valid for its intended application (Sargent, 2009).

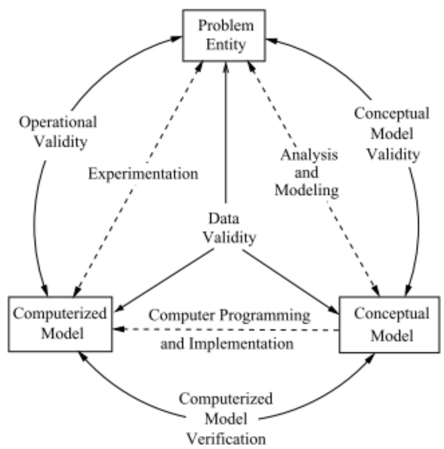

Figure 5.6: Modelling cycle of Sargent

Validation aims to answer the question whether or not is the model able to respond to real-life questions and scenarios under study. According to Schlesinger (1979), it is the "*substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model*". However, there is no standard way for validation the model. In literature described by Sargent (2005), there are several validation methods that can be applied. The input parameters and output can be validated against historical data and expert knowledge. Model assumptions and processes can be validated structural and the results of the model can be validated compared with historical data and real-life statistics.

5.3.1 Validation strategy

In this study, it is not possible to perform any validation analysis based on historical data since the FC does not have reliable data yet. Therefore, an extensive expert analysis is done.

Validation tests	Configuration Variable	Indicator
Cycle time	-	Cycle time
Expert analysis	Input parameters and distributions	Pick times, Picklists, and Pickers
	Model assumptions and processes	-
	Experimental results	-

5.3.2 Validation of the batch time

[redacted]

5.3.3 Expert analysis

Since the validation of the cycle time is not a scientifically responsible validation, and there is no historical data available yet, the model is validated doing an expert analysis. Sargent (2009) describes various validation techniques and tests used in model validation. The techniques can be used either subjectively or objectively. In this validation a subjectively technique must be used. The behaviour of the simulation models is already tested in the verification. For the expert analysis, the *Face Validity* and *Animation* technique are used. In Face Validity individuals knowledgeable about the system are asked whether the model and its behaviour are reasonable. The correctness of the logic in the conceptual model together with the reasonability of the model's input-output relationships are tested. This is partly done by showing Animations, where the model's operational behaviour is displayed graphically as the model moves through time. The validation is done interviewing three experts of the company following the following three steps 1) Input parameters and distributions, 2) Model assumptions and processes, and 3) Experimental results.

5.3.3.1 Input parameters and distributions

The model's input that needs to be validated consists of pick times, picklists, and pickers. The pick times used in the model are different than values proposed by the company. In the model a random variance is added to the values proposed. This was done to include a different pick time for picking items from different shelve heights. The experts agreed to the pick times in the model. With the variance, they stated that there is more reliability added to the pick times and uncertainties are included as well.

The picklists that were modelled in this study consisted of ** items per batch on average. An expert showed that in the peak of 2017, the picklists consisted of ** items per batch on average. The reliability of the batch size is still doubtful because of the custom operation. The expert indicated that based on the company its estimates, the average of ** items per batch is plausible for future operations.

The number of pickers, representing the model entities, were determined beforehand with experts. However, the ratio of pickers used in the model possibly differs from reality. The ratio of experienced and inexperienced pickers changes often, and according to the experts cannot be set to one value. However, the output of the model shows separate values for the cycle time of both picker types and therefore, the ratio is traceable and adjustable. For this study, averages are used and thus the results are assumed to be representative of reality.

5.3.3.2 Model assumptions and processes

The experts confirmed that the assumptions made in the model are reasonable. These assumptions are also used in the models the experts produced and are common in the expertise. The processes modelled were simplifications of reality. According to the experts, the simplified processes capture all important steps of order picking. Some processes were merged, but this does not influence the results. Using Animation techniques, the processes were showed to the experts. They confirmed the correctness of the layout of the fulfilment centres, and the movements of the pickers were in accordance with their expectations.

5.3.3.3 Experimental results

5.4 Verification

This paragraph includes the description of the verification strategy, followed by the verification checks. Finally, the specific verification runs and results are presented.

5.4.1 Verification strategy

There are two main components to a verification process and these are equally important. First, the checks are done to understand if the model is functioning against the requirements. These are extremely practical as they are used while building the model and verifying the stepwise implementation of the different mechanisms and processes in the model. After this, and once the model is ready, the verification runs are performed. Optimally, runs should be performed on all existing variables, its combinations, and for all key performance indicators.

Table 5.4: Verification strategy

Verification tests	**Configuration variable**	**Indicator**
Continuity	Pick time	Cycle time
Degeneracy	Process times, number of pickers	Cycle Time, Distance travelled
Consistency	Walk speed	Cycle Time, Distance travelled

5.4.2 Verification checks

In this section the steps in which the model was verified is described. The verification steps are explained below:

- **Model correctness:** The de-budding and checking the model is done for each process and sub-process separately. Most of those were built separately and then added once their correctness was verified. By following the separate steps during building, errors were contained to their specific part of the model, solved and then implemented in the final model.
- **Balance checks:** The balance checks are performed using the visual aids of Simio (i.e. labels and the Pivot Grid in the Results tab). All entities created match with those either still in the system or leaving the system.
- **Event tracing:** When building the model, the trace capability of Simio was used. The trace capability allows the researcher to follow each step of each process with the respective entity and understand fully if the model's logic matches the conceptualized model.
- **Input checks:** Based on the picklists used as input together with the associated scenario based number of (in)experienced pickers, it can be verified that the model created the expected number of pickers

5.4.3 Verification runs

In this sub-section the model is verified performing tests to ascertain the model behaves as expected when extreme cases or changing conditions occur. The verification is done according to the strategy presented in Table 5.4. The results are discussed below.

5.4.3.1 Continuity test

In the continuity test, the results of running the model are tested with slightly different parameters for scenario 1. Using the start- and finish batch time as a fixed parameter, Figure 5.7, Figure 5.8, and Figure 5.9show how the cycle times change when the picking time (PT) is changed in 10% increments. In Figure 5.7 can be seen that, as expected, all pickers taken into account, the relationship of picking time compared to the time it takes to complete a batch is linear. The linear relationship is determined to be significant, since the p-value is 0.000 ($p<0.05$) and the confidence interval shows that there is significant difference between the results (see Appendix E3.2). Looking at experienced and inexperienced pickers separately, it seems that there is more variety in the results. Due to the fact that there is variance in the picking times within the picker type, it seems logical that with increasing the picking time by 10%, the variance is increased as well.

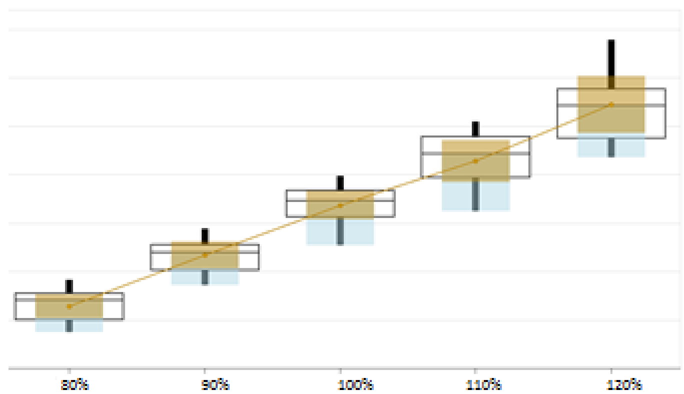

Figure 5.7: Variable PT time - Cycle time

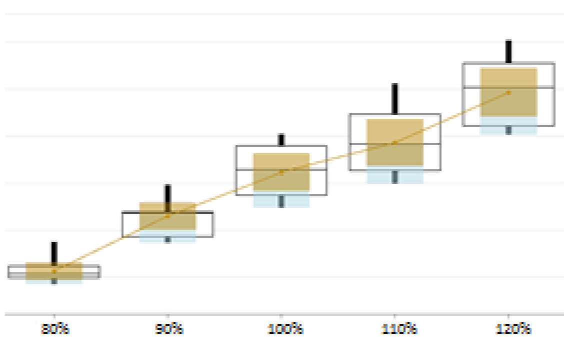

Figure 5.8: Variable PT time - Cycle time for experienced picker

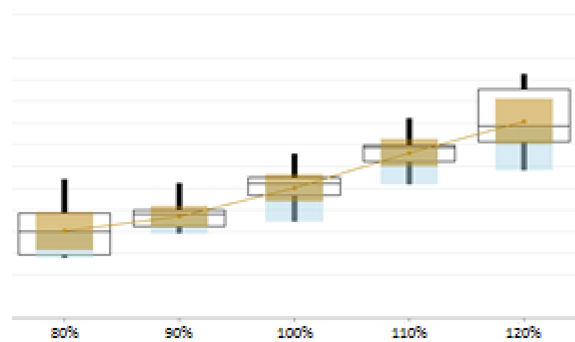

Figure 5.9: Variable PT time - Cycle time for in experienced picker

5.4.3.2 Degeneracy tests

In a degeneracy test the response of the model to extreme cases in verified. The test includes changing the factors of the server process times and the number of pickers into zero or infinite. The modified process times lead to different cycle times. When the process times are set to zero, the cycle time is only dependent of the walking distance (and walk speed). The process times treated as infinite causes problems in the system. Setting the picker parameter to zero, results in no pickers in the system. As can be expected, the simulation cannot run. An infinite number of pickers, results in the system warning for an unexpected high number of 'agents'. The maximum number of pickers is exceeded and the system is not able to simulate this scenario.

5.4.3.3 Consistency tests

In the consistency test is tested what happens when increasing the walking speed of the pickers. The results of the simulation were tested on significance (see Appendix E3.2). As can be seen in Figure 5.10, the cycle time decreases significant ($p<0.05$) while increasing the walking speed. Here, the 95% confidence interval of the differences does not contain 0 and therefore, the difference is significant. Since the cycle time is dependent of walking times together with processing times, a non-linear relationship is expected here. This is what happens. It is expected for the walking distance to stay the same, since the walking distance is not dependent of the walking speed. The simulations show results as expected, as can be seen in Figure 11.

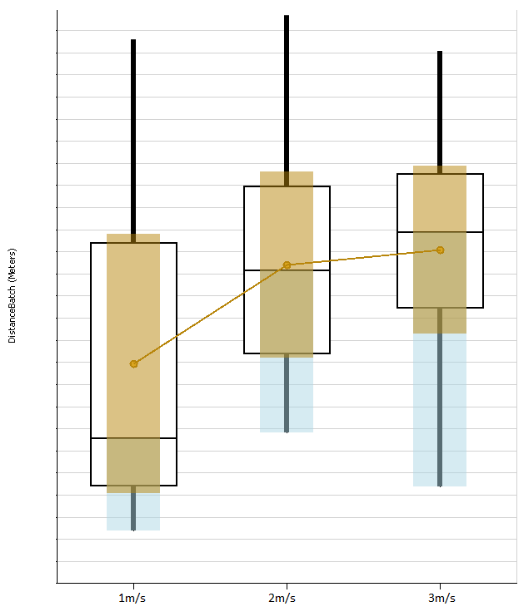

Figure 5.11: Variable walking speed - Travel distance

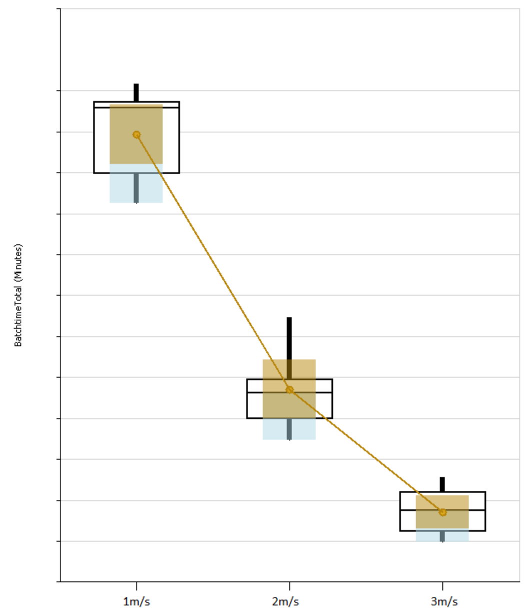

Figure 5.10: Variable walking speed - Cycle time

5.5 Conclusion

In this chapter, the model is explained for testing the design alternatives. A conceptual model was elaborated by setting up the input, the model itself and the output. Then, the model implementation was explained. The model is tested by combining Excel calculations and by performing a discrete event simulation. The model was validated by experts of the company of this study, and the model built in Simio was tested by some verification steps. In the next chapter, the model results are explained.

Chapter 6 Results of order picking optimization model

6.1 Optimized performance situation compared to current situation

In this chapter, the results of the model are analysed after running the model. The goal of this analysis to compare the performance indicators of the base scenarios (in regular and peak periods) with the scenarios that represent the alternatives. The results will be discussed per model using the corresponding key performance indicators. First the utilization of the tote is described, then the cycle and batch time of picking are shown, and at last the walking distances are compared. In the following section, further calculations are made for explaining the consequences of the performances of the alternatives.

The goal of this analysis is to understand whether or not different alternatives are statistically different. In addition to this, it is necessary to understand how large the differences are since a value might be statistically equivalent but not relevant in a real-life situation. As Lane (2015) stated "finding that an effect is significant does not tell you about how large or important the effect is." A short summary on the concept of hypothesis testing is given, and the appliance in this study is presented. In statistics it is critical to determine if the experiment "treatments" had an effect or not. This is done through hypothesis testing. The first hypothesis states that there is no effect of the treatment, which is referred to as the null hypothesis H_0. The hypothesis H_0 can be rejected or accepted based on the error type of the decision making process (i.e. Type I (α) and Type II error (β)). The p-value relates to the first type error. Type 2 error (β) is reduced by increasing the sample size.

In order to test if the difference between the samples (alternatives) is statistical significant, means and variances are tested. Neyman and Pearson their approach is used and relies on a pre-defined α value. If $p<\alpha$, then H_0 is rejected and the magnitude of the significance is not important (Lane, 2015). This means that the alternative hypothesis H_1 is accepted. On the contrary, if $p>\alpha$ the null hypothesis cannot be rejected. A 5% level of statistically significance is used, this means that testing is done at an α-level of 0.05 (95% confidence). The p-value is determined by running 50 replications per scenario and comparing the results by performing a paired-samples t-test. The significances of the output of the scenarios can be found in Appendix E3.2. Besides, another method to test the significance is with confidence intervals of the results. Confidence intervals provide information about statistical sensitivity of the results, as well as the direction and strength of the effect (Shakespeare et al. (2001)).

6.1.1 Utilization tote

The utilization of the totes is calculated as explained before. The utilization of the tote is expressed in percentages and shows the filling degree of the tote. The results can be seen in Table 6.1 and Table 6.2. In both tables, all utilities of the alternatives change slightly compared to the base alternative.

Table 6.1: Results of utilization of tote in regular period

Regular period	Item utility	Weight utility	Volume utility
Base	*60%**	*85%**	*40%**
Class-based	*61%**	*85%**	*42%**
Volume-based	*61%**	*86%**	*41%**
Zone decomp.	*61%**	*87%**	*42%**

Table 6.2: Results of utilization of tote in peak period

Peak period	Item utility	Weight utility	Volume utility
Base	*61%**	*86%**	*39%**
Class-based	*62%**	*87%**	*40%**
Volume-based	*62%**	*87%**	*45%**
Zone decomp.	*62%**	*87%**	*46%**

** fictional values in terms of confidentiality*

The small differences in the output of the alternatives can be declared by some restrictions within the batching algorithm that is used to make the pick lists for modelling the scenarios. In this alternative the batching algorithm should have made the pick-lists in a sequence that the largest and heaviest items are picked first and the smallest, light-weighted items are picked at last. However, the batching algorithm of the company has placed all items within a zone randomly in a batch without taking sizes and weight into account. This means that for example in the alternative where the concept of optimization is based on volume-based storage, is not considered as meant. When all low-volume items should have been placed in one batch, a higher item utility could have been reached. Another reason for the relatively low utilities for items and volumes are the high utilities for weight. The batching algorithm has terminated the process of batching on the weight criteria. As mentioned in the validation, in reality it is more likely for the algorithm to terminate the process on the volume criteria. However, a higher item utility could possibly be obtained by implementing a filling gauge in the algorithm for filling the tote more efficiently (to be continued in Chapter 7.2). Another obvious alternative for optimizing the performance could be changing the type of totes that leads to better utilization of the tote. A different tote type can be for example a tote with a higher volume or a tote with a different shape and dimensions. Testing the possibilities of using different totes can be an interesting topic for future research.

6.1.2 Cycle picking time

The results of the cycle picking time are separated into the regular and peak period. The results for regular periods can be seen in Table 6.3 and Figure 6.2. As can be seen in the figure, all optimization alternatives score significantly better than the base alternative. Since all alternatives are significantly different with a p-value 0.000, according to Knaub (1987), it may be preferred to use the confidence intervals. The confidence intervals for the difference between the alternative means can be seen in Appendix E3.2. Since the intervals do not contain 0, it can be seen that the difference in this study is significant. Although, it can be seen that the average cycle time is negatively influenced by the cycle time of the inexperienced picker. This is a logical consequence of hiring inexperienced pickers. However, it would be desirable to decrease the difference in process time between inexperienced and experienced pickers. The inexperienced pickers are trained in a test environment first before picking in the new fulfilment centre, these effects are not captured in these results yet.

Table 6.3: Results of cycle picking time in regular period

Regular period	Cycle picking time regular period		
	[min/batch]	[min/batch/ experienced picker]	[min/batch/ inexperienced picker]
Base alternative			
Class-based			
Volume-based			
Zone decomposition			

Table 6.4: Results of cycle picking time in peak period

Peak period	Cycle picking time peak period		
	[min/batch]	[min/batch/ experienced picker]	[min/batch/ inexperienced picker]
Base alternative			
Class-based			
Volume-based			
Zone decomposition			

Performing the class-based randomized storage alternative, the pickers tend to need the least time to pick a batch. This could be expected since several literature reviews (Yu et al. (2009) and Pedrielli et al. (2016)) showed that the class-based storage decreased the cycle picking time for different companies in different applications. Therefore, it could be expected that this alternative should lead to a major decrease in cycle picking time. However, both the volume-based storage and zone decomposition alternative score better than the base alternative. Before, it was expected for the volume-based storage and zone decomposition alternatives to score better than the other optimization alternatives since the alternatives focus on reducing the walking distance. The difference in performance can be declared by the operations of the batching algorithm used to create the picklists. The batching algorithm did not take walking distances into account. Hereby, batches were not created based on the meant storage policies implemented in these alternatives. Taking into account for the volume-based randomized storage that all small items can be picked in one batch can lead to a higher item utility as mentioned before. This means that in one pick tour more items are picked, and more items could be picked per batch. For the zone decomposition, more efficient batches could have been created when walking distances were taken into account as well. This should have led to lower cycle times than obtained by the current simulation.

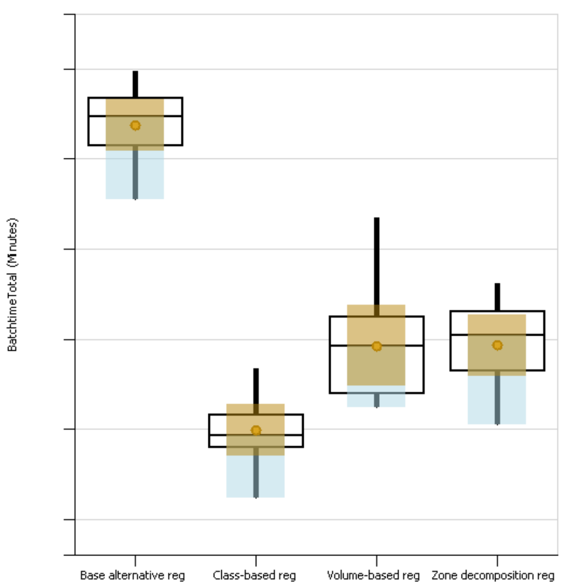

Figure 6.2: Results cycle picking time regular period

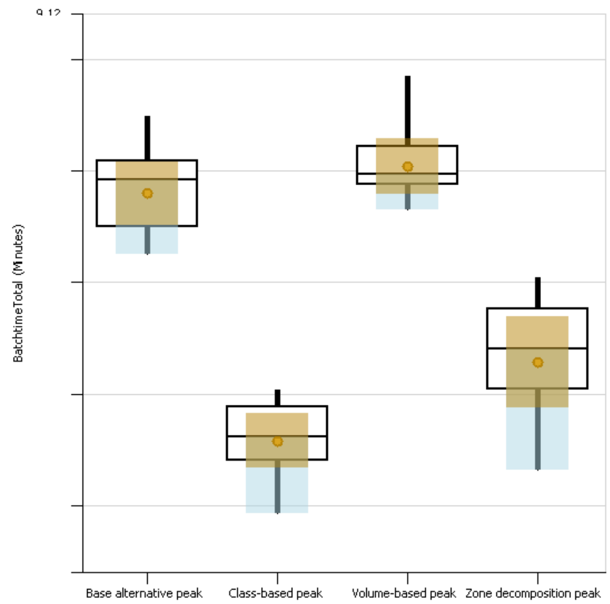

Figure 6.1: Results cycle picking time peak period

The results for peak periods can be seen in Table 6.4 and Figure 6.1. Since during peak periods more inexperienced than experienced pickers are picking the items, it can be seen in the table that the cycle time of the inexperienced picker influences the average cycle picking time. Similar to the regular period, in the peak period, the class-based randomized storage alternative helps the pickers to complete a batch in the least amount of time. Here, the 95% confidence interval of the differences does not contain 0 and therefore, the difference is significant. The zone decomposition alternative scores second best. Implementing zone decomposition could lead to even lower cycle times for the in experienced pickers since sub-zones are used here. When the pickers need to pick in only a part of the zone, the picker has less chance to get lost in the aisles. This probably should influence the average cycle picking time. It could be interesting implementing the class-based randomized storage, and during peak periods implement zone decomposition as well. This can lead to even lower process times during the peak than simulated. The volume-based randomized storage shows an unexpected results having a comparable cycle picking time than the base alternative with an insignificant difference ($p(0.308) > \alpha(0.05)$). Presumably, the operations of the batching algorithms explained earlier influenced the results of the simulation. The picklists made, do not differ significant from the picklist of the base alternative.

6.1.3 Travel distance of the picker

In literature it was found that optimizing the order picking performance could be done by decreasing the travel distance of the pickers between picks. In this section the results of the simulation regarding the distance travelled by the order pickers per batch are discussed (see Table 6.5). The results are split into regular and peak periods The results show significant differences. The 2-tailed significance is 0.000 again and therefore, the confidence interval was used. All alternatives are significant on a 95% confidence interval of the difference, since the intervals do not contain 0. During regular periods all alternatives show a decrease in travel distance per batch compared to the base alternative. In peak periods only the class-based storage and zone decomposition alternatives show a decrease. For both periods, implementing the class-based storage policy, the least travel distance per batch is reached. The variance of the travel distance is the smallest for the class-based storage alternative as well, this means that this alternative shows the most stable and reliable results.

Table 6.5: Results travel distances in regular and peak period

	Travel distance [m/batch]	
	Regular period	Peak period
Base alternative		
Class-based		
Volume-based		
Zone decomposition		

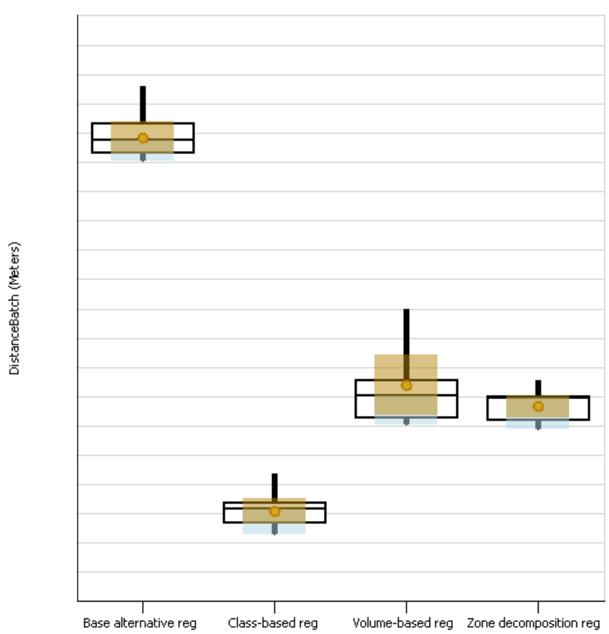

Figure 6.4: Results batch travel distance regular period

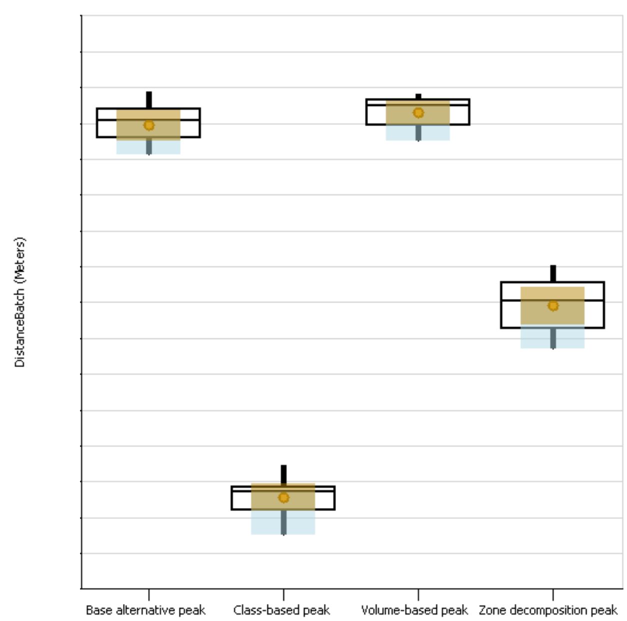

Figure 6.3: Results batch travel distance peak period

6.1.4 Order picking labour costs

In the previous sections, the direct results of the simulation are considered, explained, and the significance is ascertained. These simulation results are used for calculating the total processing speed of order picking and the costs. In Appendix E3.3 the elaborate version of calculations can be found. Below, the costs are determined for both regular and peak periods. Later on the total costs on yearly basis are shown.

On an average regular day, ** orders that are placed have to be processed in the fulfilment centre of this study. In the background analysis, it was stated that on a regular day an average order consists of ** items. This leads to *200,000** items that need to be processed on a regular day. Based on these data together with the output of the model, the gross costs (taxes included) of the operators, a percentage on the price included for supervisors on the floor, and 12% included for inefficiencies, breaks and toilet visits of operators, the variable gross price per day for only the order picking process can be calculated. The savings for each alternative can be calculated by comparing the costs with the base alternative.

First the number of items that one picker is able to process per day is calculated batch on the cycle time calculated in the simulation. Secondly, the number of operators needed to process the average items determined are calculated. Then, based on the gross calculations, the gross price and the savings are calculated. The results can be seen in **Error! Reference source not found.**.

Table 6.6: Costs calculation regular day

Regular day	Items/day/ picker	#Pickers needed	Gross labour picking costs	Saving
Base alternative	[redacted]			-
Class-based				13.4%
Volume-based				11.3%
Zone decomposition				10.0%

On an average peak day, ** orders are placed that need to be processed in the fulfilment centre of this study. In the background analysis, it was stated that on a peak day an average order consists of ** items. This leads to *360,000** items that need to be processed on a peak day. With these data, together with the data explained for calculating the gross price for regular days, the calculation for peak days can be done. The results are shown in **Error! Reference source not found.** in Appendix E.

Table 6.7: Costs calculation peak day

Peak day	Items/day/ picker	#Pickers needed	Gross labour picking costs	Saving
Base alternative	[redacted]			-
Class-based				9.0%
Volume-based				-0.3%
Zone decomposition				6.1%

Most interesting for companies are the costs on yearly basis. The savings obtained by the alternatives are compared with the total variable costs of the company. The total variable costs taken into account in this study are the variable labour costs of all processes in the fulfilment centre. An extensive explanation can be found in Appendix E3.3. The variable costs of regular and peak periods are converted into costs per year.

In Table 6.8, an overview is made per alternative for the total variable costs and the picking costs per year. As can be seen in the column 'Pick percentage', the order picking costs are around 10% of the total labour costs of the fulfilment centre. An elaborate calculation of these costs taking all processes in the FC into account can be found in Appendix E3.3. The base alternative has the highest picking costs and the design alternatives show savings on the total costs per year of 1.4%, 0.9%, and 1.0% respectively. The saving picking column shows the savings of the design alternatives in regard to the picking costs of the base alternative per year of 14.1%, 8.5%, and 9.8% respectively.

Table 6.8: Total costs on yearly basis

	Total costs/year	Picking costs/year	Pick percentage	Saving total	Saving picking
Base alternative			11.4%	-	-
Class-based			10.2%	1.4%	14.1%
Volume-based			10.6%	0.9%	8.5%
Zone decomposition			10.5%	1.0%	9.8%

From the yearly savings overview, it can be concluded that the highest savings at yearly basis are obtained by implementing class-based randomized storage. The savings are 1.4% of the total variable costs that were taken into account. Implementing zone decomposition causes a saving of 0.9%. This alternative causes major savings during peak periods as well. As stated before, it could be promising implementing this alternative dynamically during peak periods. Probably, even higher savings can be obtained then.

However, the picking costs are around 10% of the total variable costs. In future operations, the savings will increase even more due to the fact that more processes are going to be (semi-)mechanized and less operators are needed. The order picking process is harder to change into a mechanized operation, since the variability of the product characteristics and high value or vulnerability of products. High investments are needed to change the storage area in a fulfilment centre into a mechanized order picking system. Nevertheless, the company expects a major growth in customer orders in the following years. Therefore, it is necessary that a higher performance during order picking is obtained. The savings obtained by the alternatives calculated for 2018, can cause even higher savings for the upcoming years taking the growth into account.

6.2 Conclusion

In this chapter, the results of the simulation were discussed. The key performance indicators of this study were explained and calculated using the output of the simulation.

The utilization of the tote based on number of items, weight and volume did not change for the different alternatives. The small differences in the output of the alternatives can be declared by some restrictions within the batching algorithm that is used to make the pick lists for modelling the scenarios. Therefore, the utilization of the tote was not improved implementing the alternatives. Further research could possibly focus on this aspect, for example analysing the usage of different types of totes. In Chapter 7.3 this is explained in more detail.

The second key performance indicator is the cycle picking time. The cycle picking time was analysed in both regular and peak periods. In a regular period, all three alternatives tend to score better than the base alternative. The time it takes an operator to complete a batch is the least for the class-based randomized storage alternative. This could be expected since several literature reviews showed that the class-based storage decreased the cycle picking time for different companies in different applications. However, both volume-based randomized storing and zone decomposition alternatives score better than the base alternative as well. The difference in performance can be declared by the operations of the batching algorithm used to create the picklists. The batching algorithm did not take walking distances into account. Hereby, batches were not created as meant in these alternatives. In peak periods, again the class-based storage alternative helps the pickers to complete a batch in the least amount of time. It could be interesting implementing the class-based randomized storage permanent, and during peak periods implement zone decomposition as well. This can lead to even lower process times during the peak.

Then, the results of the travel distance were analysed. During regular periods all alternatives show a decrease in travel distance per batch compared to the base alternative. In the peak periods only the class-based storage and the zone decomposition alternatives show a decrease. For both periods, performing the class-based storage policy, the travel distance per batch is the least. The variance of the travel distance is the smallest for class-based storage as well, this means that this alternative shows the most stable and reliable results.

At last, the order picking costs were determined based on the cycle picking time and the travel distance. Together with the total variable labour costs, the share of costs savings of the order picking process were compared. For the class-based storage alternatives, up to 1.4% savings can be obtained of the total variable labour costs in the fulfilment centre. Looking at only order picking costs, 14% of the costs can be saved. The volume-based and zone decomposition alternatives save up to 0.9% and 1.0% respectively. However, the zone decomposition alternative causes major savings during peak periods as well. As stated before, it could be promising implementing this alternative dynamically during peak periods. Probably, even higher savings can be obtained then. In future operations, the savings will increase even more due to mechanization of for example packing operations, and an expected growth in customer orders. The savings obtained by the alternatives calculated for 2018, can cause even higher savings for the upcoming years taking the growth into account.

The overall conclusion of the results of the model is that implementing the class-based randomized storage policy permanently seems to be the most promising alternative for optimizing the order picking process during both peak and regular periods. Significantly costs savings can be obtained, keeping mechanization and growth into account. Looking at cycle time and travel distances, the zone decomposition is a policy that could be deployed dynamically during peak periods. It is relatively easy for the batching algorithm to adjust the parameter of dividing the zone in two sub-zones or not when needed.

Chapter 7 Conclusion, discussion and recommendations

This research focused on the seasonal impacts that influence the performance of the order picking process during both regular and peak periods. In this research the seasonal impacts are determined to improve the performance of the process. Theories were used for setting up alternatives. These alternatives were modelled and the results were compared. This chapter first describes the conclusion of this study, by answering the sub research questions and main research question. The second section contains a discussion of the results of this study, followed by recommendations for further research and the company of the case study.

7.1 Conclusion

The objective of this research was to investigate and identify the opportunities and possibilities regarding the order picking process to react to the seasonal impacts that influence differences in the performance of order picking during regular and peak periods. As a result of the seasonal decomposition performed on historical data of the company, insight was gained in the seasonal patterns of customer orders. The presented results together with theories of order picking performance optimization found in literature were used for setting up alternatives. These alternatives were tested and evaluated by comparing the results with the base alternative. This section provides the answer to the main research question by answering the five sub research questions.

7.1.1 Improvement order picking regular versus peak periods (main research question)

The main research question is formulated as follows:

'How can the performance of the order picking process be improved taking seasonal influences into account for regular and peak periods?"

In this study, it became clear there is not one answer on how to improve the performance of the order picking process, especially taken seasonal influences during regular and peak periods into account. However, three design alternatives were elaborated and tested for improving the order picking performance. The focus of the alternatives is decreasing travel distances between picks in a cycle picking tour. Testing the alternatives gave insight into the performance indicators: savings in cycle time picking, travel distances, and costs by changing the picklists based on order picking policies. This study has shown the added value of combining theories found in literature and objectives of a company. The conclusions of the study provide serious cost savings for the company. It is estimated that, implementing class-based randomized storage in the FC, next year the net present costs could be reduced by €*** or by 12% of the order picking costs. How this is done is explained by answering the following five sub research questions.

7.1.2 Seasonal influences (sub research question 1)

The first sub research question is formulated as follows:

1. *What different seasonal, monthly, and weekly influences can be differentiated, and when do they occur?*

The seasonal influences, together with its time of occurring, are analysed and determined performing a time series data analysis. Using seasonal decompositions, daily, weekly, and monthly influences were assorted. Based on these influences, regular and peak periods could be distinguished. An overview of the most important conclusions is shown in Table 7.1. In peak periods, the number of orders increases together with the number of multi-orders. Therefore, the impact on the number of items is amplified during peak periods. Since more items need to be processed in the FC, the workload of the order pickers increases significantly in the storage area.

Table 7.1: Overview of conclusions seasonal influences: regular vs peak period

	General	**Regular period**	**Peak period**
Number of orders	Improved efficiency in fulfilling mono-orders is necessary. Multi-orders form largest picking volume.	Number of orders is dependent on sales and releases.	More orders in peak periods lead to more picks in FC.
Number of items	Multi-orders cause higher number of items that need to be picked.	Number of items is dependent on sales and releases.	More multi-orders, amplified number of items during peak.
Items/order	More items/order in total leads to more picks.	Most of orders are mono-orders.	More items per order.
Weight/item	More items per batch can be picked when there is a decrease in weight/item	During regular period, higher weight/item, less items/batch, more travel time per item.	During peak lower weight/item, more items/batch, less travel time per item.
Volume/item	More items per batch can be picked when there is a decrease in volume/item	During regular period, higher volume/item, less items/batch, more travel time per item.	During peak lower volume/item, more items/batch, less travel time per item.

7.1.3 Order characteristics (sub research question 2)

The second sub research question is formulated as follows:

2. *What are the characteristics of orders during peak periods compared to regular orders?*

Different characteristics of orders could be differentiated. In the time series analysis, the items per order, items per category, weight per item, and volume per item were looked into. Again, a distinction was made between regular and peak periods. In peak periods, the items per order are significantly increased while the variance of items decreased. The increase of the workload occurs especially during the peak period during the Holidays. During this period, the weight per item and volume per item decrease, which means that batch sizes can be adjusted in such a way that more items can be picked in one zone.

7.1.4 Theories improving order picking (sub research question 3)

The third sub research question is formulated as follows:

3. *What are possible policies proposed in theories for improving the order picking performance?*

Improving the performance of the order picking process can be done by three interdependent policies. The first policy is the *storage policy*. The storage policy determines how to assign items to storage locations within the warehouse. Storage locations can be changed which can lead to a reduction in travel distances of the pickers. Second, the *routing policy* can be used for improving the order picking performance. Literature showed that serious time savings can be obtained using optimal routing algorithms. The algorithm determines a tour of minimum length that allows for picking all items included in the picking order. The *zoning policy* is the third policy. The main objective of zoning is to achieve maximum utilization of the picking resources, by distributing the total picking workload equally among the defined zones. The last policy is the order consolidation policy. Order consolidation is the transformation of customer orders into order pick lists (batches). In order to calculate the length of a picker tour, the sequence has to be determined according to which the items contained in the picking order will be picked. Its main objective is to reduce the order picker's travel time per order

7.1.5 Solutions improving order picking performance (sub research question 4)

The fourth sub research question is formulated as follows:

4. *What are possible solutions that can be generated in order to improve the performance of order picking during peak periods?*

Possible solutions in order to improve the performance of order picking during peak periods were conducted according to the primary interdependent policies found in the third sub research question. Infinite solution possibilities can be found, however based on these policies three alternatives were proposed:

- Class-based randomized storage

  As described in literature, an interesting alternative for optimizing the order picking performance by minimizing travel distance is implementing class-based storage based on fast moving and slow moving products. While the items are grouped based on fast, medium, and slow moving products, the items still can be stored randomized within each class. The fast moving product, classified as class A, are stored near to each other following an across-aisle storage near to the I/O point. The slow moving products, class C, are stored at the end of the aisles because these products have to be picked the least often. The medium moving products, class B, are stored in between. The end of the area leads to highest travel times, and therefore class C products are stored over there.
- Volume-based randomized storage

  Implementing a class-based storage based on volumes leads to sufficient filling of totes. The storage concept can be still randomized, which means that still all articles are divided over all zones. The difference in storage is, that at the beginning of the route of the operator, the items with largest volumes are stored. This can be obtained by dividing the items in for example 3 classes based on volume (small, medium, and large volume). Storing the items such a way that the larger volumes are stored in the first part of the route the batch suggest, leads to a more efficient filling of the tote. When the largest item is picked the least, can lead to a situation the product does not fit in the tote anymore. Starting with the larger volumes and ending with the smaller items will lead to a situation where more items fit in a tote. Then, more items can be picked per tour which leads to smaller travel distances per item.
- Zone decomposition

  Implementation of zone decomposition (decomposing the existing zones in two sub-zones during peak periods), fewer operators per sub-zone are working. The chance of congested aisles is decreased. Each operator still picks the same amount of items, but then in a smaller zone. Implementing this temporary parameter in the algorithm, therefore, leads to less travel distance per operator and thus shorter travel times per batch. Half of the travel time can be obtained while picking twice as many items.

7.1.6 Most promising solution (sub research question 5)

The last sub research question is formulated as follows:

5. *What solution is most promising in the case of improving order picking during peak periods?*

Three alternatives were proposed for optimizing the performance of the order picking process. The alternatives were tested to determine if optimization in the performance is achieved, and if so, the measure of it. Key performance indicators were used for measuring possible improvements in performance. The key performance indicators are cycle picking time and the order picking costs. The travel distance was explained as well. The tests were done by setting up a conceptual model that represents a simplification of the order picking system described in this study. Secondly, four alternatives were tested in the model for both regular and peak periods. At last, the model results were evaluated using the key performance indicators of this study. An overview of the results of the other performance indicators is given in Table 7.2 for the design alternatives. The utilization of the tote based on number of items, weight and volume, did not change for the different alternatives and therefore, is not included into the conclusions.

Table 7.2: Conclusions of design alternatives for all performance indicators

Conclusions	Cycle picking time	Travel distance	Order picking costs
1. Base alternative	Cycle picking time starting point	Travel distance starting point, during peak less travel distance than in regular period	Order picking costs starting point
2. Class-based storage	For both regular and peak period, for cycle picking time almost 14% of time savings is reached	For regular and peak period, 26% and 24% respectively of travel distance can be saved	On yearly basis, the order picking costs can be reduced with 14.1%. Savings during whole year.
3. Volume-based storage	For regular period, time savings are reached, for peak period no optimization was found.	For regular periods a saving of 17% is estimated, in peak there was no difference in distance compared to base alt.	On yearly basis, order picking costs can be reduced with 8.5%. Highest savings during regular periods.
4. Zone decomposition	For both regular and peak period, almost 10% of savings is reached	For regular and peak period, on the travel distance 18% and 11% respectively savings can be reached.	On yearly basis, the order picking costs can be reduced with 9.8%. Highest savings in peak periods.

As can be read in the table, the three design alternatives all seem to be promising for future order picking operations compared to the base alternative. The results of this study almost seem to be too good to be true. However, the results of this study can be seen as the impression that major savings can be reached changing the order picking strategy in general. For companies, focusing on the reduction of travel distance for the operators can lead to more efficient processes in the fulfilment centre and in the end cause a decrease in labour costs. The three design alternatives proposed in this study all cause savings and faster fulfilment on yearly basis. This means that implementing the alternatives, during the order picking process less pickers are needed. On future's perspective, the fulfilment centre is able to process all orders in the future taking growth into account.

Keeping these notes into account, it can be concluded that implementing the class-based storage policy into the order picking process, taking seasonal influences into account, is the alternative with the best results for both regular and peak periods. In this design alternative the picker is able to complete a batch in the least amount of time. However, it could be interesting implementing the class-based randomized storage permanent, and during peak periods implement zone decomposition dynamically as well. This can lead to even lower process times during the peak.

The overall conclusion of the results of the model is that implementing the class-based randomized storage policy permanently seems to be the most promising alternative for optimizing the order picking process during both peak and regular periods. Looking at cycle time and travel distances, the zone decomposition is a policy that could be deployed dynamically during peak periods. Even higher savings can be obtained in future operation. The savings will increase even more due to mechanization of for example packing operations, and an expected growth in customer orders. The savings obtained by the alternatives calculated for 2018, can cause even higher savings for the upcoming years taking the growth into account.

7.2 Discussion

This section discusses several aspects of this study.

The data availability is a point of discussion in this study. At the start of this study, the fulfilment centre of the company was not in operation yet. During the study, the operation started and data became known. Nevertheless, the available data is not realistic yet to the situations sketched in this study. Therefore, estimates were made about process times, realistic batch sizes, and the order picking operation in the FC. However, improvements focused on travel distances, and this was not affected to these estimates. The estimates could not be compared with historic data, since there is no historic data yet. Fortunately, validations could be done by interviewing order picking experts.

However, for the time series analysis, data was used from operations of the company in another fulfilment centre. Since the fulfilment centre of this study takes over a part of the operations of the other FC, selected historic data of this FC was used. Probably, this might cause differences in results compared to real life. For the time series analysis, the seasonal decomposition method was used. More sensitive methods could have been used as well, more detailed results could have been calculated. Nevertheless, seasonal patterns have been determined using the seasonal decomposition method, and the characteristics of regular versus peak periods have been mapped.

Another aspect that is debatable about this study is the implementation of the alternatives. The picklists of all eight scenarios were created by the batching algorithm of the company. The limitations of the batching algorithm caused a different output of the optimization alternatives as meant. The tote utilization percentages did not differ from each other, since the algorithm divides all items randomly over the batches. Since all scenarios consisted of the same items, the dividing was done the same for all alternatives. The volume-based randomized storage alternative was meant to optimize the tote utilization, since all small items were stored together. Hence, more small items could have been picked in the tote here. Unfortunately, the algorithm did not take this into account. The zone decomposition alternative should have had a large decrease in travel distance, but since the algorithm does not take a route minimization into account, the output showed less travel distance reduction than intended.

In the simulations performed, some assumptions were made for simplification of the model. In the model it was assumed that all products ordered are in storage. In real life always mistakes occur: products are not stored where they should, products are missing and pickers cannot find the products. These mistakes cause delays in the cycle picking time. Working with hand-held devices can lead to jamming devices or errors. Congestion of pickers was not taken into account as well, however, in real life it would happen that pickers get in each other's way. These influences were captured as human influences and were not taken into account in this study. However, these influences should have led to different cycle times in real life.

In this study, the alternatives were supposed to decrease walking distances of the order pickers, so that it would take the picker less time to complete a batch. However, there are more methods and policies that could have been implemented for improving the performance of the order picking process. More comprehensive improvements could have been generated and tested. These opportunities are explained in the next section, where the recommendations are provided.

7.3 Recommendations

This section provides an overview of the recommendations for the company of the case study of this research and several general recommendations for further research regarding optimizing the order picking performance.

7.3.1 Recommendations for case study

At first, for the company of the case study it is recommended implementing the class-based randomized storing policy proposed in this research. As explained in several literature reviews and as proved in the simulation in this research, major savings can be obtained implementing the storing policy compared to the current situation in the fulfilment centre. The second recommendation, based on the simulations performed, is continue research into combining the class-based randomized storing policy with the zone decomposition alternative during peak periods. In practice, tests can be done in for example regular periods

Next to the alternatives paid attention to in this research, there are several recommendations for the company on different policies and processes in the fulfilment centre that may influence the order picking time positively in the future as well. Below, other design alternative interesting for the company are proposed.

In this study, attention was dedicated to the order consolidation policy, without using it in the design alternatives. An interesting alternative in the order consolidation policy is implementing a dynamic order batching algorithm. As explained in Chapter 4, dynamic picking system is used to batch customer orders by using *real-time* order fulfilment strategy. Orders arrive online and are picked in a batch, followed by later sorting per customer order. The picker travels the entire (or a part of the) warehouse and picks all outstanding order lines in one pick route. During a pick cycle, pick information is constantly updated by a pick device. Even more efficient batches can be created and the performance of the order picking process increases.

Besides the order consolidation policy, the routing policy was discussed as well. Combining these policies gives rise to a challenging alternative. The batching algorithm of the company can be optimized by implementing a heuristic that minimizes the travel distance while batching (for example using the Vehicle Routing Problem). Batches can be created by adding items based on largest time savings between the items without exceeding the capacity constraint of the tote.

Another alternative that can be elaborated in future research is a gauge for accurately filling the totes. In the current batching algorithm, the number of items batched in a tote depends on the breaking point of a maximum number of items in a tote together with a maximum allowed weight and volume of a filled tote. These parameters are important in the batching algorithm because the total items in a tote determine the number of items that are picked in a zone in a picking tour. The number of items per batch is determined based on the duration of one pick wave. A so-called gauge can be used for accurately filling the tote, based on these parameters. Then, the gauge is able to measure to what extent the tote already has been filled. In the algorithm, a calculation is applied to fill the totes as efficient as possible based on weight and volume. An extra parameter, the number of items in a tote, can be added to the gauge. The maximum number of items allowed in a tote could be changed in for example peak periods. When the tote is filled with more items, more items are picked within a particular zone. Since operators travel the whole route of the zone picking to complete a batch, more items are picked using such a gauge while the same distance is travelled. A higher efficiency is obtained. During October, November, and December the average volume per item and weight per item both are lower than in a regular month. Therefore, it would be useful to apply the extra parameter to minimize walking distance per item which results in a decreased travel time.

In the study, it was proposed using different totes for increasing the tote utilization. Several studies can be found according to the use of different sizes and designs of totes. It is recommended for the company to look into different possibilities and challenges.

In this study, comparing the results of the simulation of the alternatives, it was suggested that it could be promising combining alternative 2 and 4 (class-based randomized storage with a dynamically zone-decomposition during peak periods). However, another option for optimizing the performance of the order picking process can be combining different policies as well. The utilization of the totes did not change simulating the design alternatives. By using different sizes of totes, the utilization can be optimized.

7.3.2 Recommendations for further research

One of the main recommendations for further research is the implementation of the alternatives proposed in this study in practice and then the comparison with the theoretical results. Then, this can be used for example for implementation of the alternatives to a fulfilment centre similar to the fulfilment centre of this study can be interesting as well. It can be investigated if the order picking optimization alternatives of this study are applicable to other FCs as well. For implementing the design alternatives of this study, a similar background analysis must be conducted for capturing seasonal influences which can be different than determined here. For setting up the alternatives, insight is needed into the order characteristics as it influences the order picking process significantly.

Another recommendation for further research is to include more combinations of factors. Since the research scope of the fulfilment centre used in this study is limited and the research time in insufficient, other factors that affect the performance of picking are not included in the study. Further research can be carried out on the design of the fulfilment centre layout and congestion problems if more order pickers pick at the same storage location at the same time. This would make the research more comprehensive and more adaptable to the diversity of the order picking processes in different fulfilment centres.

Also, further research can be extended by including all the sequential process of order retrieval, e.g. order receiving, inventory replenishment and distribution operations. Including more processed, the integration of the warehouse activities will be increased. By simulation with actual data, overall logistics performance and customer service level can be improved.

Bibliography

Bartholdi III, J., & Hackman, S. (2011). Warehouse and distribution science. *Release 0.94*, 23-31.

Bartholdi, J. (1995, April). *A routing system based on spacefilling curves.* Retrieved from http://www2.isye.gatech.edu/~jjb/mow/mow.pdf

Berg, J. v. (1999). A literature survey on planning and control of warehousing systems. *IIE Transactions, 31*, 751-762.

Brockman, T., & Godin, P. (1997). Flexibility for the future in warehouse design. *IIE Solutions*, 22+.

Cai, J., Xiangdong, L., Xiao, Z., & Liu, J. (2009). Improving supply chain performance management: A systematic approach to analyzing iterative KPI accomplishment. *Decision Support Systems, 46*(2), 512-521. doi:https://doi.org/10.1016/j.dss.2008.09.004

Cergibozan, C., & Serdar Tasan, A. (2016). *Order batching operations: an overview of classification, solution techniques, and future research.* New York: Springer Science+Business Media New York.

Chan, F., & Chan, H. (2011). Improving the productivity of order picking of a manual-pick and multi-level rack distribution warehouse through the implementation of class-based storage. *Expert Systems with Applications, 38*, 2686-2700.

Chen, M., & Wu, H. (2005). An association-based clustering approach to order batching considering customer demand patterns. *Omega, 33*(4), 333-343.

Chloe, K., & Sharp, G. (1991). Small Parts Order Picking: Design and Operation. Retrieved June 2017, from Small Parts Order Picking: Design and Operation: http://www.isye.gatech.edu/logisticstutorial/order/article.htm

Clarke, G., & Wright, J. (1964). Scheduling of vehicles from a central depot to a number of delivery points. *Operational Research*, 568-581.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2 ed.). New York: Academic Press.

Dallari, F., Marchet, G., & Melacini, M. (2009). Design of order picking system. *The International Journal of Advanced Manufacturing Technology, 42*, 1-12.

Damsri, S., Payakkapong, P., & Hirunwong, A. (2007). A comparative study of decomposition methods in time series data forecasting with seasonal and nonseasonal variation. *Kasetsart Journal - Social Sciences, 28*(2), 221-227.

De Koster, R. d., Le-Duc, T., & Roodenbergen, K. (2007). Design and control of warehouse order picking. *European journal of operational research, 182*, 481-501.

De Koster, R., & Van der Poort, E. (1998). Routing orderpickers in a warehouse: a comparison between optimal and heuristic solutions. *IIE Transactions, 30*, 469-480.

De Koster, R., De Poort, E., & Van der Wolters, M. (1999). Efficient order batching methods in warehouses. *International Journal of Production Research, 37*(7), 1479-1504.

Dukic, G., & Oluic, C. (2005). Order picking methods: Improving order-picking efficiency. *International Journal of Logistics Systems and Management, 3*(4), 121-132.

Dukic, G., & Opetuk, T. (2016). Warehouse layouts. *Research Gate.* doi:10.1007/978-1-4471-2274-6_3

Field, A. (2009). *Discovering statistics using spss* (3 ed.).

Gademann, N., & Van de Velde, S. (2005). Order batching to minimize total travel time in a parallel-aisle warehouse. *IIE Transactions, 37*(1), 63-75. doi:10.1080/07408170590516917

Giannikas, V., Lu, W., Robertson, B., & McFarlane, D. (2017). An interventionist strategy for warehouse order picking: Evidence from two case studies. *International Journal of Production Economies, 189*, 63-73.

Gibson, D., & Sharp, G. (1992). Order batching procedures. *European Journal of Operational Research, 58*(1), 57-67.

Gilbreth, F. (2017, 09 15). *Motion study*. Retrieved from Get my uni: http://getmyuni.azureedge.net/assets/main/study-material/notes/mechanical_engineering_production-operation-management_motion-study_notes.pdf

Glock, G., Grosse, E., Elbert, R., & Franzke, T. (2016). Maverick picking: the impact of modifications in work schedules on manual order picking processes. *International Journal of Production Research*. doi:10.1080/00207543.2016.1252862

Gong, Y., & de Koster, R. (2008). A polling-based dynamic order picking system for online retailers. *IIE Trans, 40*, 1070-1082.

Gong, Y., Winands, E., & De Koster, R. (2010). A real-time picking and sorting system in e-commerce distribution centers. *MHIA, Material Handling Industry of America*. Retrieved from http://www.mhi.org/downloads/learning/cicmhe/colloquium/2010/gong.pdf

Grosse, E., Glock, C., & Neumann, W. (2015). Human factors in order picking systems design: a content analysis. *IFAC - PapersOnLine, 48*(3), 320-325.

Gu, J., Goetschalckx, M., & McGinnis, L. (2007). Research on warehous eoperation: A comprehensive review. *European Journal of Operational Research, 177*(1), 1-21.

Hall, R. (1993). Distance approximations for routing manual pickers in a warehouse. *IIE Transactions, 25*(4), 76-87.

Hariharan, R., & Zipkin, P. (1995). Customer-order information, leadtimes, and inventories. *Management Science, 41*(10), 1599-1607. doi:https://doi.org/10.1287/mnsc.41.10.1599

Harvey, A., & Peters, S. (1990). Estimation procedures for structural time series models. *Journal of Forecasting, 9*, 89-108.

Henn, S. (2012). Algorithms for on-line order batching in an order picking warehouse. *Journal of Computer Operations Research, 39*, 2549-2563.

Henn, S., Koch, S., & Wascher, G. (2012). Order batching in order picking warehouses: a survey of solution approaches. (L. Springer-Verlag, Ed.) *Warehousing in the Global Supply Chain - Advanced Models, Tools and Applications for Storage Systems*, 105-137.

Hsieh, L., & Tsai, L. (2006). The optimum design of a warehouse system on order picking efficiency. *The International Journal of Advanced Manufacturing Technology, 28*(5), 626-637.

Hylleberg, S. (1992). *Modelling seasonality*. Oxford: Oxford University Press.

Jarvis, J., & McDowell, E. (2007). Optimal product layout in an order picking warehouse. *IIE Transactions, 23*(1), 93-102.

Kijne, H. (1996). Time and motion study: beyond the Taylor-Gilbreth controversy. *Scientific Management*, 63-92.

Kitagawa, G. (2010). *Introduction to Time Series Modeling*. Boca Raton: Taylor & Francis Group, LCC.

Knaub, J. (1987, August). Practical Interpretation of Hypothesis Tests. *The American Statistician, 41*(3), 246-247.

Kofler, M., Beham, A., Wagner, S., & Affenzeller, M. (2010). Reassinging storage locations in a warehouse to optimize the order picking process. *European Modeling and Simulation Symposium, 22*.

Koopman, S., & Hoogerheide, L. (2013, May). *Analysis of historical time series with messy features: The case of commodity prices in Babylonia.* Retrieved from VU University Amsterdam: http://personal.vu.nl/s.j.koopman/papers/Babylonia.pdf

Krauth, E., Moonen, H., Popova, V., & Schut, M. (2005). Krauth, E., Moonen, H., Popova, V., & Schut, M. (2005, June). Performance indicators in logistics service provision and warehouse management–a literature review and framework. *Europa International Conference*, (pp. 19-22).

Lane, D. (2015). *Online Statistics Education: A Multimedia Course of Study.* Retrieved from Online Statbook: http://onlinestatbook.com/

Larco, J., De Koster, R., Roodbergen, K., & Dul, J. (2016). Managing warehouse efficiency and worker discomfort through enhanced storage assignment decisions. *International Journal of Production Research*. doi:10.1080/00207543.2016.1165880

Lee, H., & Whang, S. (2001). E-fulfillment: winning the last mile of e-commerce. *Journal Summer*, 54-62.

Lovell, M. (1963). Seasonal adjustment of economic time series and multiple regression analysis. *Journal of the American Statistical Association*, 993-1010. doi:10.1080/01621459.1963.10480682

Lu, W., McFarlane, D., Giannikas, V., & Zhang, Q. (2016). An algorithm for dynamic order-picking in warehouse operations. *European Journal of Operational Research, 248*(1), 107-122.

Markidakis, S., & Wheelwright, S. (1987). *The handbook of forecasting: A manager's guide.* New York: Wiley.

Moola, A., & Bisschoff, C. (2012). Validating a model to measure the brand loyalty of fast moving consumer goods. *Journal fo Social Sciences, 31*(2), 101-115.

Murray, M. (2017, February). Order picking in the warehouse. *The Balance*. Retrieved from Thebalance: https://www.thebalance.com/order-picking-in-the-warehouse-2221190

Nemtajela, N., & Mbohwa, C. (2017). Relationship between inventory management and uncertain demand for fast moving consumer goods organisations. *Procedia Manufacturing, 8*, 699-706.

Onal, S., Zhang, J., & Das, S. (2017). Modelling and performance evaluation of explosive storage policies in internet fulfilment warehouses. *International Journal of Production Research*, 1-14. doi:10.1080/00207543.2017.1304663

Pan, C., & Liu, S. (1995). A comparative study of order batching algorithms. *International Journal of Management Science, 23*(6), 691-700.

Pan, J., & Wu, M. (2012). Throughput analysis for order picking system with multiple pickers and aisle congestion considerations. *Computers & Operations Research, 39*, 1661-1672.

Pedrielli, G., Vinsensius, A., Chew, E., & Lee, L. (2016). Hybrid order picking strategies for fashion e-commerce warehouse systems. *2016 Winter Simulation Conference: Simulating Complex Service Systems, WSC 2016*, 2250-2261. doi:10.1109/WSC.2016.7822266

Performance. (2017, 09 12). Retrieved from Business Dictionary: http://www.businessdictionary.com/definition/performance.html

Petersen, C. (1997). An evaluation of order picking routing policies. *International Journal of Operations & Production Management, 17*(11), 1098-1111.

Petersen, C., & Aase, G. (2004). A comparison of picking, storage, and routing policies in manual order picking. *International Journal of Production Economics, 92*(1), 11-19.

Petersen, C., & Schmenner, R. (1999). An evolution of routing and volume-based storage policies in an order picking operation. *Decision Sciences: A Journal of the Decision Sciences Insitute, 30*(2), 481-501.

Pierce, D. (1979). Seasonal adjustment when both deterministic and stochastic seasonality are present. *National Bureau of Economic Research*, 242-280. Retrieved from http://www.nber.org/books/zell79-1

Rouwenhorst, B., Reuter, B., Stockrahm, V., van Houtum, G., Mantel, R., & Zijm, W. (1999). Warehouse design and control: Framework and literature review. *European Journal of Operational Research, 122*(3), 515-533.

Ruben, R., & Jabobs, F. (1999). Batch construction heuristics and storage assignment strategies for walk/ride and pick systems. *Management Science*, 575-596.

Sargent, R. (2005). Verification and validation of simulation models. *Proceedings of the 37th conference on Winter simulation* (pp. 130-143). winter simulation conference.

Sargent, R. (2009). Verification and validation of simulation models. *Proceedings of the 2009 Winter Simulation COnference*, *37*, pp. 162-176. doi:10.1109/EMR.2009.5235461

Schlesinger, S. (1979). Terminology for model credibility. *Simulation, 32*(3), 101-105.

Scholz, A., & Wascher, G. (2017). Order Batching and Picker Routing in manual order picking systems: the benefits of inegrated routing. *Central European Journal of Operations Research, 25*(2), 491-520. doi:10.1007/s10100-017-0467-x

Schriber, T., & Brunner, D. (2000). Inside discrete-event simulation software: how it works and why it matters. *Simulation Conference, 2000. Proceedings. Winter, 1*, 90-100.

Schriber, T., Brunner, D., & Smith, J. (2012). How discrete-event simulation software works and why it matters. *Proceedings of the 2012 Winter Simulation Conference*.

Shakespeare, T., Gebski, V., Veness, M., & Simes, J. (2001). Improving interpretation of clinical studies by use of confidence levels, clinical significance curves, and riskbenefit contours. *Lancet*, 1349-1353.

Suhartono, S., & Subanar, S. (2005, June). A comparative study of forecasting models for trend and seasonal time series: does complex model always yield better forecast than simple models? *Jurnal Teknk Industri, 7*(1), 22-30.

Tarn, J., Wen, H., Razi, M., & Perez, A. (2003). E-fulfillment: the strategy and operational requirements. *Logistics Information Management, 16*(5), 350-362. doi:10.1108/09576050310499345

Taylor, S., & Letham, B. (2017, January 13). *Forecasting at scale.* Retrieved from Revolutionanalytics: https://facebookincubator.github.io/prophet/static/prophet_paper_20170113.pdf

Thuij, G. (2017, March). *Online bestedingen 2016*. Retrieved June 2017, from Thuiswinkel: https://www.thuiswinkel.org/nieuws/3348/online-bestedingen-passeren-de-grens-van-20-miljard-in-2016

Tompkins, J., White, J., Bozer, Y., Frazelle, E., & Tanchoco, J. (2010). *Facilities planning* (4 ed.). New Jersey: John Wiley & Sons.

Unknown. (2017). *R-project for statistical computing*. Retrieved from R-project: https://www.r-project.org/

Van Nieuwenhuyse, I., & De Koster, R. (2009). Evaluating order throughput time in 2-block warehouse with time window batching. *International Journal of Production Economics, 121*, 654-664.

Varga, A. (2001). Discrete event simulation system. *Proceedings of the European Simulation Multiconference (ESM'2001).*

Verbraeck, A. (2016). TIL4030-2.1 Problem definition and requirements specification. Delft, Zuid-Holland, The Netherlands.

Wascher, G. (2004). Order picking: A survey of planning problems and methods. *Supply Chain management and Reverse Logistics*, 323-347.

White, K., & Ingalls, R. (2009). Introduction to simulation. *Proceedings of the 2009 Winter Simulation Conference.*

Xu, Z., Liu, T., Li, K., & Dong, W. (2014). Evaluation order throughput time with variable time window batching. *International Journal of Production Research, 52*(8), 2232-2242.

Yu, M. (2008). Enhancing warehouse performance by efficient order picking. *No. EPS-2008-139-LIS*.

Yu, M., & De Koster, R. (2009). The impact of order batching and picking area zoning on order picking system performance. *European Journal of Operational Research*, 480-480.

Zandin, K. (1990). *MOST Work Measurement Systems.* New York: Marcel Dekker.

Zhang, G., & Qi, M. (2005). Neural network forecasting for seasonal and trend time series. *European Journal of Operational Research, 160*, 501-514. doi:10.1016/j.ejor.2003.08.037

Appendix A Interviews

Appendix B Case study

Appendix C Seasonal decomposition

C1 Holidays and sales dates

Table C.1: Dates of Holidays

Date	Holiday
5-12-2015	Sinterklaas evening
25-12-2015	Christmas (1)
26-12-2015	Christmas (2)
31-12-2015	Old year's day
1-1-2016	New year's day
14-2-2016	Valentine's day
25-3-2016	Good Friday
27-3-2016	First day of Easter
28-3-2016	Second day of Easter
27-4-2016	Kingsday
1-5-2016	Labour Day
5-5-2016	Liberation Day
8-5-2016	Mother's day
15-5-2016	Whit Sunday
16-5-2016	Whit Monday
19-6-2016	Father's day
21-7-2016	National holiday
15-8-2016	Our Lady Ascension
1-11-2016	All Saints' Day
11-11-2016	Ceasefire WW-I
12-11-2016	Entry Sinterklaas
5-12-2016	Sinterklaas evening
25-12-2016	Christmas (1)
26-12-2016	Christmas (2)
31-12-2016	Old year's day
1-1-2017	New year's day
14-2-2017	Valentine's day
14-4-2017	Good Friday
16-4-2017	First day of Easter
17-4-2017	Second day of Easter
27-4-2017	Kingsday
1-5-2017	Labour Day
5-5-2017	Liberation Day
14-5-2017	Mothers' day

25-5-2017	Ascension
4-6-2017	Whit Sunday
5-6-2017	Whit Monday
18-6-2017	Fathers' day

C2 Computing in R

The seasonal decomposition calculations were done in R. R is a free software environment for statistical computing and graphics (R-project for statistical computing, 2017). Excel worksheets could be loaded, and multiple calculations could be done. An example of a report in R is shown in Figure C.1

```

#import file
library(datasets)
library(Ecfun)
library(readr)
Tabel2 <- read_csv("C:\\Users\\egelder\\Dropbox\\Thesis\\Data analyse\\R\\Data\\week25.csv")
Tabel3 <- read_csv("C:\\Users\\egelder\\Dropbox\\Thesis\\Data analyse\\R\\Data\\week25_perdag.csv")

io = Tabel2[[16]]
ma = Tabel3[[1]]
di = Tabel3[[2]]
wo = Tabel3[[3]]
do = Tabel3[[4]]
vr = Tabel3[[5]]
za = Tabel3[[6]]
zo = Tabel3[[7]]

#import data
library(Ecdat)
timeseries_io=io
plot(as.ts(timeseries_io))

#decomposition
ts_io = ts(timeseries_io, frequency = 24)
decompose_io = decompose(ts_io, "multiplicative")

plot(as.ts(decompose_io$seasonal))
plot(as.ts(decompose_io$trend))
plot(as.ts(decompose_io$random))
plot(decompose_io)

boxplot(ma, di, wo, do, vr, za, zo,  outline = FALSE, names = c("Monday","Tuesday","Wednesday", "Thursday", "Friday", "Saturday", "Sunday"),
        main= "Variance of number of items per order week 25", xlab="Day", ylab="Items per order", col = "lightgray")
abline(h = 1.64, col="red", lwd=2)
text(y = boxplot.stats(ma)$stats, labels = boxplot.stats(round(ma, digits=2$stats,x=0.5, cex=0.6)))
text(y = boxplot.stats(di)$stats, labels = boxplot.stats(round(di, digits=2$stats,x=1.5, cex=0.6)))
text(y = boxplot.stats(wo)$stats, labels = boxplot.stats(round(wo, digits=2$stats,x=2.5, cex=0.6)))
text(y = boxplot.stats(do)$stats, labels = boxplot.stats(round(do, digits=2$stats,x=3.5, cex=0.6)))
text(y = boxplot.stats(vr)$stats, labels = boxplot.stats(round(vr, digits=2$stats,x=4.5, cex=0.6)))
text(y = boxplot.stats(za)$stats, labels = boxplot.stats(round(za, digits=2$stats,x=5.5, cex=0.6)))
text(y = boxplot.stats(zo)$stats, labels = boxplot.stats(round(zo, digits=2$stats,x=6.5, cex=0.6)))
```
Figure C.1: Report of regular week: seasonal decomposition and boxplot construction

C3 Output data analysis

Appendix D Key Performance Indicators

As explained in the main text of the report, performance indicators have been determined for measuring the performance of the order picking system. The indicators are explained below and an overview is given in Table D.1. In the table, the most promising indicators are coloured green. These are used in the main text for measuring the order picking performance and therefore, these indicators are called Key Performance Indicators.

Table D.1: Overview of performance indicators

	IT	Product				Labour
	Order	**Item**	**Weight**	**Volume**	**Tote/batch**	**Picker**
Costs	€/order	€/item	€/kg	€/m^3	€/batch	€/picker
Utilization	order/tote %	items/tote %	kg/tote %	m^3/tote %	items/batch %	items/picker %
Process time	sec/order orders/hour	sec/item items/hour	sec/kg	sec/ m^3	sec/batch	sec/picker
Distance	m/order	m/item	m/kg	m/ m^3	m/batch	m/picker
Lead time	hours/order	hours/item	-	-	-	-
Accuracy	%	%	%	%	%	%
Processed in time	%	%	%	%	%	%

Costs

- IT costs
    - Order costs [€/order]: represents the costs made during the order picking process per processed order. Since the model of this study measures performance per item, the costs per order are not a performance indicator.
- Product costs
    - Item costs [€/item]: represents the costs made per processed item during the order picking process. The cost per item is a useful indicator, because extensive costs overviews can be calculated with this value. Knowing the number of items ordered on a daily basis and the cost per item, gives insight on the profits that are possibly obtained by changing storage policies.
    - Weight costs [€/kg]: represents the costs made per amount of weight. This is not measured in this study.
    - Volume costs [€/m^3]: represents the costs made per amount of volume. This is not measured in this study.
    - Batch costs [€/batch]: represents the costs made per batch. This can be measured based on the time it takes an operator to pick the items of a batch combined with the labour costs of an operator. This is not measured in the model, since the item costs give more insight into changes into the costs.
- Labour costs
    - Operator costs [€/picker]: represents the costs made per operator working in the fulfilment centre. This is not an indicator, nor a performance indicator, but variable is useful for calculating the costs of the order picking process since the total operator costs are dependent of the number of pickers needed to pick all ordered items.

Utilization

- IT utilization
    - Order utilization [%]: represents the utilization of a tote using the percentage of the number of orders in a tote against the order capacity. Since the batching algorithm of the company of this study does not keep orders together during batching, this is an indicator that is not relevant in this study.
- Product utilization
    - Item utilization [%]: represents the utilization of a tote using the percentage of the number of items in a tote against the item capacity of the tote. It is wishful for the tote to be filled maximum. Therefore, the item utilization is used as KPI.
    - Weight utilization [%]: represents the utilization of a tote using the percentage of the weight in a tote against the weight capacity of the tote. It is wishful for the tote to be filled maximum. Therefore, the weight utilization is used as KPI.
    - Volume utilization [%]: represents the utilization of a tote using the percentage of the volume in a tote against the volume capacity of the tote. It is wishful for the tote to be filled maximum. Therefore, the volume utilization is used as KPI.
    - Batch/tote utilization [%] does not apply for this study. The utilization is measured in the utilizations explained above.
- Labour utilization
    - Picker utilization [%]: represents the part of total items processed by one operator. Since a distinction is made between experienced and inexperienced pickers, it is interesting to measure this indicator. This indicator is measured, since it is interesting to see the share of the pickers. However, the indicator is not used as KPI for measuring the performance in this study.

Processing time

- IT processing time
    - Order throughput time [sec/order] (Glock et al. (2016)) is an important measure for a fulfilment centre. The order throughput time is not taken into account as KPI, because the simulation is done on item level. The average time it takes to pick an item gives more information than the average time it takes to pick an order because the number of items in an order is not a fixed number.
- Product processing time (cycle time picking according to Pedrielli et al. (2016))
    - Average time per item [sec/item]: represents the time needed to pick an item, the set up time, travel time and batch finishing time included. Since the items need to be processed as fast as possible, time is an important performance indicator. The amount of time per item is used as KPI.
    - Average number of items per hour [items/hour]: represents the number of items that can be picked per hour. This performance indicator is important for determining the throughput rate of the fulfilment centre. The items per hour are used as KPI in this study.
    - Average time per batch [sec/batch]: represents the time needed to complete a batch. This performance indicator is used as KPI.
- Labour processing time
    - Picker time [sec/picker]: represents the picking time per operator. This indicator is measured, since experienced and inexperienced pickers are taken into account in the model. It is not a KPI, but it is interesting knowing the share of picking time of experienced against the share of inexperienced operators.

Distance

- IT distance
  - Order distance [m/order]: represents the distance travelled by operator per order. This is not considered in the model.
- Product distance (Chan & Chan, 2011)
  - Item distance [m/item]: represents the distance travelled by operator per item. This is not considered in the model. It is wanted to decrease the travel distance on batch level. The travel distance between item is what matters.
  - Weight distance [m/kg]: represents the distance travelled by operator per kg. This is not considered in the model.
  - Volume distance [m/m^3]: represents the distance travelled by operator per m^3. This is not relevant in the model.
  - Batch distance [m/batch]: represents the distance travelled by operator per batch. In this study, it is desirable for the batch distance to be minimized. The batch distance can be minimized, when travel distance between picks is minimized. This in an important KPI in this study.
- Labour distance
  - Picker distance [m/picker]: represents the distance travelled per operator. This is not considered to be an important performance indicator in this study.

Lead time is a measure of an organization's ability to quickly serve customer demands (Cai et al. (2009)). It measures the speed of service and indicates the average time from the customer ordering the products until receiving the package. This indicator is not considered in this study, since only the order picking process is part of the scope. The other processes in the fulfilment centre together with the transport are not part of this study.

- IT lead time
  - Order lead time [hour/order]: represents the lead time of an order.
- Product lead time
  - Item lead time [hour/item]: represents the lead time of an item.

Accuracy is an indicator that measures the faults made during order picking. Since this study does not take human factors into account, this performance indicator is not used as KPI. In the model it is assumed that all items batched are in storage on the given storage location. It is assumed as well that all items in a batch fit in a tote and therefore, none of the items required rework.

- IT accuracy
  - Order accuracy [%]: represents the percentage of orders requiring rework.
- Product accuracy
  - Item accuracy [%]: represents the percentage of orders requiring rework.
  - Weight accuracy [%]: represents the percentage of orders requiring rework.
  - Volume accuracy [%]: represents the percentage of orders requiring rework.
  - Batch accuracy [%]: represents the percentage of orders requiring rework.
- Labour accuracy
  - Operator accuracy [%]: represents the percentage of operators that caused orders requiring rework.

Another performance indicator is the **processed in time**-indicator. This performance indicator measures a certain number of to be processed items that are processes in the planned time and that could be sent in time. This indicator is not used as a KPI because cut off times of transport companies are not taken into account in the model.

- IT processed in time
  - Orders processed in time [%]: represents the percentage of orders processed in time.
- Product processed in time
  - Item processed in time [%]: represents the percentage of items processed in time.
  - Weight processed in time [%]: represents the percentage of weight specific items processed in time.
  - Volume processed in time [%]: represents the percentage of volume specific items processed in time.
  - Batch processed in time [%]: represents the percentage of batches processed in time.
- Labour processed in time
  - Picker processed in time [%]: represents the percentage of orders/items processed in time by a specific operator (experienced and inexperienced pickers).

Appendix E Discrete event simulation

E1 Generation of picklists

E2 Discrete event simulation in Simio

E2.1 System of zone

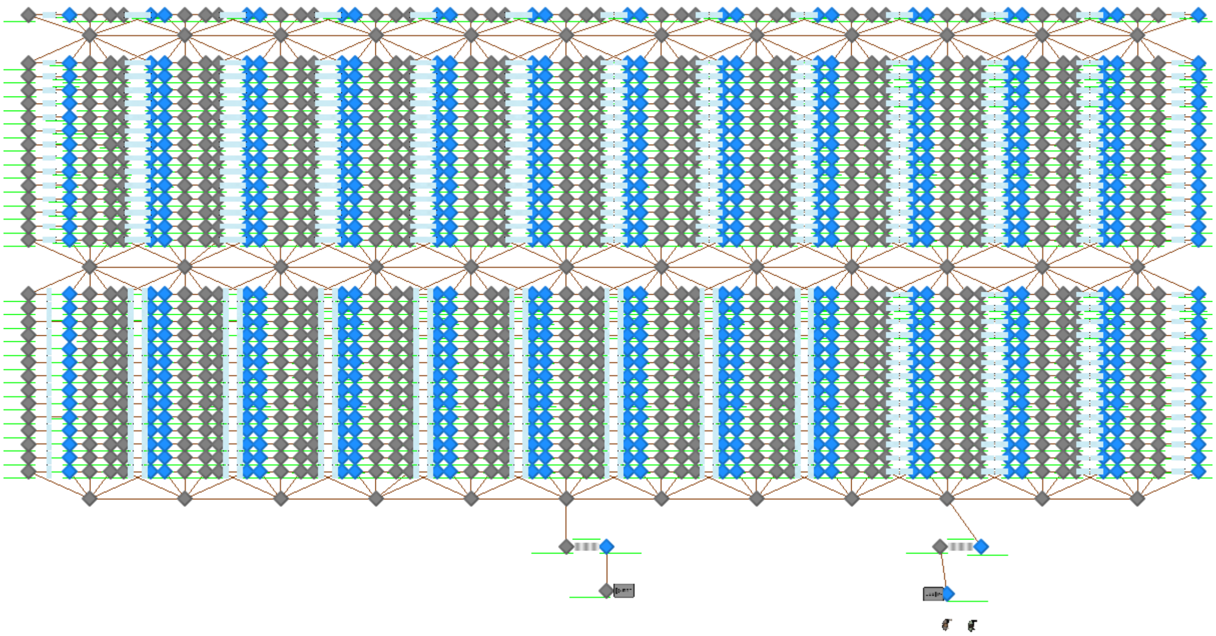

Figure E.1: Zone layout in Simio

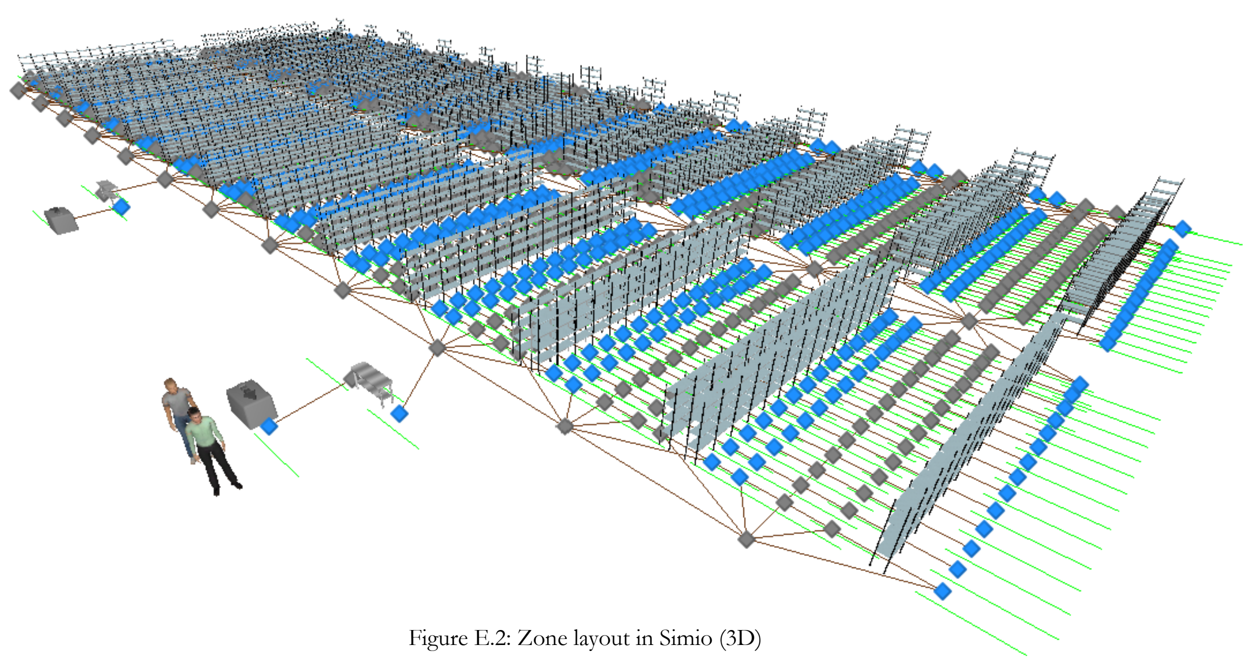

Figure E.2: Zone layout in Simio (3D)

E2.2 Data tables in Simio

E2.2.1 Scenarios

As explained in the main text, the picklists are scenario dependent. In the simulation tool Simio, the picklists are read in data tables. The column key scenario was set to key property. The key property can be set as a variable for each scenario in Simio. Setting the variable to column 'Scenario 1', the simulation chooses a random batch of the Batch-column. When a random batch X is chosen, the entity is sent to the locations that are linked to Batch X. The data table is shown in Table E.1.

Table E.1: Data table of scenarios in Simio

Column key		
Scenario 1	Batch 1	Location 1
		Location 2
		…
		Location n
	Batch 2	Location 1
		Location 2
		…
		Location n
	…	
	Batch n	Location 1
		Location 2
		…
		Location n
Scenario 2	Batch 1	Location 1
		Location 2
		…
		Location n
	Batch 2	Location 1
		Location 2
		…
		Location n
	…	
	Batch n	Location 1
		Location 2
		…
		Location n
…		
Scenario 8	Batch 1	Location 1
		Location 2
		…
		Location n
	Batch 2	Location 1
		Location 2
		…
		Location n
	…	
	Batch n	Location 1
		Location 2
		…

		Location n

E2.3 Processes in Simio

In this section the processes in Simio are visualized and explained.

E2.3.1 Process times

The following process is used in Simio to setup the start, pick, and finish time of a pick tour for both experienced (pickerA) and inexperienced (pickerB) pickers.

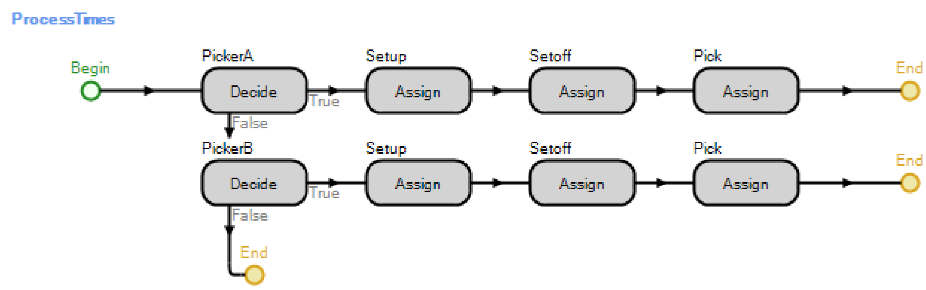

Figure E.3: Processes times in Simio

E2.3.2 Picklist

In Simio the following processes were used to let Simio read the picklists from the data tables as explained in section E2.2.1 Scenarios.

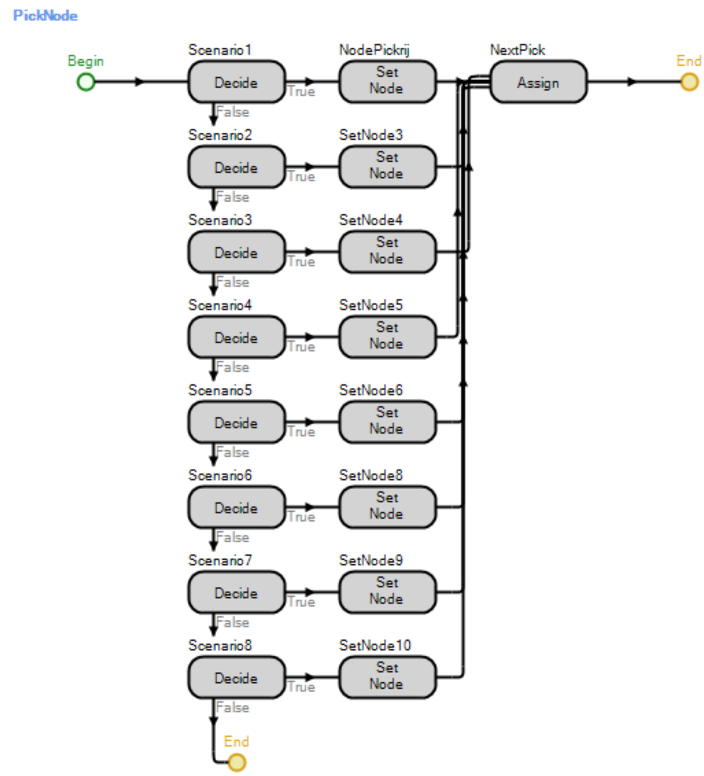

Figure E.4: Sequence of picklist setting in Simio

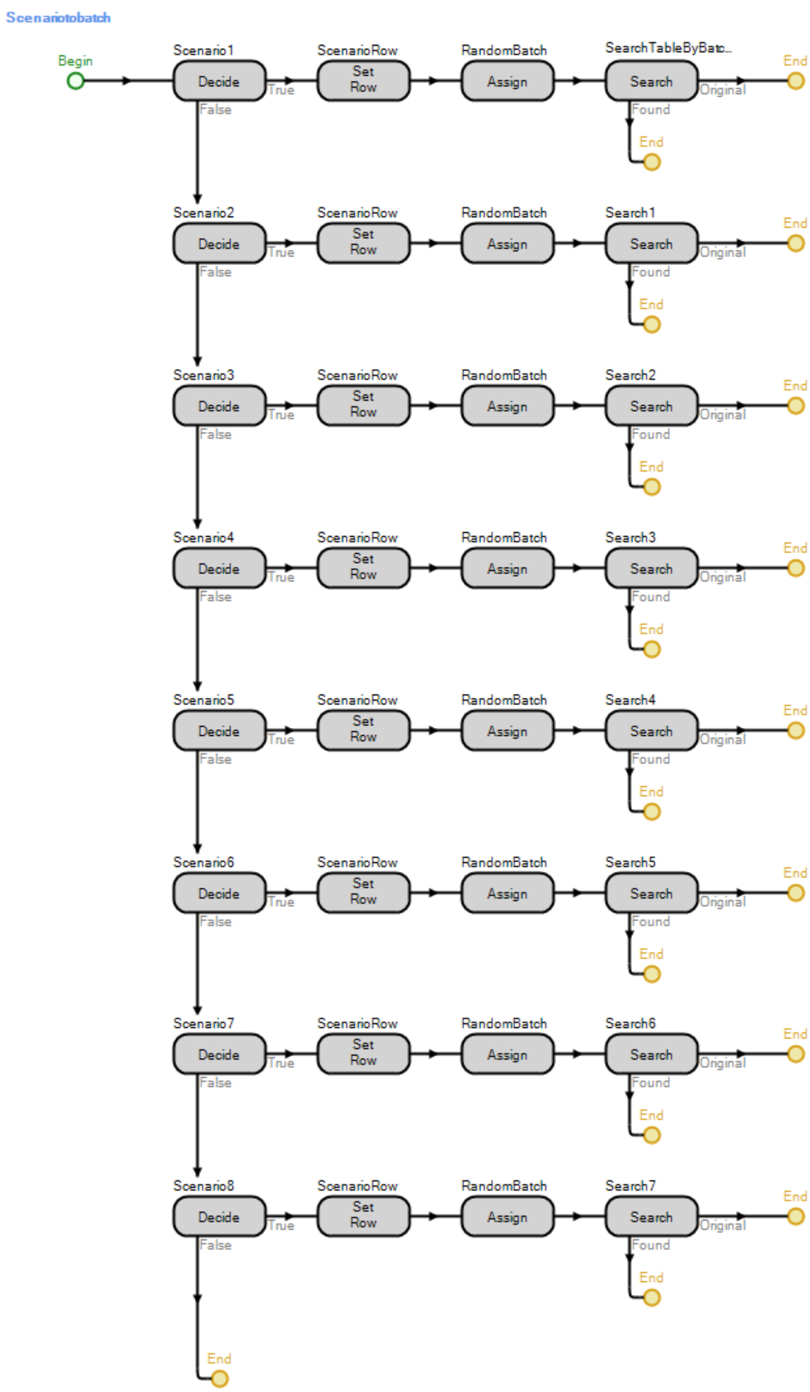

Figure E.5: Scenario setting in Simio

E3 Results of discrete event simulation