University of Twente

Master thesis

Improving the order picking performance at Scania Production Zwolle

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Management summary

In this thesis, we create a future-proof assignment model that enables Scania Production Zwolle (SPZ) to assign the workload to a minimal number of order pickers in the Low-Bay-2 warehouse (LB2-warehouse), taking into account the travel time and workload distribution of order pickers. The assignment model can be used regardless of LB2-warehouse size or truck output.

Scania is a global manufacturer of trucks, busses and engines that produces over trucks per year, which are sold in about 100 countries. The main production facility is located in Zwolle where almost 50% of all the trucks are produced. The research takes place at the Manufacturing Zwolle Engineering Logistics (MZEL) department of SPZ, which is responsible for the supply of parts from the warehouses to the assembly lines of SPZ. The LB2-warehouse, which is under the responsibility of the MZEL department, struggles with controlling the workload of order pickers at the picking process because there is no appropriate method to estimate the expected workload and to assign the workload evenly over the order pickers. As a result, order pickers in the LB2-warehouse face a varying workload throughout the day, which leads to overcapacity and undercapacity. Overcapacity is undesirable because this implies that SPZ needs to deploy more order pickers than necessary. Undercapacity is undesirable because this lowers the service level, which means that orders are not picked on time. Therefore, SPZ wants to investigate if, and how, the current picking process can be carried out with fewer order pickers and how the workload should be distributed over the order pickers. Hence, this research has the following research goal.

Design a future-proof method that assigns the workload in the LB2-warehouse of SPZ to a minimal number of order pickers taking into account the travel time and workload distribution of order pickers.

To achieve this goal, we examine the current processes and design of the LB2-warehouse. The LB2-warehouse is a manual picker-to-part warehouse where order pickers need to replenish so-called fixtures within a predefined time window (takt time). A fixture is a cart designed to carry a particular type of part. When a fixture is replenished it is transported from the LB2-warehouse to the assembly line with tugger trains. In the current situation, it is difficult to estimate the order picking workload because the number of storage locations to visit per replenishment cycle varies. In addition, the pick time per part depends on the weight, complexity, and storage method of a part which makes it difficult as well. The optimization area that is discovered is the assignment of orders (fixtures) to order pickers, also known as the Order Assignment and Sequencing Problem (OASP). To the best of our knowledge, no solution approaches are known for the OASP. However, the OASP shows a lot of similarities with the Identical Parallel Machine Problem (IPMP), Bin Packing Problem (BPP) and Vehicle Routing Problem (VRP) problem formulation for which solution approaches are known. We conclude that the BPP formulation shows the most similarities with our problem. Therefore, we model our problem based on a BPP. The main difference of our problem compared to a classic BPP is that not all items have a static size but sometimes a variable size that depend on the travel time of an order picker. As the BPP is identified as an NP-complete problem, we have to rely on approximation algorithms and metaheuristics to solve the problem. In the current situation, we need to assign 17 fixtures, which maybe enables it to solve it exactly because the solution space is relatively small. However, when we want to design a future-proof method the model should be applicable when extra fixtures are added or the truck output increases, which means that our model should be able to solve larger instances of the problem.

The solution approach combines a best-fit heuristic with the metaheuristic Simulated Annealing (SA) to obtain an assignment strategy of fixture to order picker. We evaluate the performance of an assignment strategy under stochastic conditions in a simulation model. The

stochastic conditions include varying order pick times, and a stochastic arrival and departure process of fixtures. First, the best-fit heuristic determines an initial solution and an upper bound on the number of order pickers. Second, the SA uses the outcome of the best-fit heuristic to optimize a multi-objective function. The multi-objective function focuses on minimizing the number of order pickers but also includes the balancing ratio and the travel time of order pickers. The performance of an assignment strategy is determined based on the Key Performance Indicator (KPI)s: service level, tardiness, balancing ratio, travel distance and number of congestion situations in aisles.

The simulation model evaluates three interventions on the current situation. The first intervention focuses on minimizing the travel time per order picker, the second on balancing the workload over the order pickers and the third on a trade-off between the two. Table 1 shows the KPIs for each intervention.

Table 1: Key performance indicators per intervention

Key Performance Indicator	**Intervention 1**	**Intervention 2**	**Intervention 3**
FTE	4	4	4
Average service level per order picker	98.76%	98.95%	99.34%
Maximum tardiness of a fixture	63.70 sec	30.22 sec	35.50 sec
Balancing ratio	29.15%	3.86%	13.35%
Average travel distance per order picker	2876.68 m	5521.94 m	3119.69 m
Congestion situations in aisles	0	1266	264

When the tardiness of an intervention is above 2 minutes the tugger train process disturbes and parts do not arrive at the assembly line on time, which could cause a line stop. We conclude that all interventions provide an assignment strategy that does not lead to any disturbances in the tugger train process or line stops. Intervention 2 performs well on the balancing ratio KPI, but leads to a travel distance that almost doubles compared to intervention 1, and much congestion in multiple aisles. Therefore, we do not recommend to implement intervention 2. We advise SPZ to implement intervention 1 when SPZ wants to minimize the travel distance per order picker as much as possible or reduce congestion as much as possible. We advise SPZ to implement intervention 3 when SPZ wants an improved workload balancing ratio. A disadvantage of intervention 3 is that order pickers need to travel a bit more, which does not add value to the order picking process.

We apply intervention 3 to three near-future scenarios and compare the performance with the current situation to provide future proof recommendations. We choose to use intervention 3 for the future scenarios because this intervention leads to a significant improved workload ratio and a limited increase in the travel distance. The first scenario evaluates the current situation with a daily truck output of . This scenario serves as benchmark for the other scenarios that we evaluate. The second scenario evaluates an increase in the daily truck output to , the third an expansion of the LB2-warehouse with extra picking aisles and a daily output of trucks, and the fourth an expansion of the LB2-warehouse with extra picking aisles and a daily output of trucks. Table 2 shows the KPIs for each scenario.

Table 2: Key performance indicators per scenario when applying intervention 3

Key Performance Indicator	**S1: Current situation**	**S2: Daily truck output:**	**S3: Expansion of LB2-warehouse**	**S4: Truck output: & Expansion of LB2-warehouse**
FTE	4	5	5	5
Average service level per order picker	99.34%	99.73%	98.30%	93.85%
Maximum tardiness of a fixture	35.50 sec	4.14 sec	108.44 sec	47.36 sec
Balancing ratio	13.35%	28.58%	13.54%	26.08%
Average travel distance per order picker	3119.69 m	2954.26 m	3817.85 m	4262.52 m
Congestion situations in aisles	264	798	1044	1053

In scenarios 2,3 and 4 an additional order picker is required in the LB2-warehouse. We conclude that all scenarios provide an assignment strategy that results in a tardiness below 2 minutes, which means that the scenarios do not lead to any disturbances in the tugger train process or line stops. In scenarios 2 and 4, where the truck output increases, we observe a more unevenly distributed workload over the order pickers than in scenarios 1 and 3. We conclude that a workload increase makes it more difficult to balance the workload over the order pickers. Despite an extra order picker in scenarios 3 and 4, the average travel distance per order picker increases due to the increase in output of trucks. In addition, the number of congestion situations rise as well because order pickers need to be in the same picking aisle more often.

In the near future SPZ wants to increase to a daily truck output of trucks. This requires an expansion of the LB2-warehouse to have sufficient storage capacity for an output of trucks. After the expansion of the LB2-warehouse and at a truck output of trucks, 1 order picker can be saved in the High-Bay warehouse (HB-warehouse) and the return on investment on the expansion of the LB2-warehouse is years.

We conclude that this research provides a future-proof assignment model that assigns the workload in the LB2-warehouse of SPZ to a minimal number of order pickers taking into account the travel time and workload distribution of order pickers. The assignment model is future-proof because it can be used regardless of LB2-warehouse size or truck output.

Preface

This report is the result of my master thesis project at Scania Production Zwolle to finalize my study in Industrial Engineering and Management at the University of Twente. I would like to thank several persons who contributed to this thesis.

First of all, I would like to thank my colleagues at Scania Production Zwolle. Although I had to work a lot from home because of the Covid-19 pandemic, they were always willing to help me with my graduation project. I look back on a pleasant and educational period at the MZEL department and experienced it as an open and helpful department where the atmosphere was always very good. In particular, I would to thank my company supervisor, Gerben Stoffers, for his effort during the guidance of my Master Thesis.

Furthermore, I want to thank Peter Schuur and Marco Schutten of the University of Twente for their critical view, guidance and support. The feedback really helped me to write a thesis of this quality.

Finally, I want to thank my family, friends, and my girlfriend Remi for supporting me during tough times and for providing feedback on this thesis. I learned a lot about myself and we will see what the future brings. I hope that I can continue to improve myself and keep learning.

Stan te Molder, March 2022

Acronyms

BASP Batch Assignment and Sequencing Problem.

BP Batch Picking.

BPP Bin Packing Problem.

CLKIT Consumption Location KITting.

ERP-system Enterprise Resource Planning system.

FF Factory Feeding.

FTE Full Time Employee.

FTWB Fixed Time Window Batching.

HB-warehouse High-Bay warehouse.

ILP Integer Linear Programming.

IPMP Identical Parallel Machine Problem.

JIT Just-in-Time.

KIT Kitting.

KPI Key Performance Indicator.

LB2-warehouse Low-Bay-2 warehouse.

LF Line Feeding.

LPT Longest Processing Time.

LS List Scheduling.

MZEL Manufacturing Zwolle Engineering Logistics.

OASP Order Assignment and Sequencing Problem.

OBP Order Batching Problem.

SA Simulated Annealing.

SEQ Internal Sequencing.

SPS Scania Production System.

SPZ Scania Production Zwolle.

UOL up-to-order level.

USB Unit Supply Boxes.

USP Unit Supply Pallets.

VRP Vehicle Routing Problem.

VTWB Variable Time Window Batching.

WMS Warehouse Management System.

Contents

1 Introduction

This chapter introduces the company and describes the background of the assignment. First, Section 1.1 introduces the company where the research conducts. Subsequently, Section 1.2 describes the research motivation and Section 1.3 provides a problem cluster to get insight into the existing problems in the process. Then, Section 1.4 addresses the scope of this research. Finally, Section 1.5 defines the research questions

1.1 Company introduction

Scania is a global manufacturer of trucks, busses and engines. In 2020, Scania produced over 80,000 trucks that are sold in about 100 countries around the globe. Worldwide, around 50,000 people are employed at Scania. The production facilities of Scania are located in Europe and Latin America. Scania's vision is to be the global leader in sustainable transport. To pursue this vision, Scania constructed the Scania Production System (SPS), shown in Figure 1.1. The SPS contains the principles and methods that lead to continuous improvement and reflect the company's culture. The core values of Scania are embedded in the pillars of the SPS, which are: Customer first, Respect for the individual and Elimination of waste.

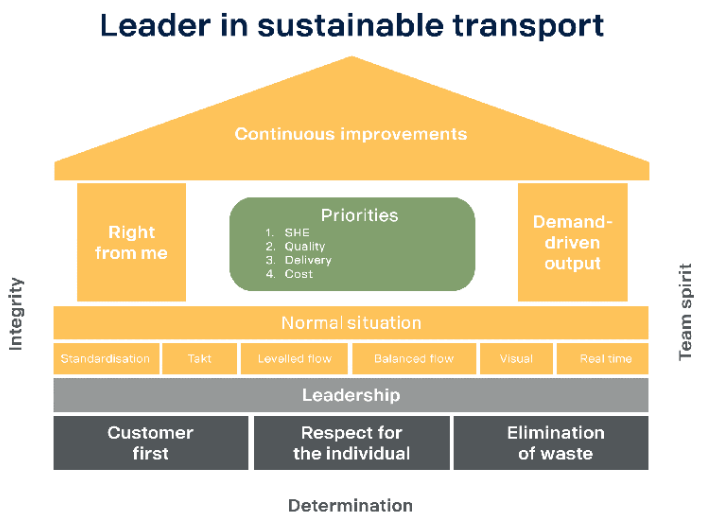


Figure 1.1: Scania Production System.

The main production facility is located in Zwolle where almost 50% of all the trucks are produced on two assembly lines. Despite having only two assembly lines, SPZ is capable to produce many different types of trucks with a limited set of parts due to Scania's modular product system. Furthermore, the production line of SPZ is known for their Just-in-Time (JIT) delivery of parts and balanced workload. The assembly line at Scania consists of multiple consecutive workplaces where a group of assemblers have to complete a predetermined set of tasks within the takt time. The takt time is the time interval at which the mechanics need to complete their tasks to meet the demand of trucks.

1.2 Research motivation

This research takes place at the MZEL department of SPZ. MZEL is responsible for the supply of parts from the storage areas to the assembly lines of SPZ. Each storage area uses different supply methods to ensure the supply of parts to the assembly lines. Appendix A provides an overview of the supply methods and their storage areas. Figure 1.2 shows the inbound storage areas of SPZ. The storage area Platform 2 represents the LB2-warehouse. The LB2-warehouse struggles with controlling the workload of order pickers at the picking process because there is no appropriate method to estimate the expected workload and to assign the workload evenly over the order pickers. Currently, SPZ uses the daily forecast on the number of picks in a picking aisle to estimate the workload in a picking aisle. However, the picking time per part varies, making it difficult to estimate the actual workload expressed in terms of time. As a result, order pickers in the LB2-warehouse face a varying workload throughout the day, which leads to overcapacity and undercapacity in the LB2-warehouse. Overcapacity is undesirable because this implies that SPZ needs to deploy more order pickers than necessary. Undercapacity is undesirable because this lowers the service level, which means that orders are not picked on time. Therefore, SPZ wants to investigate if, and how, the current picking process can be carried out with fewer order pickers and how the workload should be distributed over the order pickers.

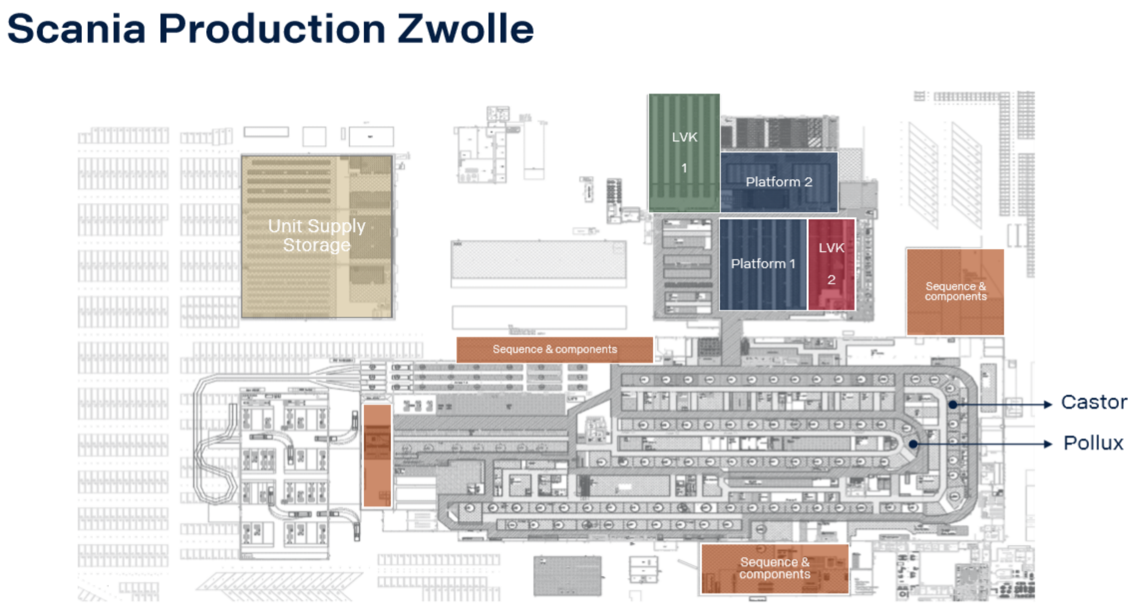


Figure 1.2: Production map of Scania

1.3 Problem identification

To identify a problem, it is essential to understand its cause, relationship, impact and context. A helpful method to visualize this is to create a problem cluster described by Heerkens & van Winden (2012) in the managerial problem-solving method (MPSM). Figure 1.3 represents the problem cluster with in the blue box the action problem. The action problem describes a discrepancy between a norm and a reality. The norm is that there is no undercapacity or overcapacity of order pickers in the LB2-warehouse. However, the reality is that there is undercapacity or overcapacity of order pickers in the LB2-warehouse. Underneath the action problem, the causes of the action problem are shown. If the problem has impact, is possible to change and has no preceding cause, the problem is identified as a solvable core problem. Below the figure, we elaborate on the solvable core problems.

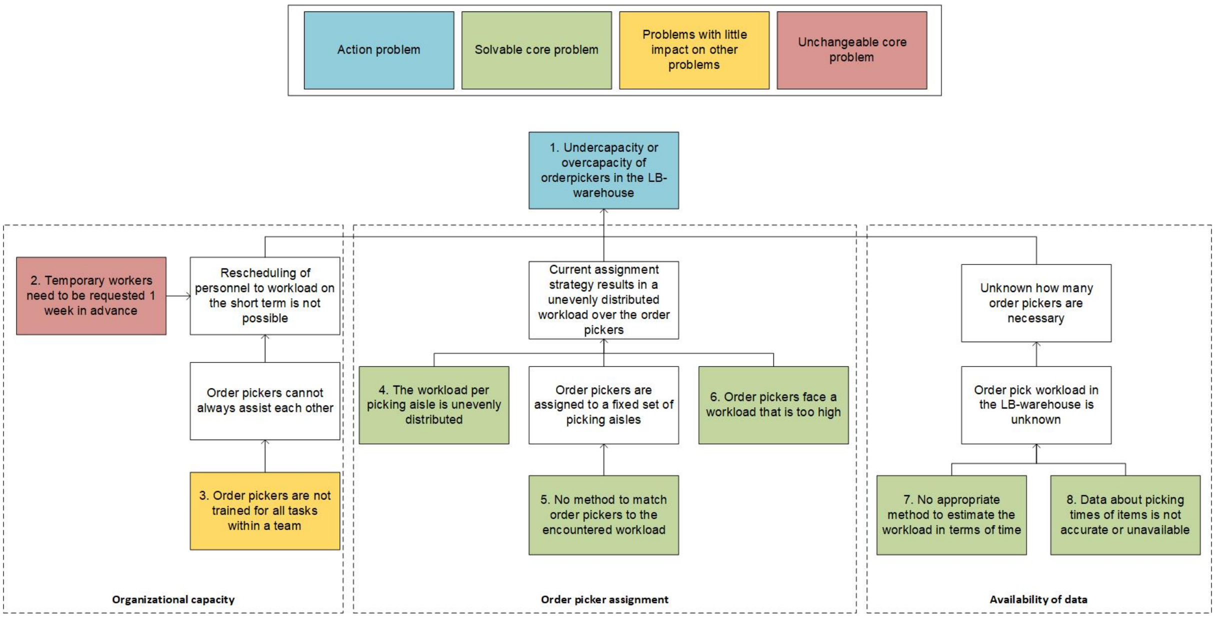


Figure 1.3: Problem cluster

Organizational capacity
When over or undercapacity arises in the LB2-warehouse, SPZ cannot solve this on a short-term by rescheduling order pickers from other warehouses because not all order pickers are trained for all tasks within a team (problem 3). This problem could be solved by training order pickers so that they can carry out all tasks. However, this costs time and money and will not solve the action problem. In addition, it is not possible to hire extra temporary order pickers on a short-term because extra personnel needs be requested 1 week in advance and cannot be shortened (problem 2).

Order picker assignment
The over or under capacity in the LB2-warehouse is partly due to the current order picker assignment strategy, whereby order pickers are assigned to a fixed set of picking aisles. Since the workload per picking aisle varies considerably, some order pickers face a workload that is too high (problem 6), while others face a low workload. As a result, the workload is unevenly distributed over the order pickers. We can solve this problem in two ways. We can either divide the workload evenly per picking aisle (solving problem 4) or assign order pickers to the workload in a different way (solving problem 5).

Availability of data
The under and overcapacity of order pickers in the LB2-warehouse is also a result of the unavailability of a method to determine the required number of order pickers for the LB2-warehouse. SPZ cannot determine the required number of order pickers because the workload in the LB2-warehouse is unknown. The workload in the LB2-warehouse is unknown because in the current situation there is no method to estimate the workload in terms of time (problem 7) and because data on pick times is not accurate or unavailable (problem 8).

From the problem cluster we derive the following 5 solvable core problems.

4. The workload per picking aisle is unevenly distributed
5. No method to match order pickers to the workload
6. Order pickers face a workload that is too high
7. No appropriate method to estimate the workload in terms of time
8. Data about picking times of items is not accurate or unavailable

Core problem 4 and 5 both result in an unevenly distributed workload over the order pickers. We can solve our action problem by keeping the current assignment strategy and distributing the workload evenly over the aisles (solving core problem 4) or we can design a new assignment strategy that assigns the workload evenly over the order pickers (solving core problem 5). We choose to solve core problem 5 because storage locations of parts are regularly moved and new parts are added, which alters the workload in the picking aisle with every modification. Developing a method that assigns the workload to order pickers and take into account the maximum workload of an order picker prevents excessive workloads for order pickers, which solves core problem 6.

Core problem 7 can be solved by developing a method that estimates the workload in the LB2-warehouse. However, solving core problem 7 requires a solution for core problem 8 because without accurate data it is not possible to estimate the workload. Gathering data on the picking times of parts solves core problem 8 and enables the development of a method that determines the workload in the LB2-warehouse. If core problem 7 and 8 are solved, it is possible for SPZ to estimate the workload in the LB2-warehouse. When the required workload can be defined, SPZ can determine how many order pickers are needed in the LB2-warehouse, which prevents under and over capacity in the LB2-warehouse. To solve the core problems, we define the following research objective.

Design a future-proof method that assigns the workload in the LB2-warehouse of SPZ to a minimal number of order pickers taking into account the travel time and workload distribution of order pickers.

1.4 Scope

The Enterprise Resource Planning system (ERP-system) of SPZ cannot register the order pick activities of all supply methods in the same way. As a result, it is not possible for these supply methods to determine the workload and thus we cannot assign the workload to order pickers. Therefore, the scope of this research is on the LB2-warehouse because this warehouse mainly uses the supply method Consumption Location KITting (CLKIT) for which sufficient data from the ERP-system can be gathered to determine the workload. The LB2-warehouse of SPZ consists of 6 picking aisles with around 192 storage locations.

1.5 Research questions

This section proposes research questions that require an answer to achieve our research goal. Each research question is answered in 1 or 2 chapters.

Research question 1: What is the current situation of the LB2-warehouse? - Chapter 2: Current situation

(a) How is the production of trucks organized at SPZ?
(b) How are the operations organized in the LB2-warehouse?
(c) How is the personnel planning organized in the LB2-warehouse?
(d) What is the current order picking performance at the LB2-warehouse?
(e) What is the current assignment strategy in the LB2-warehouse?
(f) Which data is available regarding the order picking workload at the LB2-warehouse?

Research question 2: Which methods are described in literature to improve the order picking process in a order picking warehouse? - Chapter 3: Literature review

(a) What are the main processes, functions, resources, and organizational issues of a warehouse?
(b) What are warehouse design and operational planning problems?
(c) How to select an appropriate order picking method for a warehouse?
(d) How can we classify the LB2-warehouse of SPZ?
(e) Which methods can be used to assign order pickers to the workload?

(f) What are possible solution approaches to improve the order picking processes in a warehouse?

Research question 3: How can the order picking performance of the LB2-warehouse of SPZ be improved? - Chapter 4: Solution design

(a) Which factors in the current order picking process should be improved to increase the order picking performance in the LB2-warehouse of SPZ?
(b) Which problem formulation suits our problem?
(c) How can we formulate our problem mathematically?
(d) How can we solve the mathematical model?
(e) What is the objective of our model?
(f) What are the inputs and output of the model

Research question 4: What is the order picking performance (improvement) in the LB2-warehouse after implementing the solution approach? - Chapter 5: Simulation model - Chapter 6: Experimental results

(a) How are the order pickers assigned to the workload at each intervention?
(b) What is the impact of interventions on the order picking performance?
(c) How will the order picking performance change in the future?
(d) Is the solution approach future-proof?

Chapter 7 presents the conclusions, recommendations and discussion of this research

2 Current situation

This chapter answers the research question: What is the current situation of the LB2-warehouse? First, Section 2.1 describes how the production of trucks is organized at SPZ. Second, Section 2.2 describes the design and operations of the LB2-warehouse. Third, Section 2.3 discusses the personnel planning. Fourth, Section 2.4 addresses the current assignment strategy. Fifth, Section 2.5 elaborates on the current order picking performance. Sixth, Section 2.6 explains about the available data regarding the workload in the LB2-warehouse. Finally, Section 2.7 concludes the chapter.

2.1 Production process

This section provides a general description of the production process at SPZ and provides an answer on research question 1a.

The production location consists of two assembly lines, which are the Castor and Pollux. The Castor assembly line produces standard trucks, while the Pollux assembly line produces special trucks. The part supply to these assembly lines uses several warehouses where parts are temporarily stored (shown in Figure 1.2). The production of trucks at SPZ starts with the construction of the frame. Subsequently, the frame moves to multiple consecutive workplaces on the Castor or the Pollux, where mechanics assemble parts on the truck at the workstations. Each assembly line has its own takt time, which is defined as the time between the completion of two consecutive trucks. After each takt time a cycle ends and a complete truck leaves the factory from the last workplace. Meanwhile, all preceding trucks move to the next workplace. On a normal production day, the value of the takt time of the castor assembly line is minutes resulting in a production of trucks and the value of the takt time of the Pollux assembly line is around minutes resulting in a production of trucks.

2.2 Design and operations of the LB2-warehouse

This section describes the design and operations of the LB2-warehouse and gives an answer on research question 1b. First, Section 2.2.1 discusses the warehouse design and explains which type of parts are stored in the LB2-warehouse. Second, Section 2.2.2 explains about the order picking process in the LB2-warehouse. Third, Section 2.2.3 describes the transportation process of parts from the LB2-warehouse to the assembly line.

2.2.1 Warehouse design

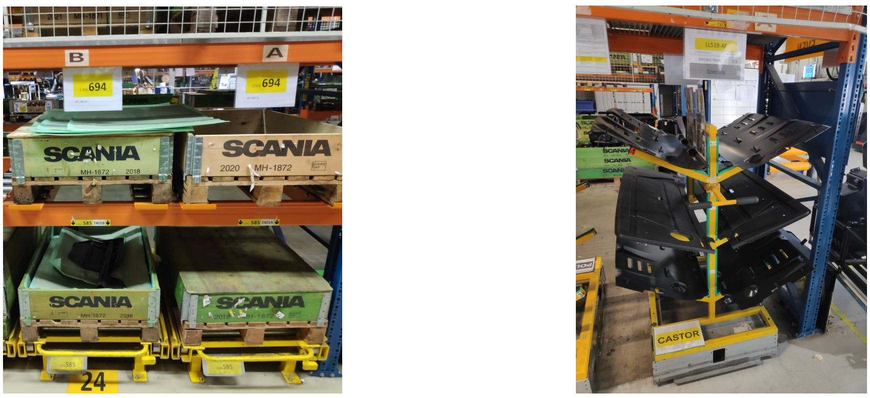
The LB2-warehouse stores small to medium-sized parts that are used for the assembly of trucks. Examples of these parts are tank brackets, exhaust pipes and heat shields. Part storage in the LB2-warehouse is based on product families, which means that in each aisle, the parts that make up an order are placed close together. As a result, the travel distance for order pickers to pick all the parts for an order is minimized because all pick locations are close to each other. The LB2-warehouse consists of picking aisles and supply aisles, which are divided alternately. The supply of parts to the LB2-warehouse is facilitated by reach trucker drivers that deliver the incoming goods from trailers to the LB2-warehouse. In a supply aisle, shown in Figure 2.1a, order pickers are not allowed to walk and operate to ensure employees safety. Vice versa, in a picking aisle shown in Figure 2.1b, reach trucks are not allowed to drive and operate to ensure safety.

(a) Example of supply aisle
(b) Example of picking aisle

Figure 2.1: Types of aisles in the LB2-warehouse

2.2.2 Order picking process

The LB2-warehouse primarily uses the CLKIT order picking method. This order picking method is manually organised with order pickers that walk to the storage locations to pick parts on fixtures. A fixture is a cart that is specifically designed to carry a particular type of part (Figure 2.2b). The design of a fixture ensures optimal handling and ergonomics for the order picker. A fixture carries multiple parts of a part group, where each unique part in a part group has its own part number. For example, an exhaust pipe is available in different lengths based on the length of the chassis. The long and short exhaust pipes have two different part numbers but are in the same product group and are carried on the same fixture. The consumption rate of the part numbers is not equal because different types of trucks are produced and not all the truck chassis need the same amount of each part number. Order pickers pick the required parts for a fixture from a pallet box, shown in Figure 2.2a. The pallet boxes are stored on the ground floor and are easily accessible for the order pickers. Pallet boxes are stored in a two-bin system at fixed locations in the LB2-warehouse. When a pallet box is empty and needs a replenishment order pickers replace the empty pallet box with a new pallet box from the two-bin storage and place the empty pallet back. Reach trucker drivers who regularly drive through the aisles can then see that the two-bin stock needs to be replenished. Order pickers are responsible to pick the fixtures within the takt time of the fixture. The takt time of a fixture is based on the demand of the parts that the fixture carries. In a picking aisle a digital board with a countdown clock per fixture is installed to help the order pickers to keep track of the requested fixtures and their takt times.



(a) Example of pallet boxes
(b) Fixture carrying protection plates

Figure 2.2: Example of a pallet box and a fixture

2.2.3 Transport of fixtures to assembly line

The supply of parts from the LB2-warehouse to the assembly line is carried out with tugger trains. A tugger train, shown in Figure 2.3a, consists of a tractor with a minimum of 3 and a maximum of 5 wagons behind it. The wagons are loaded with fixtures by the tugger train driver. Figure 2.3b shows a loaded tugger train.

(a) An empty tugger train

(b) A loaded tugger train

Figure 2.3: Empty and loaded tugger train

The tugger train driver drives fixed train routes between the LB2-warehouse and the assembly line to transport the requested fixtures to the workstations at the assembly line. When the tugger train driver arrives at a workstation the tugger train driver unloads a replenished fixture and loads an empty fixture on the tugger train. When all required workstations are visited, the tugger train driver returns to the LB2-warehouse and places the empty fixtures in the loading areas. The train routes are driven at fixed times and are defined in a train schedule. The train routes in the train schedules are usually dedicated to one or two aisles in the LB2-warehouse, which means that the fixtures that belong to a train route are picked in the same aisle.

The operations of the production system, the order picker, tugger train driver and reach truck driver are closely interconnected, which is schematically represented in Figure 2.4.

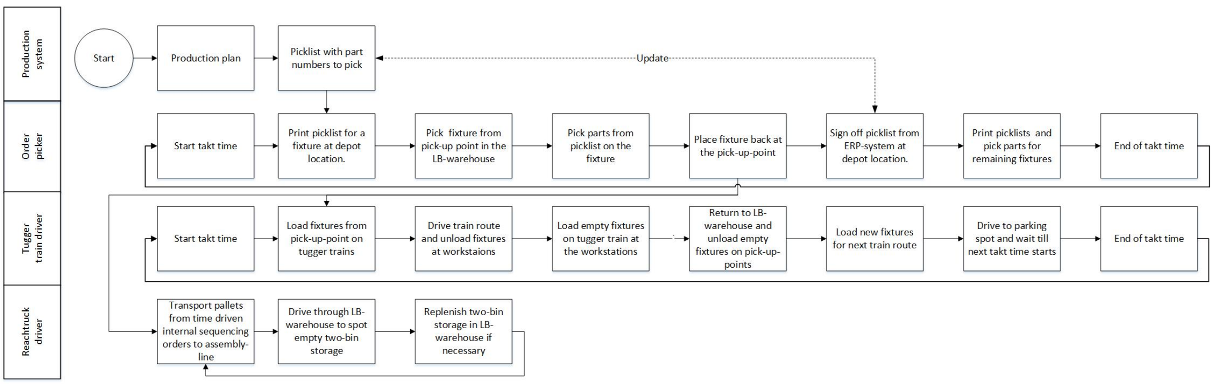


Figure 2.4: Operations in the LB2-warehouse

2.3 Personnel planning

This section discusses the personnel planning in the LB2-warehouse and gives an answer on research question 1c.

On a daily basis, the personnel planning in the LB2-warehouse is organised in two consecutive working teams for employees: the F-team and the G-team. The two teams work a morning shift or an evening shift and the teams switch shifts every week. The teams consist of a permanent group of employees and several flex-workers who work on temporary basis. In the

LB2-warehouse a supervisor is responsible for the operations. A supervisor instructs several team leader areas, containing 5-10 operators. An operator can have different functions such as tugger train driver, order picker or reach truck driver. An operator works according to a so-called ”Working Standard”. The working standard describes in detail the tasks the operator needs to perform. For example, the predetermined set of tasks to pick a fixture. A request for additional flex-workers must be made one week in advance to a temporary employment agency. The number flex-workers that will be hired is based on experience, occurred workload peaks and on the basis of the predicted number of picks per day per aisle.

2.4 Current assignment strategy in the LB2-warehouse

This section addresses the current assignment strategy that the LB2-warehouse uses, which provides an answer on research question 1e.

In the current situation, each order picker is assigned to a fixed set of picking aisles (shown in Figure 2.5) and is responsible to pick the parts for the fixtures in those aisles (shown in Table 2.1). Order pickers do not assist each other with picking activities but only pick in their own picking aisles. An advantage of this situation is that there is no congestion in the picking aisles, that travel distances are minimal and that it is easier to manage the responsibilities of the order pickers. For example, if a fixture is picked late, it is easy to remind the responsible order picker his responsibilities. However, the fixed assignment of order pickers to aisles leads to an unequal distribution of the workload over the order pickers because the number of picks per aisle varies.

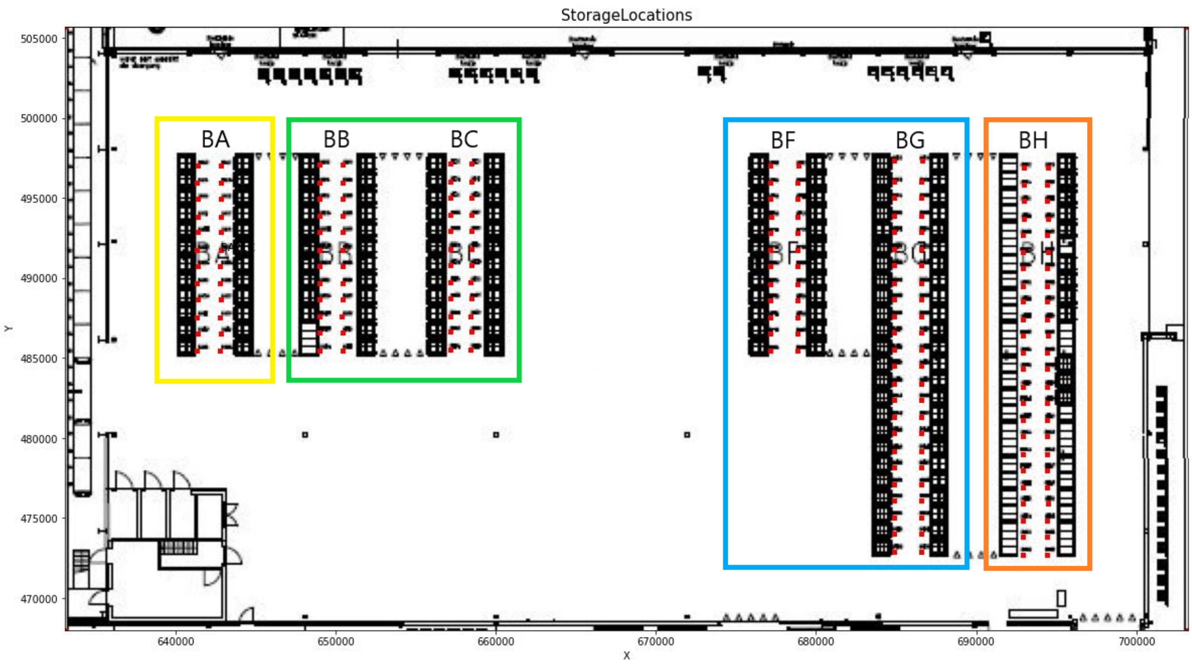


Figure 2.5: LB2 warehouse

Table 2.1: Assignment of fixture to order picker

Order picker 1	LL322-DBP-BA	LR322-DBP-BA	SL323-DBP-BA	SR322-DBP-BA	
Order picker 2	LR450-DBP-BB	SL393-DBP-BB	LL336-DBP-BC	SL330-DBP-BC	
Order picker 3	Y10A106-PX-DBP-BG	Y10A156-DBP-BG	Y11B136-BP-BF	Y07C146-DBP-BF	Y07C154-P-DBP-BF
Order picker 4	LL734-LINKS-DBP-BH	LR734-RECHTS-DBP-BH	SR578-RECHTS-DBP-BH	SL580-LINKS-DBP-BH	

2.5 Order picking performance in the LB2-warehouse

This section describes the current order picking performance, which includes the average number of parts picked per day, average number of replenishment per fixture, the average number of parts per fixture and the average number of parts picked per aisle. This section gives an answer on research question 1d.

Figure 2.6 shows the average number picked parts in LB2-warehouse versus the indexed number of produced trucks from 1 February 2021 till 1 June 2021. The indexed number of produced trucks is calculated by dividing the daily number of produced trucks by the average number of produced trucks over the whole period. The two lines follow the same pattern, indicating that the number of parts picked depends on the number of trucks produced. The peaks in the graph are a result of production stops at the assembly line. If we exclude the peaks from production stops, the number of parts picked in LB2-warehouse is relatively constant.

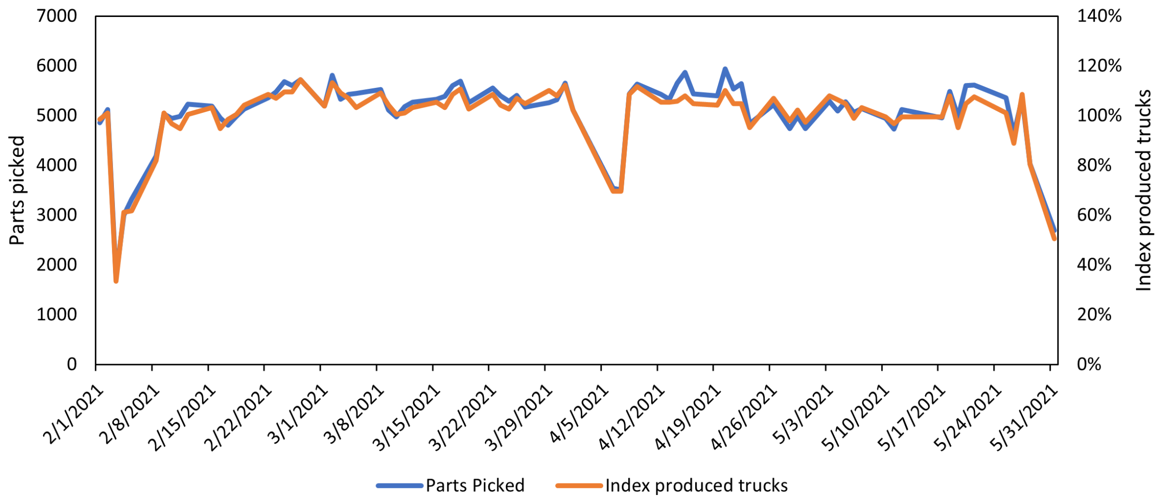


Figure 2.6: Average parts picked in the LB2-warehouse vs indexed number of trucks

Figure 2.7 shows the average number of replenishments per fixture in the LB2-warehouse. The last 2 letters of the fixture name indicate in which aisles the fixture is replenished. The error bars in the figure represent the standard deviation of the average number of replenishments. The standard deviation is low and constant, indicating that the number of replenishments per day is relatively constant.

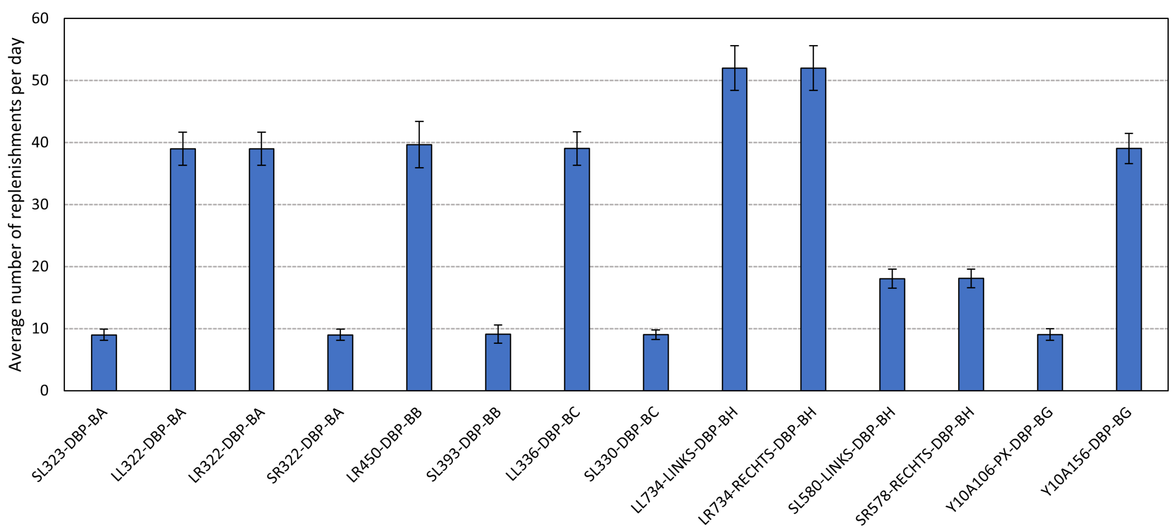


Figure 2.7: Average number of replenishment per fixture between 04-01-21 and 05-01-21

Figure 2.8 shows the average number of parts per fixture and the average number of unique parts per fixture. The number of parts on a fixture varies per replenishment cycle because not all trucks need the same quantity of a part. The error bars represent the standard deviation on the number of parts per fixture. A unique part is defined as a part with its own part number and storage location. The number of unique parts that have to be picked is either not constant. For example, on average 7 unique parts are picked on fixture "LR450-DBP-BB". However, it can happen that during a replenishment cycle 9 unique parts have to be replenished on this fixture. Since every unique parts has its own storage location, an order picker has to visit a variable number of storage locations per replenishment cycle to pick all the required parts for a fixture.

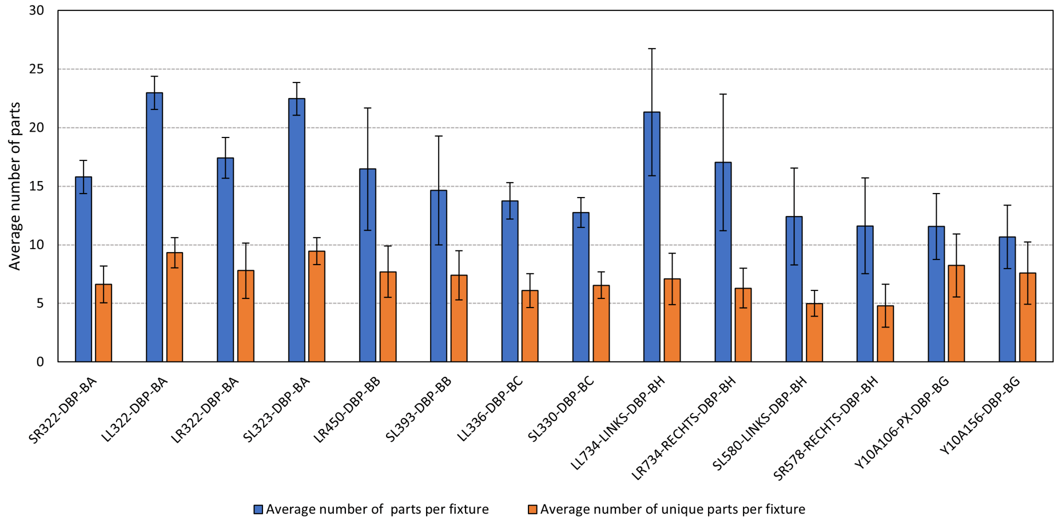


Figure 2.8: Average number of parts per fixture & Average number of unique parts per fixture (The data is about the period 04-01-21 and 05-01-21)

The LB2-warehouse is divided into 6 order picking aisles, where 5 of these picking aisles use the CLKIT supply method. These aisles are the BA, BB, BC, BG and BH aisles. Figure 2.9 shows the average number of picks per hour on a production day. The number of picks is an average of 1 month of production. The number of picks per aisle is relatively constant except between 14:00 and 15:00. At 14:00, the morning shift ends and the evening shift takes over at 14:45. There is no production for 3 quarters of an hour during this change, which explains the drop. The number of picks per hour is relatively constant because of the takt-flow in the warehouse. Order pickers in the LB2-warehouse cannot work ahead because an empty fixture must be returned first. The number of picks in the BH and BA aisles is significantly higher than in the other aisles because the fixtures that belong to these picking aisles require more replenishments on a day.

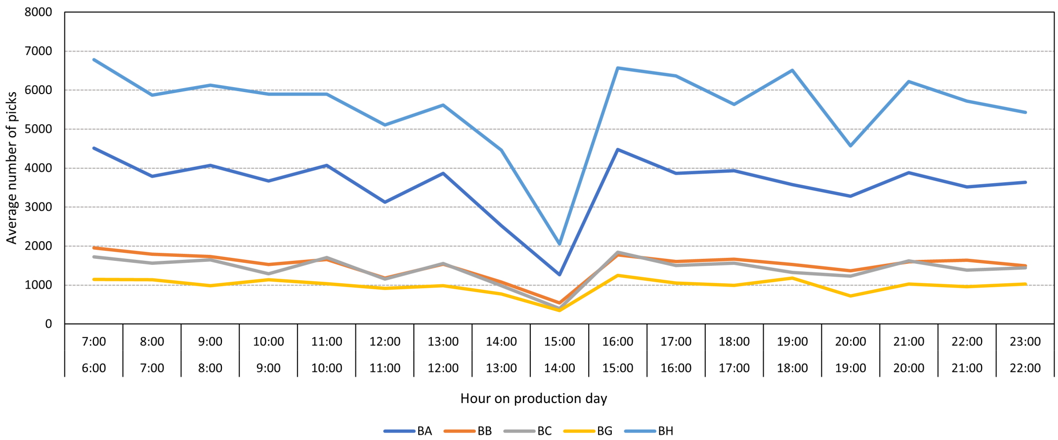


Figure 2.9: The average number of picked parts per hour in an aisle on a production day

2.6 Data regarding workload

This section answers research question 1f and elaborates on the available data regarding the order picking workload in the LB2-warehouse.

As discussed in Section 2.2.2 order pickers have to visit a variable number of storage locations per replenishment cycle. The variable number of storage locations affects the order pick time of a fixture because if a fixture requires less storage locations to visit, the fixture can be replenished faster. Another factor that influences the order pick time is the handling time of parts. At the moment, SPZ has no data available regarding the handling times of the parts. However, from observations and interviews with order pickers we conclude that the handling time per part can vary considerably. Factors that influence the handling time of a part are the weight, complexity and storage method.

Currently, SPZ uses the forecast on the number of picks per aisle to estimate the workload at the LB2-warehouse. The forecast is based on the number and type of trucks that will be produced. Table 2.2 shows the forecast of the number of picks per aisle on each day for a normal production week. The target number of picks indicates a benchmark on the number of picks that is realistic to pick in the picking aisle. Based on this forecast, team leaders and supervisors make an expectation of the workforce that is required for each picking aisle. If the forecast on the number of parts to pick is considerably higher than the target number of picks, more need for assistance from team leaders or other colleagues during the day is necessary. Alternatively, additional flex workers are deployed in the picking aisles to support the picking process.

Table 2.2: Forecast of number of picks per aisle (data between 08-23-2021 and 08-27-2021)

Aisle	**BA**		**BB**		**BC**		**BG**		**BH**	
Day	**Tot Qty**	**Target**	**Tot Qty**	**Target**	**Tot Qty**	**Target**	**Tot Qty**	**Target**	**Tot Qty**	**Target**
2021-08-23	1991	1950	556	650	507	450	644	650	2166	1950
2021-08-24	1966	1950	444	650	474	450	606	650	2147	1950
2021-08-25	1553	1950	360	650	358	450	484	650	2056	1950
2021-08-26	356	1950	83	650	72	450	142	650	384	1950
2021-08-27	355	1950	86	650	88	450	152	650	360	1950

The forecast only indicates how many picks are expected, but does not provide any information about the time that these picks require. Since the picking time varies per part, a high forecast on the number of picks does not imply a high workload for the order pickers in that aisle. Vice versa, a low forecast on the number picks does not imply a low workload for the order pickers in that aisle. SPZ would like to express the workload in the LB2-warehouse in terms of time with which a more accurate calculation can be made about the required workforce in the picking aisles. In addition, if the workload can expressed in terms of time, it is easier to assign the workload evenly over the order pickers.

2.7 Conclusions

This section summarizes the main conclusions of this chapter

This chapter discussed the lay-out of the production processes, current way of working, the performance and the available data related to workload in the LB2-warehouse.

The LB2-warehouse stores small to medium-sized parts that are used for the assembly of trucks. The part storage is based on product families, which reduces travel distance for order pickers to pick an order. In the LB2-warehouse order pickers need to pick the parts on fixtures within the takt time of a fixture. A fixture is a cart that is specifically designed to carry a particular type of part. When a fixture is picked the transport of the fixture to the assembly line is carried out with tugger trains.

In the BA and BH aisle the number of picks a significant higher because the fixtures that belong to these picking aisles require more replenishments on a day. The number of parts and the number of unique parts that need to be picked in a replenishment cycle of a fixture is not constant because not all trucks need the same type and quantity of a part. As a result, an order picker has to visit a variable number of storage locations during a replenishment cycle.

Currently, each order picker is assigned to a fixed number of picking aisles and is responsible to pick the parts for the fixtures in those aisles. An advantage of this situation is that there is no congestion in the picking aisles, that travel distances are minimal and that it is easier to manage the responsibilities of the order pickers. However, the fixed assignment of order pickers to aisles leads to an unequal distribution of the workload over the order pickers because the number of picks per aisle varies.

The variable number of storage locations affects the order pick time of a fixture because if a fixture requires less storage locations to visit, the fixture can be replenished faster. Another factor that influences the order pick time is the handling time of parts. Currently, SPZ has no data available regarding the handling times of the parts but from observation we conclude that the handling time per part can vary considerably.

Supervisors and team leaders of the LB2-warehouse use the forecast of the number of picks per aisle per day as an indicator for the expected workload. Since the number of storage locations to visit per replenishment and the pick time per part varies the currently used forecast method to predict the required workforce is inadequate.

3 Literature Review

This chapter provides a literature review that classifies the problem and explores how literature can contribute to this research. Section 3.1 classifies warehouses and describes the basic functions of a warehouse. Subsequently, Section 3.2 addresses the warehouse decisions that need to be made when designing a warehouse. Next, Section 3.3 elaborates on the selection of an appropriate order picking method for a warehouse. Section 3.4 discusses order-batch assignment strategies. Section 3.5 covers the routing and sequencing of order picking tours in a warehouse. Section 3.6 classifies SPZ's LB2-warehouse and seeks for possible optimization areas. Section 3.7 compares the Order Assignment and Sequencing Problem (OASP) with equivalent problem formulations. Subsequently, Section 3.8 elaborates on optimization techniques and simulations models. Finally, Section 3.9 concludes the chapter.

3.1 Warehouse classification

In this section we classify warehouses and discuss the processes, resources and organizational issues of a warehouse. As a result, we answer research question 2a.

Warehouses are an essential component of any supply chain. The primary task of a warehouse is to buffer the material flow along the supply chain to take care of the variability that occurs from product seasonality, batching in production and transportation uncertainties. Warehouse functions in modern business environments are becoming important more than ever. Today's warehouses face challenges to meet the demand for high service quality with low cost, taking into account faster delivery, rapid proliferation of products and smaller shipments (Manzini, 2012; Gu et al., 2007).

In general, two types of warehouses designs can be distinguished: distribution warehouses and production warehouses. In a distribution warehouse, products from multiple suppliers are collected for delivery to a number of customers and the orders from customers often consist of multiple order lines with different stock keeping units (SKUs) in small quantities. A production warehouse stores raw materials, semi-finished products and finished products in the production plant. The raw materials and semi-finished products are transported to the production plant to assemble or construct a finished good (Roodbergen, 2001).

According to Gu et al. (2007) the main processes in warehouse operations are to receive SKUs from suppliers, store the SKUs, receive orders from customers, retrieve SKUs and assemble them for shipment, and ship the completed orders to customers. In the design and operation of warehouses, many issues influence these processes. For example, resources (e.g., space, labor and equipment) need to be allocated among the different warehouse functions. It is essential to implement, operate and coordinate every process carefully in order to meet the system requirements (e.g., service, capacity, throughput and service) at the minimum resource cost. In a warehouse the following processes can be distinguished (Rouwenhorst et al., 2000).

Receiving: this process involves the receipts of materials coming into the warehouse. In this step, products may be checked or transformed and wait for transportation to the next process. Ensuring the right product, quantity and quality is essential.

Storage process: the received items are placed in storage locations. In this process, it is essential to determine in advance the quantity, storage mean and location that will be stored. The storage area may be split up into two separate areas: *the reserve area:* storage of products in the most economical way and *the forward area:* storage of products that require easy retrieval.

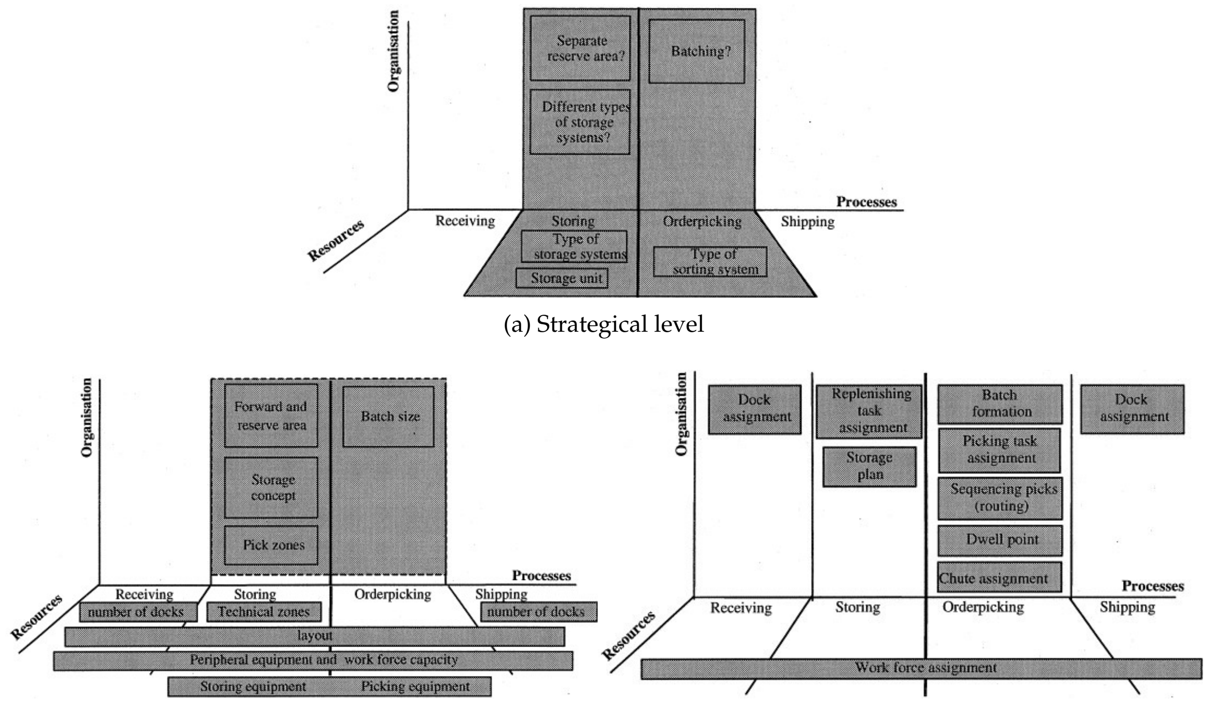
Order picking: is the process of retrieving the right amount of the right products for a set of customer orders. Sometimes the retrieved items must be sorted and/or consolidated. Consolidation is the process of grouping orders that have the same destination

Shipping: is the activity of checking, packing and loading the orders in trucks, trains or any other carriers.

Additionally, Rouwenhorst et al. (2000) and Frazelle (1992) distinguish the resources and organizational issues of a warehouse into:

- Assigning the *storage unit* (e.g., pallets or boxes) to a *storage system* (e.g., shelves or pallet racks)
- The retrieval of the storage unit from the storage system. This can be done manually (order pickers) or with *pick equipment* (reach truck). *Order pick auxiliaries* such as bar code scanners are used to support this process
- A *Warehouse Management System (WMS)* to monitor the warehouse processes
- Material handling equipment that is used for preparation of the retrieved items to the expedition. For example, *sorting systems*, *palletizers* and *truck loaders*.
- Assignment of *personnel* to the above mentioned resources. (e.g., operator assignment and order pick policy)

Each warehouse decision relates to the processes, resources or organisational aspects and are made on three hierarchical levels. Literature distinguishes these levels as strategic, tactical and operational. Warehouse decisions on the *strategic level* impact the long-term competitive strategy and refer to policies and plans to utilize the resources. Strategic decisions often involve the layout of the storage area and storage equipment(e.g., shape, number of warehouse blocks, storage method). *Tactical decisions* have impact on the medium-term, typical tactical level decisions are the size of the picking zones, the dimension of the storage capacity and the storage assignment. *Operational decisions* have an impact on daily operations, such as batch formation and job assignment. Decision on the strategic and tactical level determines the constraints of the decisions on the operational level. Figure 3.1 shows the different perspectives discussed in this section and their strategic (3.1a), tactical (3.1b) and operational (3.1c) decisions.



(a) Strategical level

(b) Tactical level

(c) Tactical level

Figure 3.1: Warehouse decisions per hierarchical level (Extracted from Rouwenhorst et al., 2000)

3.2 Warehouse design and operational planning problems

This section answers research question 2b: What are warehouse design and operational planning problems?

Table 3.1 shows a classification of warehouse design and operational planning problems. In this research, we do not focus on the physical design of a new warehouse but on improving the existing processes in a warehouse. Specifically, improving the order picking process in warehouse which includes the decisions *order picking method selection*, *order-batch assignment*, *routing and sequencing of order picking tour*.

Table 3.1: Design and operations problems (Based on Gu et al., 2007)

Design and operation problems			**Decisions**
Warehouse design	Overall structure		• Material flow
			• Department indentification
			• Relative location of departments
	Sizing and dimensioning		• Size of the warehouse
			• Size and dimension of departments
			• Pallet block-stacking pattern (for pallet storage)
			• Aisle orientation
			• Number, length , and width of aisles
			• Door Locations
	Equipment selection		• Level of automation
			• Storage equipment selection
			• Material handling equipment selection (order picking, sorting)
	Operation strategy		• Storage strategy selection (e.g., random vs dedicated)
			• Order picking method selection
Warehouse operation	Receiving and shipping		• Truck-dock assignment
			• Order-truck assignment
			• Truck dispatch schedule
	Storage	SKU-department assignment	• Assignment of items to different
			• warehouse departments
			• Space allocation
		Zoning	• Assignment of SKUs to zones
			• Assignment of pickers to zones
		Storage location assignment	• Storage location assignment Specification of storage classes (for class-based storage)
	Order picking	Batching	• Batch size
			• Order-batch assignment
		Routing and sequencing	**• Routing and sequencing of order picking tours**
			• Dwell point selection (for AS/RS)
		Sorting	• Order-lane assignment

3.3 Order picking method selection

This section addresses the selection of an appropriate order picking method for a warehouse (research question 2c). Section 3.3.1 classifies the order picking systems. Subsequently, Section 3.3.2 describes how orders are released in a warehouse. Next, Section 3.3.3 elaborates on order picking zones in a warehouse. Finally, Section 3.3.4 describes several batching strategies.

According to Gu et al. (2010) the following 4 questions must be answered in the selection of an appropriate order picking method.

1. **Order picking system:** Will orders be (partly) picked by machines or manually by order pickers?
2. **Order release system:** How will the orders be released in the warehouse?
3. **Order picking zones:** Will the warehouse be divided into pikcing zones?
4. **Batching strategy:** Will orders be picked in batches or separately?

3.3.1 Order picking system

In order to answer question 1, we classify existing order picking systems in this section. According to De Koster et al. (2007) order picking systems can be classified into the following types.

Automated systems
In an automated order picking system, the picking is done fully automatically by a robot and no humans are involved in the process. Automated systems consist of robot-to-part systems and parts-to-robot systems. In a robot-to-part system, a robot moves to the storage area and carries out the pick, whereas in a parts-to-robot system, the requested part moves to the robot and the robot carries out the pick and packing in a picking station (Yasmeen et al., 2020).

Picker-to-part systems
In a picker-to-part system order pickers walk or drive to a picking location to pick the items. Picker to part systems can be subdivided into floor-level and high-level picker-to-part systems. In floor-level picker-to-part systems, items must be stored at a height that enables them to be accessed by an order picker. Often used floor-level order picking methods are picking of individual items from packages stored as unit loads, picking from bins on shelves or picking from storage drawers. In high-level storage systems, order pickers are on board of an order pick truck (OPT) and travel to the storage location. The storage location are located on different levels in high storage racks. Most warehouses use floor-level picker-to-part systems because of their low initial cost, easy installation, easy reconfigurability and low maintenance cost compared to high-level picker-to-part systems (Yu, 2008).

Part-to-picker systems
In a part-to-picker system the picking location with the item is brought to the order picker. The storage and retrieval is done automatically using an automated storage and retrieval system (AS/RS). An AS/RS is an automated crane that is fixed in an aisle and used to retrieve one or more unit loads in that aisle. The load is brought to an I/O point where the order picker picks the required number of items. After picking, the remaining load is stored again (Le Duc, 2005).

Put system
The system consist of a retrieval and distribution process. The retrieval process is the same as in a part-to-picker or picker-to-parts system. However, in the distribution process an order picker distributes the picked units from the retrieval process over multiple customer orders ('puts'). Put system are often applied when a large number of customer order lines have to be picked in a short time window (De Koster et al. (2007)).

3.3.2 Order release system

In an order picking warehouse it is common practice to release orders in a so-called pick wave. In a picking wave, orders for a common destination (for example, departure at a fixed time with a particular carrier) release together as a so-called wave and have to be picked within a predefined time window. When an order picker picked all the required items, the order transfers to a consolidation area where all orders from the same wave are sorted. If all orders in a wave are picked and sorted a new wave of orders release. If wave picking is applied, a decision must be made on the number of picking waves and the length of a picking wave.

3.3.3 Order picking zones

If a warehouse is divided into multiple zones a fixed number of order pickers occupy a zone and are responsible for the picks in that zone. There are two types of zoning, which are progressive zoning and parallel (or synchronized) zoning. In progressive zoning, an order picker picks all the required items in his zone and transfers the partial order to the next order picker. The order finishes when all the zones containing pick lines are visited. In parallel order picking, the order pickers in a zone can work on the same batch simultaneously. When the order picker has picked all the required items in their zone, the partial order transfers to a merging area where the partial order is merged into one single order (De Koster et al., 2007), (Tompkins et al., 2003).

3.3.4 Batching strategy

The last question that needs an answer is whether orders will be picked in batches or separately. If the orders are picked separately (discrete picking), each order picker picks one order at a time. The order picker travels to the first location and picks the items that are on the pick list. Subsequently, the order picker moves to the next location until all items on the list are picked. To finalise the order, the order picker moves back to pick-up/drop-off point to obtain a new pick list. This process repeats until all orders are picked. If the orders are picked together (batch picking), each order picker is responsible for picking multiple orders in a picking tour. Compared to discrete picking, the pick list in a batch picking system consists of multiple orders that have to be picked together. In addition, orders have to be sorted after picking. Sorting can be done during the picking process (sort-while-pick) or when the picking process has been finished (pick-and-sort). In a batch picking system, orders are not split over the order pickers.

3.4 Order-batch assignment strategy

This section describes different types of batching strategies for a warehouse

The order batch assignment determines which order picker needs to pick a batch. To determine an order-batch assignment strategy, two questions need to be answered. The first question is how to batch the set of single orders that are released in the same pick wave, also referred to as Order Batching Problem (OBP). The second question is how should the pick waves be partitioned among the order pickers, also referred to as Batch Assignment and Sequencing Problem (BASP).

In the OBP, the aim is to pick (and sort) all the orders from a batch without exceeding the pick wave duration. By batching single orders, the throughput time of an order can be reduced. If zone picking is applied, the aim is to balance the order pick workload along the zones to improve the order pick utilization, while minimizing pick time such that the number of pickers required is minimized. In general, there are two variants of the OBP: the proximity of pick locations and time windows. *Proximity batching* allocates each order to a batch based on the proximity of the pick locations that have to be visited, to minimize the maximum lead-time of any batch. In *time window batching* orders that arrive during an interval of time (time window) are batched together. Time window batching can be divided into Fixed Time Window Batching (FTWB) and Variable Time Window Batching (VTWB). Both models try to minimize the average throughput time of orders by choosing the number of orders in a batch (in case VTWB) or the fixed time to retrieve a batch (in case of FTWB) (Choe, 1990).

In the BASP orders that need to be picked are characterized by due dates, the due date indicates the time when an order needs to be finished. A solution to the BASP determines on the basis of the due dates how batches should be assigned to the order pickers and in which sequence the order picker has to pick the batches to minimize total tardiness. Tardiness is a measure for the delay between the time the order is picked and the due date. If orders are released as single orders we note this as the OASP. The OASP is similar to the BASP except that batches are single orders that need to be assigned to the order pickers.

3.5 Routing and sequencing of order picking tours

This section addresses the different types of routing and sequencing methods to construct an order picking tour in a warehouse.

The routing and sequencing of an order picking tour determines how an order picker travels through a warehouse. The goal is to minimize the travel distance of a picking tour by using an efficient routing and sequencing strategy. Ratliff & Rosenthal (1983), Roodbergen (2001) and Cano et al. (2017) distinguish several heuristic methods, depicted in Figure 3.2, to construct a picking tour for a single-block warehouse.

- **S-shape:** every aisle that contains at least one pick is entirely traversed and aisles without picks are not entered.
- **Return:** each aisle that contains a pick is entered and left from the same end, aisles without picks are not entered.
- **Mid-point:** the warehouse is separated into two areas (see Figure 3.2). The order picker enters the pick location in the front half from the front cross aisle and pick locations in the back half from the back cross aisle. The order picker traverses the entire aisle in the first or last aisle in order to return to the depot.
- **Largest gap:** this strategy is almost similar to the midpoint strategy except that an order picker enters an aisle as far as the largest gap within an aisle, instead of the midpoint. The gap is defined as the separation between any two adjacent picks, between the first pick and the front aisle, or between the last pick and the back aisle.
- **Combined:** aisles that contains picks are entirely traversed or entered and left at the same end. The decision to traverse or to enter and leave at the same end is made by dynamic programming (Roodbergen & De Koster, 2001).
- **Optimal:** this route represents the optimal solution of the routing problem

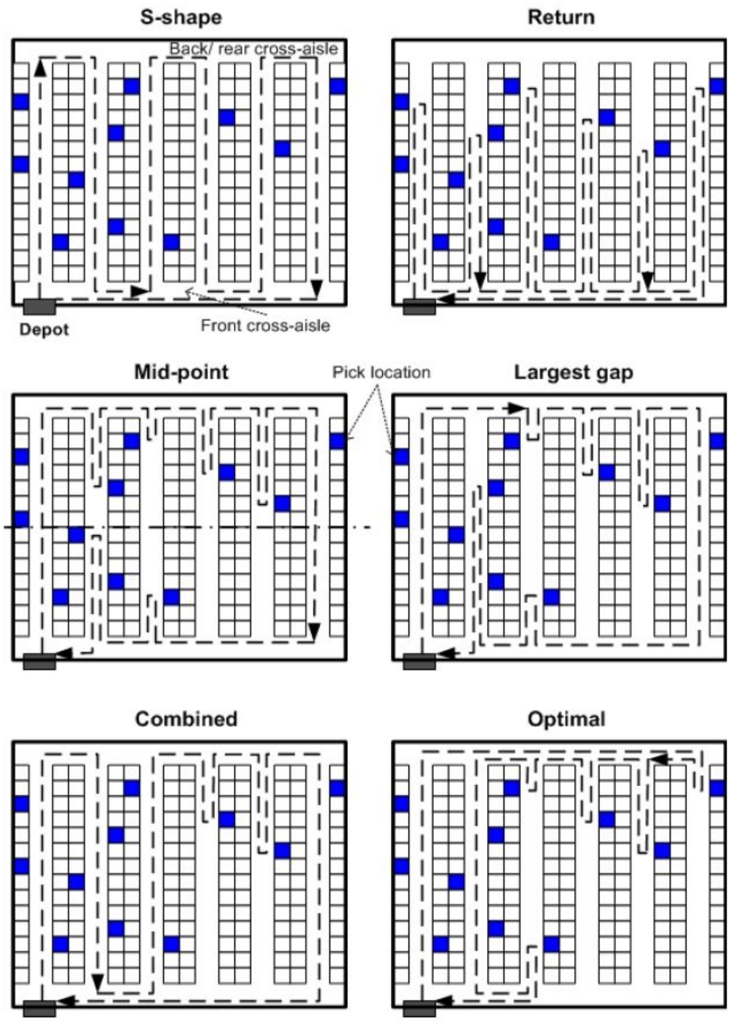


Figure 3.2: Routing methods for a single-block warehouse (Extracted from Roodbergen & De koster, 2001)

3.6 Classification of SPZ's LB2-warehouse and possible optimization areas

This section classifies SPZ's LB2-warehouse (research question 2d) and seeks for possible optimization areas in the LB2-warehouse

The LB2-warehouse of SPZ can be defined as a *production warehouse* where each SKU is stored based on product families (*class-based storage strategy*) on the ground floor (*low-level*). Order pickers are assigned to aisles (*zones*) and walk to a picking location (*Picker-to-part*) to pick and sort (*sort-while-pick*) the required items. The routing that the order pickers apply is often from the front to the back aisle or vice versa (*S-shape*). Orders are released in *waves* when a tugger train driver arrives with a couple of empty fixtures that need a replenishment. The fixtures, which consist of parts, can be seen as *single orders* with a variable number of order lines depending on the properties of the truck that is produced on the assembly line. The arrival process of the tugger train driver and thus the release of a wave is stochastic because tugger train drivers can be too early or too late due to small delays (*variable time windows*).

SPZ wants to increase the order pick performance of the current order pick system. Since the order size (e.g., number of parts on a fixture) depends on the truck output and cannot be changed, we focus in this research on the OASP. We expect that an improved assignment of order pickers to orders will lead to an improved order pick performance or an improved workload distribution among the order pickers and that it might be possible to carry out the same number of picks with fewer order pickers. We choose not to focus on the routing and sequencing of an order picking tour because parts in the warehouse are family grouped which means that the picking distance to pick all the required items for an order is already very short.

3.7 Problem formulations for the OASP

In this section we describe the problem formulation of the OASP and compare the formulation with equivalent problem formulation that have known solution approaches. As a result, this section answers research question 2e.

The OASP has the following problem characteristics (Schubert et al., 2018) :

Given

- Set of orders
- Release dates of orders
- Processing time of orders
- A limited number of order pickers

Determine:

- An assignment of order pickers to the orders and the sequence in which the orders should be processed by each order picker such that the total tardiness of all orders is minimized.

Subject to constraints such as:

- Maximum workload of order picker

To the best of our knowledge, no solution approaches are known for the OASP. However, the OASP shows a lot of similarities with the IPMP, BPP and VRP problem formulation for which solution approaches are known. In the next section, we compare the problem formulation of these problems with the problem formulation of the OASP and look for a problem formulation that best fits the OASP. Furthermore, we provide possible solution approaches for each problem formulation.

3.7.1 Identical parallel machine scheduling (IPMP)

The IPMP assigns a set of jobs to machines and sequence them in such a way that the maximum completion time (makepsan) is minimized. The OASP is equivalent to the IPMP of Pinedo & Hadavi (1991). In a IPMP jobs are processed by machines, while in a OASP orders are processed by order pickers. Each job in the IPMP needs to be processed on one of the machines with a fixed processing time without preemption. The objective is to find a schedule that optimizes the makespan.

The IPMP can be distinguished into online scheduling problems and offline scheduling problems. In online scheduling problem, an online algorithm has to make decisions without future information. Jobs arrive over time and the number of jobs to be processed is unknown in advance. The characteristics of each job e.g (processing time and due date) become available at its release time and scheduling decisions are made during the run time. In offline scheduling problems all of the information (e.g., processing times, release dates and due dates) are known in advance and scheduling decisions are made before the system starts running.

Solution approaches for the IPMP

Using the notation for scheduling problems proposed by Lawler et al. (1993), the formulation of the IPMP is denoted as $P_m \, || C_{\max}$. This problem is the most basic form of the IPMP, where the objective is to minimize the makespan without further restriction regarding machine or job availabilities. The IPMP is proven to be strongly NP-hard, which means that finding an exact solution in polynomial time is very unlikely. Therefore, approximation algorithms are often used to find near-optimal solutions. Section 3.8 discusses approximation algorithms more in depth. For small instances of the problem (e.g., machines ≤ 2 or a minimal set of jobs) often exact algorithm are used, such as a branch and bound algorithms (Liaw, 2016).

The most simple approximation algorithm to find a solution for large instance of the IPMP problem is the List Scheduling (LS) algorithm of Graham (1969). The LS algorithm assigns a job from an arbitrary ordered list to a machine whenever a machines becomes available. The LS algorithm has a worst-case ratio of 2-1/m, which means that for any instance of the problem the algorithm find a schedule with makespan no more than 2-1/m (where m is the number of machines) times the optimum makespan. Literature describes several variants of the LS algorithm, depending on how the ordered list of jobs is made. The best known LS algorithm is the Longest Processing Time (LPT) algorithm proposed by Graham (1969) with a a worst-case performance of $4/3 - 1/3m$. The LPT algorithm sorts the jobs on the ordered list in non-increasing order of their processing time before the jobs are assigned to machines. To further improve the solution of an LS algorithm or LPT algorithm, optimization techniques are often used, which we explain in Section 3.8.

3.7.2 Bin-packing problem (BPP)

The BPP concerns the assignment of items with different sizes to a finite number of bins with a fixed capacity. The goal of the BPP is to minimize the number of used bins. Figure 3.3 shows an graphical representation of a BPP. The BPP is defined as the "dual" problem of the IPMP, which means that the solution of the BPP provides a lower bound to the solution of the "primal" (minimization) problem the IPMP. In the "dual" problem of the IPMP, jobs are assigned to an unlimited number of identical machines with the objective to minimize the number of machines subject to a predetermined makespan. The goal is to find the smallest number of machines that can accommodate all jobs

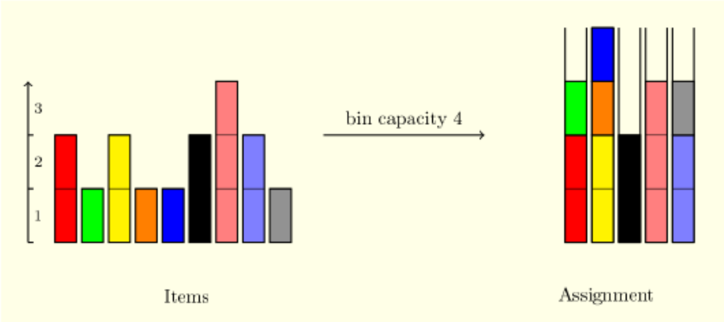


Figure 3.3: Example of bin packing problem (extracted from Achterberg, 2009)

Solution approaches for the BPP
Coffman et al. (1984) discusses four algorithms to obtain an (initial) solution to the BPP. These algorithms are next-fit, first fit, best fit and worst fit. When an initial solution has been obtained the solution can be further optimized using optimization techniques, which we discuss in Section 3.8.

- **Next-fit**: next fit starts at the most recent packed bin that is partially filled and tries to pack the item in the bin. When the item exceeds the capacity of the bin, the item is packed into the next empty bin. Initially, it starts with an empty bin.
- **First-fit**: first fit does not only tries to pack an item into the most recent packed bin but also tries to pack an item in the previous filled bins. The item is packed into the first bin where the item does not exceed the capacity of the bin. If no bin can accommodate the item, the item is packed into a new empty bin.
- **Best-fit**: best fit packs items into the bin that has the least capacity left. If the item cannot be packs to any of the bins, the item is packed into a new empty bin.
- **Worst-fit**: worst fit is the opposite of the best fit. It packs an item into a bin that has the most capacity left. If item cannot be packed into any of the bins, the item is packed into a new empty bin.

3.7.3 Vehicle routing problem (VRP)

The VRP concerns about the optimal design of routes to be used by a fleet of vehicles to serve a set of customers. Each route contains a depot location which is the start and end point of a route. At each depot location there is set of vehicles available that can move on a given road network to serve the customers. The road network can be described as a graph with arcs and vertices. The arcs represent roads and have an associated cost that depend on its distance or travel time. The vertices represent junctions between the roads of which some of them are mandatory to visit because these are the customer locations. The goal of the VRP is to find a set of vehicle routes that can serve all the customer locations with a minimal number of vehicles. In particular, to decide the sequence in which a vehicle visits a customer so that all vehicles routes can be feasibly executed. A vehicle route is feasible if all customers are visited and operational constraints are satisfied. A VRP is typically used to optimize the service in a delivery process. Figure 3.4 shows a graphical representation of a VRP.

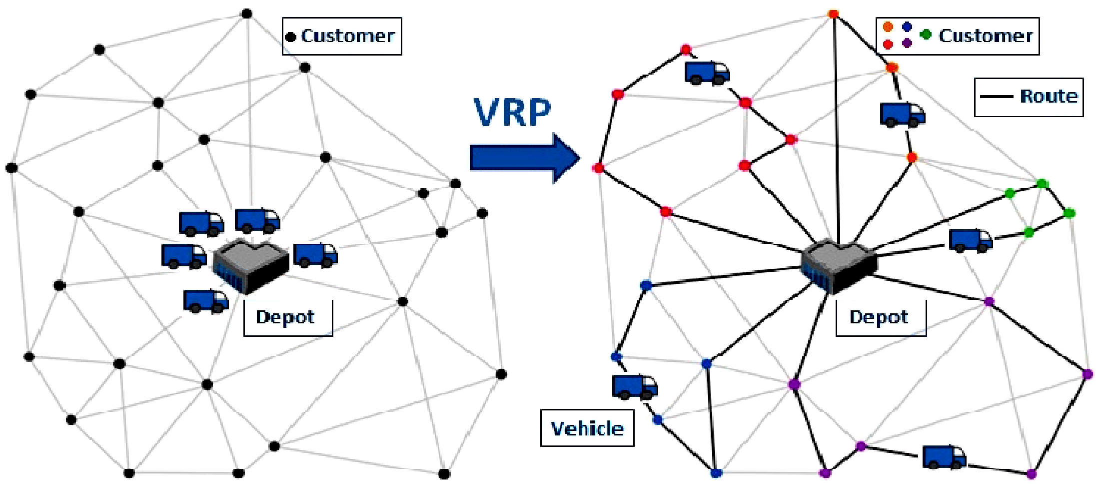


Figure 3.4: Example of VRP (Extracted from Gupta & Saini, 2017)

Solution approaches for the VRP
A VRP is often solved using metaheuristics. Metaheuristics attempt to find the best (feasible) solution out of all possible solutions of an optimization problem. Metaheuristics can search very large solution spaces of candidate solutions. However, metaheuristics do not guarantee an optimal solution is ever found (Trabelsi et al., 2010). Section 3.8.2 elaborates more in depth about metaheuristics.

3.8 Optimization techniques and simulation

This section discusses optimization techniques, which are used to improve an initial solution. First, Section 3.8.1 elaborates on mathematical models. Second, Section 3.8.2 on approximation algorithms and metaheuristics. Third, Section 3.8.3 elaborates on simulation models. As a result, this section answers research question 2f.

3.8.1 Mathematical models

A mathematical model is a representation of a system using mathematical concepts and language. Examples of mathematical models are Integer Linear Programming (ILP) models, stochastic optimization models and queuing models. ILP is the task of optimizing a linear function under linear constraints with integer values. ILP models are commonly used in the field of operation research to solve optimization problems because they can describe many real-life situations (Winston, 2004). ILP models are so-called NP-complete problems. A problem is called NP-complete when its solution can be guessed and verified within polynomial time, and if all other NP problems are polynomial-time reducible to it. Due to NP-completeness property of ILP problems, these problems cannot be solved efficiently with a mathematical solver. A mathematical solver is a piece of mathematical software that takes the problem descriptions in a generic form and calculates the solution. Therefore, approximation algorithms and metaheuristics are often used for NP-complete problems, which we explain in Section 3.8.2. An optimization model consists of the following characteristics (Zilinskas, 2006).

- **Objective function:** the objective of making decisions, maximizing or minimizing
- **Decision variables:** variables that describe a decision and determine the objective function value
- **Constraints:** the restrictions on the decision variables.

3.8.2 Approximation algorithms and metaheuristics

An approximation algorithm is a method for dealing with the NP-completeness of an optimization problem. The aim of an approximation algorithm is to find a solution that comes as close as possible to the optimal solution of an optimization problem in a reasonable amount of time. Besides a solution to the optimization problem, the approximation algorithm also gives an approximation ratio. The approximation ratio is the ratio between the solution obtained by the approximation algorithm and the optimal solution (Gonzalez, 2007).

A metaheuristic is a method that optimizes a problem by iteratively trying to improve a candidate solution with respect to a given quality measure. Metaheuristics are capable of searching large solution spaces of candidate solutions with no guarantee of finding an optimal solution. The idea behind metaheuristics is to escape from local optima and look for a global optimum by accepting worse solutions while running the heuristic. Metaheuristics require a feasible initial solution. Compared to an approximation algorithm a metaheuristic provides no guarantee on the distance of the obtained solution to the optimal solution (Gonzalez, 2007). Examples of metaheuristics are genetic algorithms, tabu search, variable neigbhorhood search and simulated annealing (SA).

A commonly used metaheuristic is SA, proposed by Kirkpatrick et al. (1983). SA is a probabilistic technique for approximating the global optimum of a given function in a large solution space (Yang, 2014). SA has the ability to escape from local minima by accepting worse solutions with a certain probability. The worse solution are accepted with a so-called acceptance probability that is based on the Boltzman probability distribution. SA diversifies at the start of the annealing process, which means that more often worse solutions are accepted and intensifies at the end of the annealing process, which means that only better solutions are accepted.

3.8.3 Simulation

Simulation is a technique to imitate the operations in real world processes. A simulation model evaluates the main characteristics and key behaviors of a process under a set of assumptions. Simulation models are used to gain some understanding of how the corresponding process behaves. In addition, simulation models are used to test interventions in the corresponding process under various scenarios. Testing interventions in a simulation model is a more cost efficient and time efficient manner to determine whether an intervention will improve the process in the real world. To create a simulation model that gives a good representation of the real world, it is important to verify and validate the simulation model with results from the real world (Law, 2015).

3.9 Conclusion

This section summarizes the main conclusions of the literature review

This chapter discussed the basic functions of a warehouse from the processes, organisational and resources perspective. Additionally, we discussed the general warehouse design and operational planning problems of warehouses. Then, we focused on the classification of order picking systems, order-batch assignment strategies, and the routing and sequencing of order picking tours. The main decisions that have an impact on the order picking performance are the size of batches, the assignment of orders/batches to order pickers and the routing and sequencing of order pickers.

The LB2-warehouse of SPZ can be classified as a low-level picker-to-part system with order picking zones where products are class-based stored and orders are released in picking waves with variable time windows. The possible optimization area that is discovered is the assignment of order pickers to orders (OASP) in order to improve the order picking processes.

For the OASP no solution approaches are known in literature. Therefore, we compared the OASP with the IPMP, BPP and VRP that have known solution approaches. The aim of the IPMP is to assign a set of jobs to machines and sequence them in such a way that the makespan is minimized. The BPP concerns the assignment of items with different sizes to a finite number of bins with a fixed capacity. The goal of the BPP is to minimize the number of used bins. The VRP concerns about the optimal design of routes to be used by a fleet of vehicles to serve a set of customers.

Examples of optimization techniques are mathematical models, approximation algorithms and metaheuristics. A mathematical model is a representation of a system using mathematical concepts and language. Commonly used mathematical models in the field of operations research are ILP models. ILP models are NP-complete, which means that its solution can be guessed and verified within polynomial time, and all other NP problems are polynomial-time reducible to it. Due to NP-completeness property of ILP problems, these problems cannot be solved efficiently with a mathematical solver. Therefore, we have to rely on approximation algorithm and metaheuristics. An approximation algorithm is a method for dealing with the NP-completeness of an optimization problem. The aim of an approximation algorithm is to find a solution that comes as close as possible to the optimal solution of an optimization problem in a reasonable amount of time. Metaheuristics searches for an global optimum by iteratively trying to improve candidate solutions with respect to a given quality measure. Metaheuristics are able to escape from local minima by accepting worse solutions. Simulation is a technique to imitate the operations in real world processes. Simulation models are used to evaluate the performance of interventions of real-world processes under various scenarios.

4 Solution design

This chapter discusses the solution design to improve the order picking performance in the LB2-warehouse of SPZ. The literature found in Chapter 3 serves as the basis for the solution design. First, Section 4.1 describes the properties of our problem. Second, Section 4.2 chooses a suitable problem formulation for our problem. Third, Section 4.3 describes how we formulate our problem based on a BPP. Fourth, Section 4.4 provides the solution approach for our problem. Fifth, Section 4.5 elaborates on the multi-objective function we use. Sixth, Section 4.6 describes the solution approach by means of a toy-problem. Seventh, Sections 4.7 and 4.8 addresses the input and output of the solution approach. Finally, Section 4.9 concludes the chapter

4.1 Properties of our problem

This section describes the properties of our problem, which includes the routing, travel distance between depots and replenishment of the order picker. This section gives an answer on research question 3a.

4.1.1 Routing

The operations in each replenishment cycle for a fixture are identical, except that the number of storage locations to visit and the number of parts to pick vary in each cycle. Figure 4.1 shows a flowchart of the set of operations that are needed to replenish a fixture and Figure 4.2 provides a graphical representation of the operations in the flowchart. When an order picker starts picking parts for a fixture, he starts from the pick-up point and walks with the fixture towards the end of the picking aisle and picks all the required parts in the meantime. As soon as all parts have been picked, the order picker returns to the pick-up point to return the fixture. The storage locations that an order picker needs to visit for a fixture often succeed each other and often contain the same storage location. Appendix B shows an example of the storage locations that need to be visited for 5 randomly chosen replenishment orders of the LR322-DBP-BA fixture. As a result, the routing and the travel distance in a replenishment cycle for a fixture is approximately the same for every cycle.

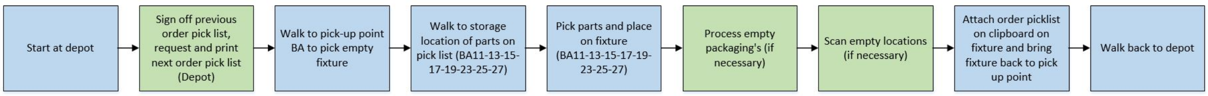


Figure 4.1: flowchart of order picking operation

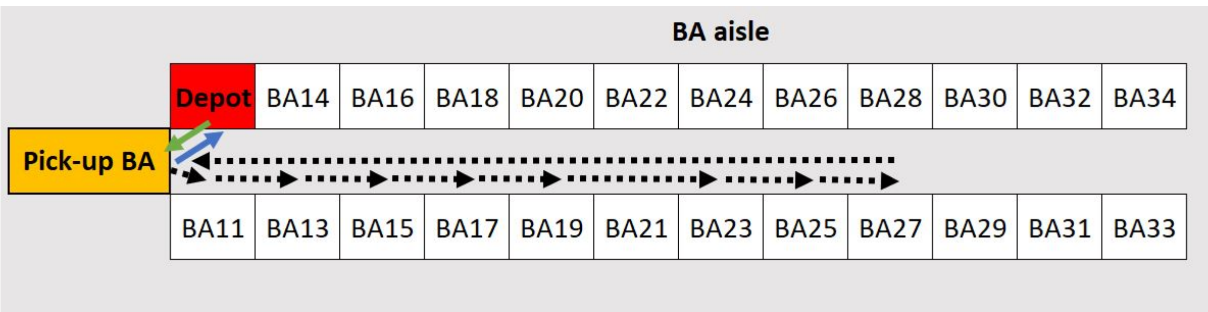


Figure 4.2: Routing of operations

4.1.2 Travel distance between depots

After replenishment of a fixture the order picker travels to the depot location of the next fixture to replenish. The travel distance that an order picker needs to travel depends on the depot location of the fixture that needs to be replenished. Suppose we have a warehouse with 6 aisles, illustrated in Figure 4.3 and an order picker that is assigned to 3 fixtures that belong to three different aisles. The fixtures arrive in the following sequence in the aisles BB,BF,BH,BB.

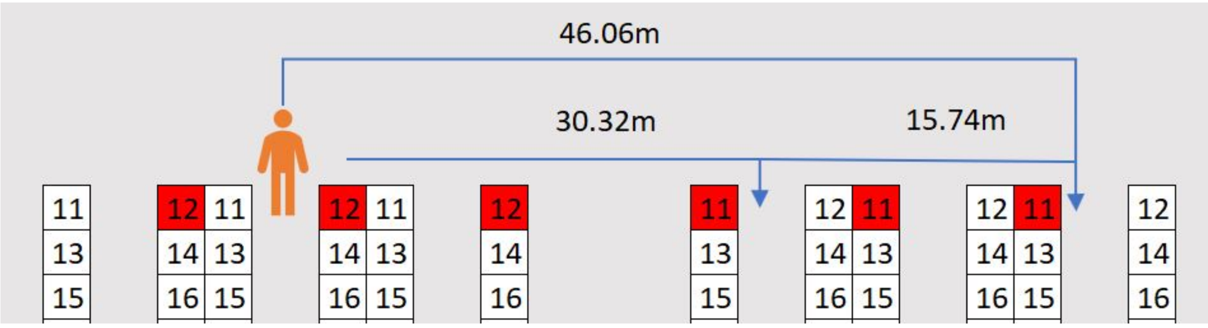


Figure 4.3: Travel distance between depot locations

When the order picker has replenished the fixture in the BB aisle, the order picker needs to travel to the depot location of the BF aisle (depot locations are indicated with a red box), which results in a travel distance of 30.32 meter (shown with the blue arrow). After replenishing the fixture in the BF aisle the order picker needs to travel to the depot location of the BH aisle, which results in a travel distance of 15.74 meter. Finally, the order picker needs to travel back to the depot location of the BB aisle, which results in a travel distance of 46.06 meter. In total, the order picker needs to travel 30.32 + 15.74 + 46.06 = 92.12 meters to all depots locations for the replenishments of the fixtures at which the order picker is assigned. Suppose that this sequences occurs 50 times on a day, then the order picker needs to travel 50 * 92.12 = 4506 meters. When an order picker is assigned to fixtures with the same depot location or a depot location nearby, the order picker needs to travel considerably less distance between the depots. Therefore, we conclude that the travel distance between the depot locations of the fixtures is an important property to take into account when assigning order pickers to fixtures.

4.1.3 Replenishment sequence

The daily number of replenishments for a fixture depends on the takt time of a fixture. Fixtures with a short takt time require many replenishments per day and fixtures with a long takt time require less replenishments per day. The daily number of replenishments can be calculated with formula 4.1.

$$\text{Daily number of replenishments} = \text{Net. Production time}/\text{Takt time} \tag{4.1}$$

The takt time of a fixture determines the sequence in which fixtures need to be replenished in the LB2-warehouse. Suppose that we have two fixtures called ”BA” and ”BF” with a takt time of 15 minutes and 30 minutes respectively and that we evaluate the replenishment moments of both fixtures. The first replenishment moment of fixture ”BA” is scheduled at 6:00 and the first replenishment moment of fixture ”BF” is at 6:05. For fixture ”BA” the second replenishment moment will be at 6:15 and for fixture ”BF” the second replenishment moment will be at 6:35. The replenishment moments of the fixtures succeed each other based on the takt time of the fixtures, which results in the following sequence shown in Figure 4.4.

Fixture BA	6:00	6:15	6:30	6:45	7:00
Fixture BF	6:05	6:35	7:05		

Sequence	BA,BF,BA,BA,BF,BA,BA,BF

Figure 4.4: Replenishment sequence first situation

The sequence in which the fixtures need a replenishment determines how often an order picker needs to travel between the depot locations. Suppose that fixture ”BA” and ”BF” from Figure 4.4 are assigned to an order picker and that the distance between both depot locations of the fixtures is equal to 39.42 meter. Then, the order picker has to travel back and forth twice from depot BA to depot BF and another time to depot BF resulting in a total travel distance of 2*(2*39.42)+1*39.42 = 197.1 meter. When the takt time reduces, the number of replenishments increases and the travel time between the depots for the order picker increases as well. Therefore, we conclude that the replenishment sequence of fixtures that are assigned to an order picker is an important factor to take into account when assigning fixtures to order pickers

4.2 Problem formulation

In Section 3.7 we discuss the problem formulations of the VRP, IPMP and BPP. This section compares these problem formulations with the properties of our problem, defined in Section 4.1, and determine which problem formulation fits our problem best. Furthermore, we explain why we choose to develop an offline planning model instead of an online planning model. This section gives an answer on research question 3b.

We want to develop a method that determines the required workforce for the LB2-warehouse. In addition, the method needs to assign fixtures to order pickers in such a way that the workload is balanced over the order pickers. We conclude from Section 4.1 that two factors are important to take into account when assigning order pickers to fixtures. These factors are the travel distance between the depot locations and the replenishment sequence of the fixtures to which the order picker is assigned. The replenishment sequence determines how many times an order picker needs to travel between the depot location and the travel distance between the depot locations determines the distance that the order picker needs to travel to reach the next depot location.

4.2.1 Offline versus online planning

We can develop a method that provides an assignment strategy before the day starts (offline planning) or we can assign fixtures to order pickers just before the arrival of a fixture in the LB2-warehouse (online planning). In the current situation, order pickers print a pick list before picking an order. More inventive ways such as order picking with a scanner or using a portable online list (e.g. tablet with picklist) are not possible because SPZ’s ERP system does not enable an online picking list. As a result, SPZ cannot switch to an online assignment model that automatically assigns order pickers to fixtures. Therefore, we focus on a offline planning model.

4.2.2 VRP

If we formulate our problem as a VRP, we formulate the vehicles as order pickers and the customers as fixtures that need to be replenished. Each fixture has a workload level that depend on the pick time of the parts on the fixture and the travel time to replenish the fixture. We restrict each order picker to a predetermined maximum workload capacity. The aim of the VRP is to find a set of order picker routes that can replenish all the fixtures with a minimal number of order pickers. Recall from Section 4.1 that in our problem the travel distance to replenish a fixture is approximately the same for each replenishment cycle. Therefore, the order picker routes to replenish a single fixture are usually the same. However, as we showed in Section 4.1 the travel time between the depots can have a major impact on the order picker route of an order picker.

4.2.3 IPMP

If we formulate our problem as an IPMP with changeover times, we formulate the identical machines as order pickers with equal operating speeds and the jobs as fixtures that need to be replenished. The job size depends on the workload of the fixture and the changeover time on the travel time between the depots of the fixtures to which an order picker is assigned. The goal in this formulation of the IPMP is to assign fixtures to order pickers with the objective to balance the workload over the available order pickers. However, the input of the IPMP requires a number of order pickers with which the most balanced workload distribution for the order pickers can be calculated. This means that we first need to develop an alternative method to determine the minimum number of order pickers.

4.2.4 BPP

If we formulate our problem as a BPP formulation, we formulate the bins with fixed capacity as order pickers with a predetermined maximum workload level and the items as fixtures. The size of the items depend on the workload of the fixture. In addition, we add variable sized items that depend on the travel time between the depots of fixtures to which an order picker is assigned. The goal in this formulation of the BPP is to assign fixtures to order pickers with the objective to balance the workload over a minimal number of order pickers that are restricted to a predetermined maximum workload level. This BPP formulation minimizes the number of order pickers and incorporates the workload level of order pickers because each order picker is restricted to a predetermined maximum workload level.

4.2.5 Choosing a suitable problem formulation

Since a VRP is primarily about generating optimal routes for order pickers and we are interested in assigning the workload to order pickers, a formulation based on a VRP is less suitable. The input of the IPMP requires a (minimal) number of order pickers. When the minimal number of order picker is obtained, we can balance the workload over the order pickers. In a BPP formulation we set the capacity of a bin equal to a predetermined maximum workload level of an order picker. Given a predetermined maximum workload for order pickers, we determine a minimal number of order pickers. We prefer finding a minimum number of order pickers over balancing the workload because we consider reducing personnel costs for SPZ more important than balancing the workload over the order pickers. Therefore, we choose a BPP formulation for our problem.

4.3 Formulating our problem based on a BPP

In this section we answer research question 3c: How can we formulate our problem mathematically? First, Section 4.3.1 discusses the assumptions and simplification we make. Subsequently, Section 4.3.2 describes the model requirements. Then, Section 4.3.3 elaborates on the mathematical model formulation of our problem

4.3.1 Assumptions and simplifications

On a normal production day, SPZ produces around trucks per day and fixtures arrive and depart approximately at every takt time of the fixture. Figure 4.5 shows an example of the planned arrival times of fixture LL322-DBP-BA that has a takt time of approximately 20:16. On a normal production day, time is reserved for small line stops. If more line stoppages occur, production cannot produce trucks per day. We assume that every day is a normal production day without additional line stops, such that each fixture arrive and depart approximately at every takt time of the fixture.

Fixture	Takt time
LL322-DBP-BA	0:20:16

Arrival times	6:00:00	6:20:16	6:40:32	7:00:48	7:21:04	7:41:20	8:01:36	8:21:52	8:42:08	9:02:24

Figure 4.5: Planned arrival times of fixture LL322-DBP-BA on a normal production day

Fixtures do not arrive and depart exactly every takt time because the fixtures are sometimes a bit too early or too late due to slack time or small delays. The delay in the arrival and departure process on a normal production day is minimal because it is due to congestion in the tugger train process, which not lead to long delays. Since the delay is minimal we assume that the arrival and departure process of the fixtures is deterministic and that fixtures exactly arrive and depart every takt time of the fixture.

We simplify our model by assuming that there is a depot location at the front of each aisle. In reality there are only depot locations at BB12, BG11 and BH11. Order pickers that pick in the BA-aisle or BC-aisle need travel to the BB12 depot location to request and print the order pick list. In addition, order pickers that pick in the BF-aisle need to travel to the BG12 depot location to request and print the order pick list. We take this simplification into account in the inputs of our of model (Section 4.7) when calculating the travel distance between depot locations.

4.3.2 Model requirements

Our model should focus on minimizing the number of order pickers and take into account the travel time and workload distribution of order pickers. Besides this general requirement, the model should meet the following requirements.

- The model should be future-proof, which means that the model should be applicable when extra picking aisles and fixtures are added to the warehouse. In addition, the model should be applicable when the daily truck output increases or decreases in the future.
- The model should be able to solve within a reasonable amount of time. Using the current problem size, the model should be solvable within 30 minutes.
- Each fixture must be assigned to one order picker. We choose to assign no more than 1 order picker to a fixture because if more than 1 order picker is assigned to a fixture there can be confusion about who should pick a fixture and when.
- The order picker must be able to pick the fixtures within the takt time of the fixtures.
- The workload of an order picker should not exceed a threshold value.

4.3.3 Mathematical model formulation

As discussed in the Section 4.2 we formulate our problem as a BPP. Therefore, this section provides the mathematical formulation of our problem formulated as a BPP.

Given a set of n fixtures with workload w_i for fixture $i = 0, \ldots, n$ and a sufficient large number of order pickers j with an identical maximum workload of c, assign each fixture to one order picker so that the total workload for each order picker on a day does not exceed c and a minimal number of order pickers is used. The workload of an order picker depends on the workload of the fixtures to which the order picker is assigned and the travel time between the depot locations of the fixtures to which the order picker is assigned.

Indices
i : Indicating the fixture number. i=1,. . . ,n, where n is the number of fixtures.
j : Indicating the order picker number. j=1,. . . ,m, where m is a large number of order pickers.

Parameters
c : Maximum daily workload of an order picker. (as percentage of PT)
PT : Net. production time on a normal day. (in seconds)
P_i : Pick time of fixture i (in seconds)
L_i : Takt time of fixture i (in seconds)
$R_i = PT/L_i$: Daily number of replenishments for fixture i
$w_i = ((R_i * P_i)/PT) * 100$: Daily workload of fixture i (as percentage of PT)

Variables
x_{ij} : 1 if fixture i is assigned to order picker j; 0 otherwise.
y_j : 1 if order picker j is used; 0 otherwise
T_j : Approximation of the daily travel time between depot locations of fixtures that are assigned to order picker j. (Tj is calculated as percentage of PT)

Objective

$$\min \quad \sum_{j=1}^{m} y_j \tag{4.2}$$

Subject to:

$$\sum_{j=1}^{m} x_{ij} = 1 \quad \text{for } i\text{=1,...,}n \tag{4.3}$$

$$\sum_{i=1}^{n} w_i x_{ij} + T_j \leq c, \quad \text{for } j\text{=1,....,}B \tag{4.4}$$

$$x_{ij} \in \{0,1\} \qquad i = 1, ..., n, \qquad j = 1, ..., B \tag{4.5}$$

The objective 4.2 minimizes the number of order pickers needed. Constraint 4.3 ensures that each fixture is assigned to one order picker. Subsequently, constraint 4.4 ensures that the total workload assigned to an order picker cannot exceed the maximum workload level of the order picker. Finally, constraint 4.5 states that x_{ij} is a binary variable that can be either 1 or 0.

T_j is an approximation of the daily travel time between the depot for an order picker. We calculate T_j based on the sequence in which the fixtures need a replenishment and the travel time between the depots. We can obtain a replenishment sequence for a fixture from the takt time of a fixture because after each takt time a replenishment needs to be carried out. The replenishment sequence of a fixture does not only depend on the takt time of a fixture but also on the production time and the first replenishment moment of a fixture. Table 4.1 shows the replenishment information of three fixtures in the warehouse between 6:00 AM and 7:00 AM. Since we do not know what time the first replenishment moment of a fixture is on an arbitrary day, we determine this by randomly choosing a time between the start of the working day and the start of the working day time + takt time. For the first fixture, this is a time between 6:00 and 6:10 and equals 6:01. Based on the first replenishment moment, the next replenishment moments are determined by continuously adding a takt time. The obtained replenishment moments per fixture are shown in the right column of Table 4.1.

Table 4.1: Replenishment information of three fixtures located in the BA, BC and BH aisle

Fixture	Depot location	Start time	Takt time	Replenishment moments fixtures					
BA	BA12	Randbetween(6:00,6:10) = 6:01	10 min.	6:01	6:11	6:21	6:31	6:41	6:51
BC	BC12	Randbetween(6:00,6:20) = 6:12	20 min.	6:12	6:32	6:52			
BH	BH11	Randbetween(6:00,6:15) = 6:08	15 min.	6:08	6:23	6:38	6:53		

Now that we have determined the sequence for the fixtures, we look per order picker to which fixtures the order picker is assigned and merge these replenishment moments of the fixtures. If we assume that the three fixtures from Table 4.1 are assigned to one order picker and we merge the replenishment moments of the fixtures we obtain the replenishment sequence represented in Table 4.2.

Table 4.2: Replenishment sequence for order picker assigned to fixtures BA, BC and BH

Replenishment time	6:01	6:08	6:11	6:12	6:21	6:23	6:31	6:32	6:38	6:41	6:51	6:52	6:53
Replenishment sequence	BA	BH	BA	BC	BA	BH	BA	BC	BH	BA	BA	BC	BH

After determining the replenishment sequence we can determine the value of T_j using the travel times between the depots. The travel times between the depots are shown in Figure 4.6. If we assume that the travel time between depot BA12 & BC12 is 15.73 seconds, between BC12 & BH11 = 52.45 seconds and between BA12 & BH11 = 75.12 seconds then we find a total travel time between depots of 542.42 for the replenishment sequence of Table 4.2. Using formula Since T_j is calculated as percentage of PT we need to divide the travel time with the net production time and multiply it with 100. In this example the net production time equals 3600 seconds (1 hour) because we only show the replenishment moments of the first hour resulting in a T_j of 15.095%.

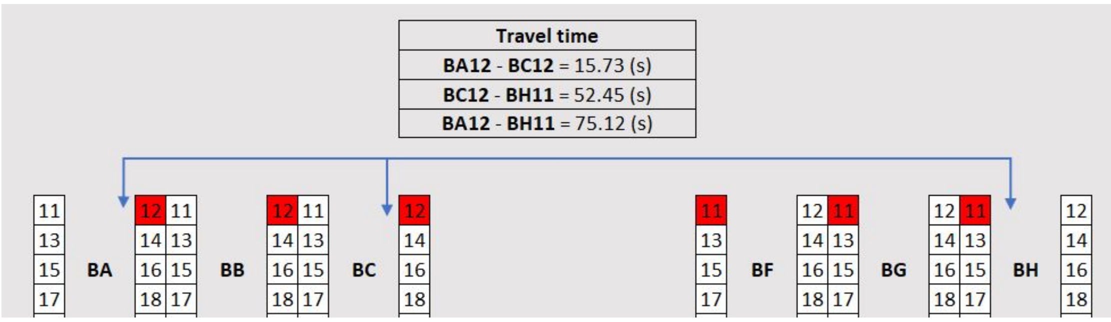


Figure 4.6: Example calculation for T_j

This method provides a good approximation of the actual travel time because it takes into account the number of replenishments per day and the sequence of the replenishments. The replenishment sequence that we use in this method is approximately the same as on a normal production day except that the first replenishment moment on day differs from reality. A discrepancy in the sequence may arise because the first replenishment moment is not chosen properly and may be earlier or later in reality. However, the discrepancy only occurs in the first replenishments cycles and is minimal on a full production day. Therefore, we consider this as a good approximation method to determine the value of T_j

The properties of the three fixtures are shown in Table 4.3. If we want to calculate the workload for the order picker we can use the left hand side of constraint 4.4 (shown in calculation 4.6). If we fill in all the values, we obtain a workload of 95.655% for the order picker. This value indicates that the order picker spends 95.655% of his time on picking the fixtures FBA, FBC and FBH, and travelling between the depot locations of these fixtures.

Table 4.3: Fixture properties

Fixture	PT (s)	P_i (s)	L_i (s)	R_i	w_i
FBA	3600	180	600	6	30
FBC	3600	300	1200	3	25
FBH	3600	230	900	4	25.56

$$\sum_{i=1}^{n} w_i x_{ij} + T_j = (30 + 25 + 25.56) + 15.095 = 95.655\% \quad (4.6)$$

4.4 Solution approach

This section describes the general solution approach with consists of two steps. First, a best-fit is used to obtain an initial solution. Second, the outcome of the best-fit heuristic is used as input for the SA to improve the solution.

Our problem consists of 17 fixtures that each have their own takt time, pick time and depot location. Obviously, the solution space is not very large, which maybe enables it to solve it exactly. However, in our model requirements of Section 4.3.2 we stated that our model should be future-proof and applicable when extra picking aisles are added or the truck output increases. As a result, the solution space and computational times increases. We choose to use the meta-heuristic SA for our problem because SA is easy to implement and has a connected solution space when appropriate neighborhood operators are used. A connected solution space enables us to find all feasible solutions to the problem.

The general solution approach consists of two steps because the SA requires an initial solution, which first needs to be determined. Section 4.6 describes how we implement the general solution approach to our problem by means of a toy problem.

- **Best-fit heuristic:** In the first step, we apply the best fit heuristic to determine an initial solution to the problem and an upper bound on the number of order pickers. We choose to use best-fit instead of worst-fit because as an initial solution we want to have tightly filled bins to ensure that the SA finds a solution with fewer order pickers more quickly. In addition, the best-fit heuristic gives more efficient results in terms of number bins used and execution time when compared to First-fit and Next-fit (Yesodha & Amudha, 2012).
- **Simulated annealing heuristic:** In the second step, the SA uses the outcome of the best-fit heuristic to optimize a multi-objective function. The multi-objective function focuses on minimizing the number of order pickers but also includes the balancing ratio and the travel time of order pickers.

4.5 Multi-objective function

This section provides an answer on the research question: What is the objective of our model?

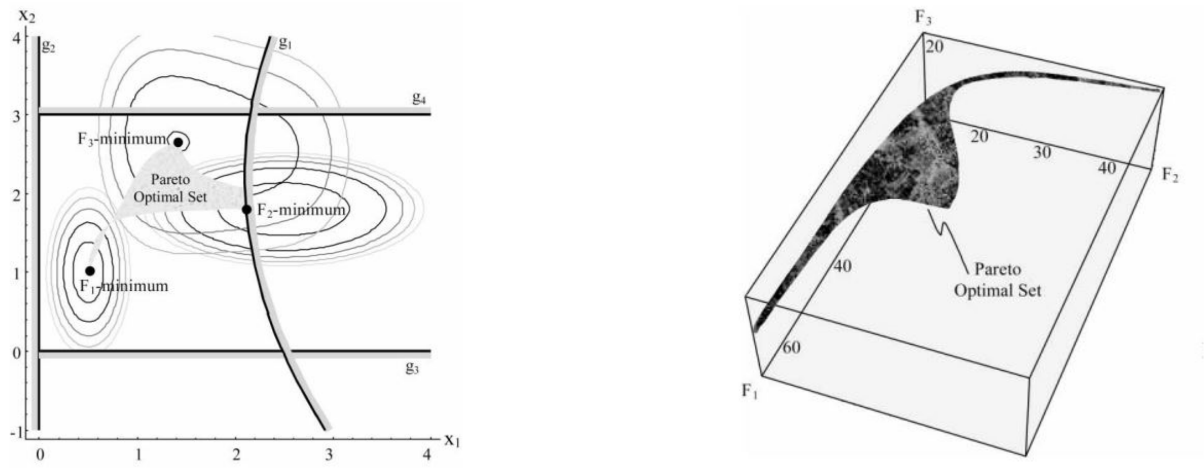
We use a multi-objective function in our SA that contains two optimization variables and one penalty function. The optimization variables are the travel time between the depots and the balancing ratio. The penalty function depends on the number of order pickers that are used. The multi-objective function searches for an optimal solution by minimizing the number of order pickers, balancing the workload over the order pickers and minimizing the travel time between the depots.

Number of order pickers
The number of order pickers indicates how many order picker are needed to pick all the fixtures in the warehouse. When more order are required the personnel cost for SPZ increases. Therefore, we want to minimize the number of order pickers.

Balancing ratio
The balancing ratio determines to what extent the workload is balanced over the order pickers. We define the balancing ratio as the difference in workload between the order picker with the highest workload and the order picker with the lowest workload.

Travel time between the depots (T_j)
The travel time between the depots determines the daily travel time between the depot for an order picker. The lower the sum of the travel time between the depots for the order pickers the lower the time order pickers spend on travelling in the warehouse. We want to minimize the travel time between the depots because travel time between depots does not add value to the order picking process.

We use the weighted sum method to combine the above mentioned objectives into one objective function. Optimizing the balancing ratio and minimizing the travel time conflicts with each other. When the balancing ratio improves, order pickers are assigned more often to fixtures with depot locations that a further apart from each other, which leads to an increase in the travel time of order pickers. Therefore, we search for a so-called Pareto optimal solution. A solution is pareto optimal if no objective can be improved without deteriorating the other objective. The set of all pareto-optimal solution is called the pareto-optimal set. Figure 4.7 shows an example of a pareto optimal set in the design space and in the criterion space. Table 4.4 shows the objective values when one of the objective is individually optimized. For example, in the first row we observe the values for F1, F2 and F3 at the point X_1^*, where F1 is optimized. The light grey box in the table represents the pareto maximum and is described as the maximum value of the objective function when that objective function is evaluated at each of the three points. The dark grey box in the table represents the lower limit of each objective function (f_m^0). The last row gives the absolute maximum of the individual objective function. We are not sure if the individual maxima of an objective function is in the neighborhood of the Pareto-optimal set. Therefore, the absolute maximum of a objective function may be irrelevant when determining a pareto optimal solution (Marler & Arora, 2005).



(a) Pareto optimal set in the design space

(b) Pareto optimal set in the criterion space.

Figure 4.7: Pareto optimal in the design and criterion space (Extracted from Marler & Arora, 2005)

Table 4.4: Objective function comparison matrix based on Marler & Arora, 2005

Objective value	F_1 values	F_2 values	F_3 values
At X_1^*	0.1000	43.0336	20.0725
At X_2^*	67.6807	0.0224	12.6562
At X_3^*	32.0687	16.9994	11.2757
Maximum	84.2615	144.2401	37.7600

In the weighted sum approach we scale our set of objectives into a single objective by multiplying each of our objectives with a predefined weight. Equation 4.7 shows the weighted sum method, where M is the number of objective functions and W_m represents the weight factor for the mth objective function and f_m^{norm} represents the normalised objective value of the mth objective.

$$\min\ F(x) = \sum_{m=1}^{M} W_m f_m^{norm}(x) \tag{4.7}$$

$$\sum_{m=1}^{M} W_m = 1 \tag{4.8}$$

$$W_i > 0 \tag{4.9}$$

We need to normalize our objective because the travel time between depots, balancing ratio and number of order pickers have different scales. To normalise the objective functions, we use the upper-lower-bound approach of Marler & Arora (2005), shown in equation 4.10. This approach is robust and ensures that the objective functions have the same scale and can be compared with each other.

$$f_m^{norm} = \frac{f_m(x) - f_m^0}{f_m^{max} - f_m^0} \tag{4.10}$$

f_m^{norm} = normalised objective value of objective m
$f_m(x)$ = objective value of objective m
f_m^{max} = Pareto maximum of objective m
f_m^0 = lower limit of objective m

Generally, the value of f_m^{norm} is between 0 and 1. However, this depends on the accuracy with which the Pareto maximum(f_m^{max}) and the lower limit (f_m^0) are determined. We approximate the value of f_m^0 by optimizing each objective individually. Therefore, we set the weight of the objective to be optimized to 1 and setting the weights of the other objectives to 0. The value we obtain with this setting determines the value of f_m^0. The value of pareto maximum (f_m^{max}) is the maximum value of the objective when the other objectives are optimized.

The weights for the objectives depend on the intervention we test. In Section 5.4 we explain how we set the weight values per intervention. To ensure that at the end of the SA a solution is found with a minimal number of order pickers we use a penalty level for an extra order picker that is five times greater than the weights for the objectives. We purposely set the penalty this high in case the value of the Pareto maximum (f_m^{max}) and the lower limit (f_m^0) are not determined precise enough. Due to an inaccurate determination of these values, the value f_m^{norm} may no longer lie exactly between zero and one. If this occurs, we still want to be sure that the solution uses a minimum number of order pickers. Therefore, we set the penalty cost high enough to prevent this.

Once the objectives are normalised and the weights are chosen, we can determine the value of the composite objective $F(x)$ by summing the weighted normalised objectives. Constraint 4.8 ensures that the sum of the weights is equal to 1 and constraint 4.9 ensures that each weight has a nonnegative value. The minimum of the weighted sum in equation 4.7 is the Pareto optimal solution, which means that the M objectives jointly achieve an optimal objective value without being dominated by any other feasible solution. Equation 4.11 shows the multi-objective function that we use for the SA.

$$\min z = W_{td} * f_{td}^{norm} + W_{br} * f_{br}^{norm} + 5 * f_{no} \tag{4.11}$$

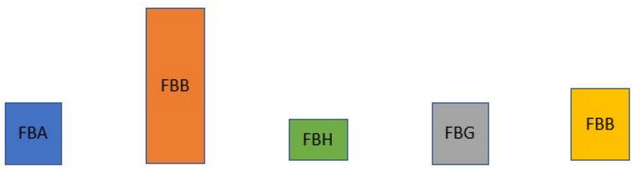
W_{td} = weight value for travel time between depots
W_{br} = weight value for balancing ratio
f_{td}^{norm} = normalised value of the travel time between depots
f_{br}^{norm} = normalised value of the balancing ratio
f_{no}^{norm} = number of order pickers used

4.6 Toy-problem

In this section we explain our general solution approach by means of a toy problem. A toy-problem provides insights in the challenges of solving our problem on a small scale. Section 4.6.1 gives the toy-problem instance. Subsequently, Section 4.6.2 describes the best-fit heuristic. Then, Section 4.6.3 describes how SA improves the initial solution of the best-fit heuristic.

4.6.1 Toy-problem instance

Figure 4.8 shows a toy problem with 5 fixtures, which are FBA, FBB, FBC FBG and FBH that need to be assigned to a minimal number of order pickers. When a minimal number of order picker is determined the fixtures need to be assigned in such a way that the workload is balanced over the order pickers. The daily workload per fixture (w_i) and number of replenishments (R_i) of the fixtures are already calculated and provided in the figure. The size of the boxes represent the value of w_i of a fixture.



Fixture	FBA	FBC	FBH	FBG	FBB
Depot	BA12	BC12	BH11	BG11	BB12
R_i	48	32	48	48	50
W_i	12.8%	32.7%	8.89%	10%	12%

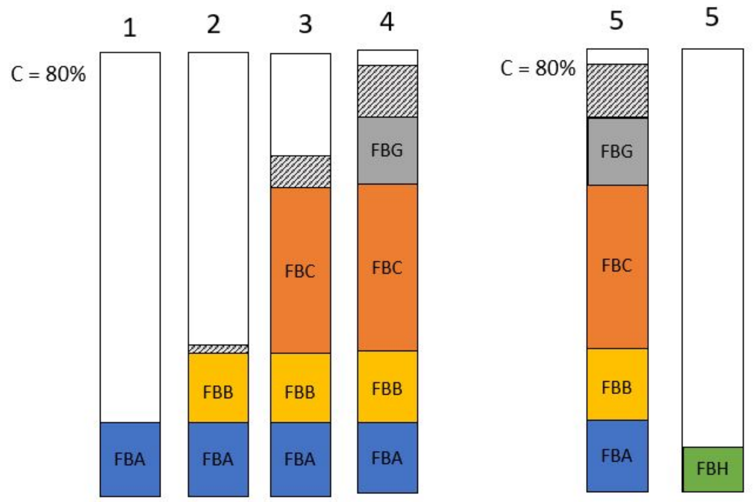
Figure 4.8: Toy-problem fixtures to assign

4.6.2 Best-fit heuristic

In the first step of our solution approach we use the best-fit heuristic to obtain an initial solution, which provides an upper bound on the number of order pickers. The best fit heuristic attemps to assign a fixture to an order picker where the workload of the order picker after assignment is the closest to the maximum workload level. When the fixture cannot be assigned to any of the order pickers the fixture is assigned to a new order picker.

Before we start assigning the fixtures, we sort the fixtures based on their depot locations. The sortation ensures that fixtures with the same depot location or a depot location close to each other are added consecutively. As a result, the increase in the travel time between the depots is minimized. In our toy-problem we start from depot location BA12 up to the depot location with the longest travel time, which is BH11.

We calculate the workload of an order picker with the left hand side of constraint 4.4. When we assign a fixture to an order picker we check if the total workload assigned to an order picker does not exceed the maximum workload level c. Subsequently, the fixture is assigned to the order picker where the workload is the closest to the maximum workload level. If the fixture cannot be assigned to any of the order pickers because the assignment leads to an infeasible solution, the fixture is assigned to a new order picker. This process continues until all fixtures are assigned. Finally, when all fixtures are assigned to order pickers we obtain a upper bound on the number of order pickers and we have an initial solution for our problem. In Appendix C the steps of the best-fit heuristic are shown in a flowchart. Figure 4.9 shows the results of the best fit heuristic for the toy-problem.



j	1	1	1	1
T_j	0	1.42	4.16	10.86
$\sum_{i=1}^{n} w_i x_{ij} + T_j$	12.8	26.22	61.67	78.38

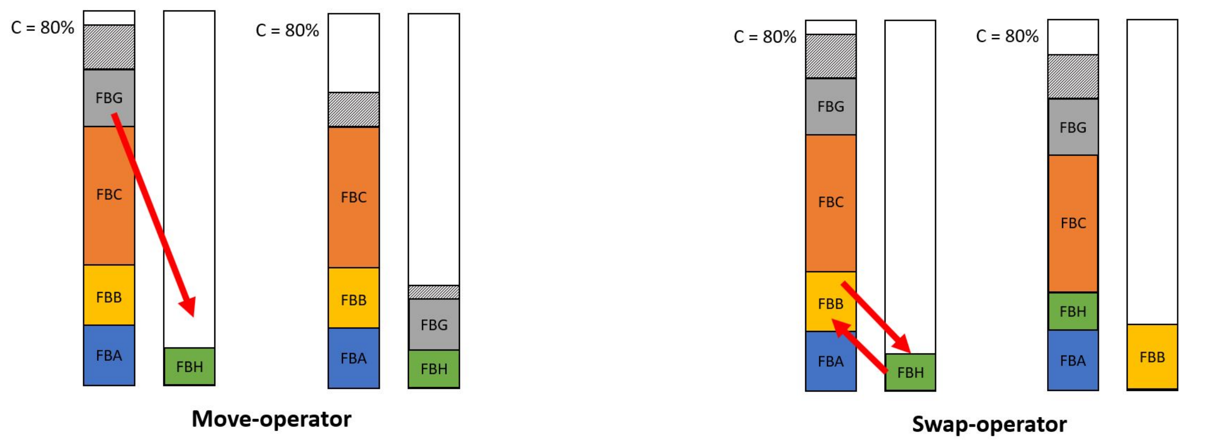
j	1	2
T_j	10.86	0
$\sum_{i=1}^{n} w_i x_{ij} + T_j$	78.38	8.89

Figure 4.9: Best fit heuristic

The rectangular boxes indicate the bins and the number above the bins indicate the step number. In step 1, we start with assigning fixture FBA to the first order picker. This assignment does not lead to travel times between depots ($T_j = 0$) because the order picker is assigned to one fixture. In step 2, we assign FBB to order picker 1 because the assignment does not exceed the maximum workload level of the order picker ($26.22\% \leq 80\%$). Notice that T_j is not zero anymore because the order picker needs to travel between depot location BA12 and BB12 to pick both fixtures. T_j is indicated in the figure with the black striped box. Up to step 4 we can assign the fixtures to one order picker. In step 5, fixture FBH cannot be assigned to the order picker because the total workload exceeds the maximum workload of the order picker. Therefore, fixture FBH needs to be assigned to a new order picker. As a result, the total workload for the first order picker remains the same and the workload for the second order picker equals the workload of FBH. The best-fit heuristic provides a upper bound of two order pickers ($j = 2$). In the next step of our approach we try to improve this upper bound and balance the workload over the order pickers using SA.

4.6.3 Simulated annealing

The solution that is obtained from the best-fit heuristic serves as input for the SA heuristic. Recall from Section 3.8 that SA is a metaheuristic that can find a global optimum by using diversification in the beginning and intensification at the end. SA accepts not only better solutions but also worse neighbor solutions with a certain probability. In SA, we minimize the multi-objective function that we described in Section 4.5. SA searches for better solution in the neighborhood using neighborhood operators. Neighborhood operators explore the solution space of the problem. We use the swap and move operator as neighborhood operators because these operators together enable us to evaluate the entire solution space and to find a (near-) global optimum. The swap operator swaps two fixtures from different order pickers and the move operator moves a fixture from an order picker to another. Figure 4.10 shows an example of a move operator and a swap operator. Appendix D provides a detailed description of the steps of the SA heuristic using a flowchart.



(a) Example of a move operator, fixture FBG is assigned to the second order picker.

(b) Example of a swap operator, fixture FBB and FBH swap with each other

Figure 4.10: Example of a move and swap operator

The move operator allows us to explore the entire solution space because the move operator can assign a fixture to a new order picker or move a fixture from an order picker that is assigned to only one fixture. When an order picker is not assigned to any fixture the number of order pickers reduces. At the start of the SA, we expect that the move operator often will find a solution with more order pickers because the SA accepts worse solution. Obviously, a solution with more order pickers is not desired. Therefore, we have set the penalty costs for an extra order picker in the objective function high enough to make it unattractive for the SA to accept a solution with an extra order picker. In the beginning of the SA, a solution with an extra order picker is found more often. As soon as the temperature of the SA decreases, only a solution with a minimal number of order pickers is accepted.

We select the move operator or swap operator based on the performance of the operator in the last 100 iterations. The number of accepted neighborhood solutions in the last 100 iterations determines the performance of the operator. The better the performance of an operator in the last 100 iterations, the higher the probability that the operator is selected. At the start of the SA, we expect the move operator to be more effective because this operator can find neighborhood solutions with more or fewer order pickers. We expect that the move operator will be more effective until a minimal number of order pickers is found. Once the minimal number of order pickers is found, an improved objective can only be found if a more balanced workload is found or the sum of the travel time between the depots reduces. Therefore, we expect that at the end of the SA the swap operator will be more effective. We initialize the performance of both operators at 50% at the start of the heuristic to ensure that both operators have an equal chance of being selected at the start. In addition, to prevent that an operator becomes dominant over time, which leads to the situation that there is no longer a chance that the other operator is chosen, the operators maintain a minimum probability of 10%.

When a move or swap is performed we check if the move or swap results in a feasible solution. If a swap or move results in an infeasible solution we do not accept the solution. When we want to balance the workload and the workload is already relatively balanced over the order pickers it is often impossible for the move operator to improve the workload balance because any move disrupts the balanced workload. Therefore, we use the swap operator, which is preferable when we want to balance the workload over the order pickers. With the use of the swap and move operator, we search for an improved solution.

If the neighbor solution has a better objective value than the current objective value we accept the solution. If the neighbor solution also has a better objective value than the current best objective value, the objective value of our neighbor solution becomes the new current best objective value. If the objective value of the neighbor solution is worse than the current objective value, the neighbor solution is accepted according to the acceptance probability distribution of Boltzman. The formula is shown in equation 4.12, where A represents the current objective value, B represents the neighbor objective and C represents the so-called temperature. If B is smaller or equal than A the acceptance probability is equal to 1, else the solution is accepted with the probability $e^{(A-B)/c}$. As can be observed, the acceptance probability depends on A,B and C, how smaller the difference between A and B the greater the chance that a worse neighbor solution will be accepted. The temperature C decreases while the heuristic runs, which means that the chance of accepting a worse neighbor solution decreases over time. When the temperature has decreased to its final temperature the SA stops running and the final solution is found.

$$P_{AB}(c) = \left\{ \begin{array}{cc} 1 & if\ B \leq A \\ e^{(A-B)/c} & else \end{array} \right\} \tag{4.12}$$

The acceptance ratio indicates to what extent we diversificate and intsensificate during the process. The acceptance ratio formula 4.13 determines what percentage of the neighborhood solutions is accepted compared to the total proposed neighborhood solutions. The acceptance ratio depends on the setting of the following parameters: starting temperature, markov chain length, decrease factor and stopping criteria.

$$\chi(c) = \frac{\text{Number of accepted worse neighborhood solutions}}{\text{Number of proposed neighborhood solutions}} \tag{4.13}$$

The starting temperature ensures that enough diversification is applied during the start of the SA. At the start of the SA we want to have an initial acceptance ratio of almost 1 because then often worse solutions are accepted (diversification). At the end of the SA we want to have an acceptance ratio of almost zero because then we want to accept only better solutions (intensification). The markov chain length indicates how much exploration is performed per temperature and the decrease factor tries to balance the intensification and diversification phase before the stopping criteria is met. Figure 4.11 shows the acceptance ratio versus the temperature for our problem. We choose a starting temperature of 1000 and an end temperature of 0.001 because this provides a good balance between diversification and intensification. Furthermore, we choose a markov chain length of 50 and a decrease factor of 0.9 because this provides a good trade-off between solution quality and the execution time. The execution time of the SA with these settings is equal to 1255 seconds. The long execution time is caused by the calculation of the travel time between the depots for the order pickers when a move or swap is performed. Specifically, determining the replenishment sequence of an order picker is very time consuming.

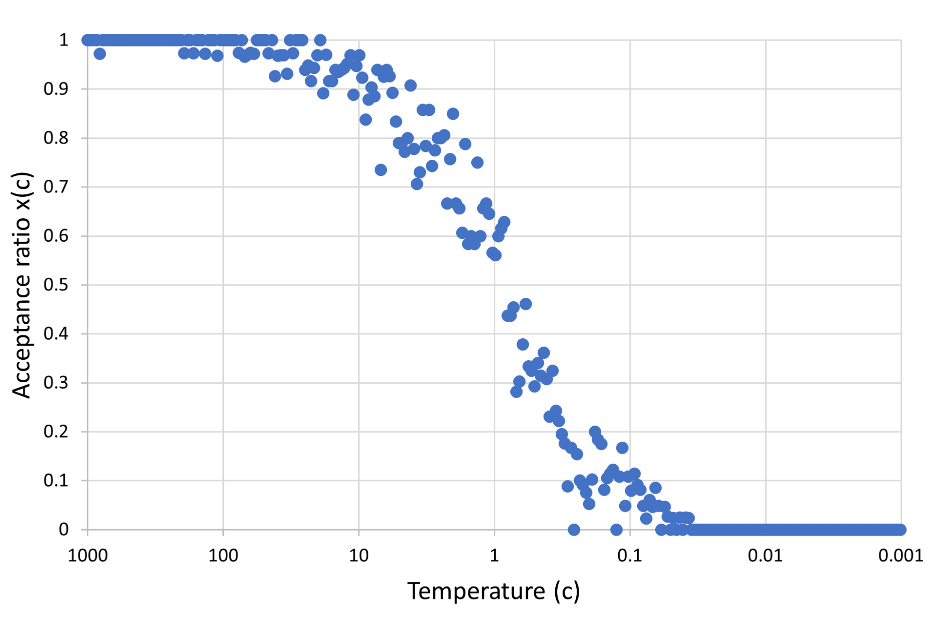
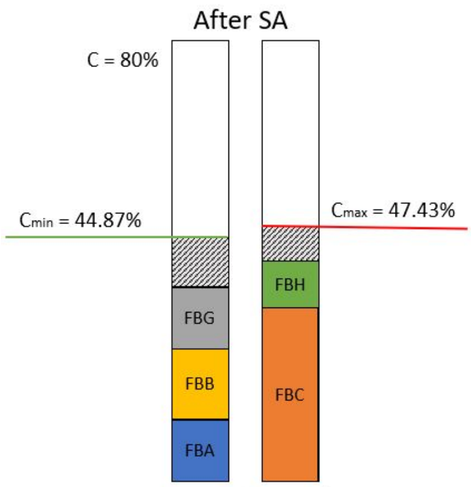


Figure 4.11: Acceptance ratio per temperature of SA

Figure 4.12 shows the final solution of the toy-problem after SA. We observe that the upper bound of 2 order pickers ($j = 2$) cannot be improved with SA. In the toy problem, this is easy to observe because the sum of the workload of the fixtures already equals 76.4 and we obtained a minimal travel time between the depots of 10.86 when we assign only 4 fixtures to one order picker (see Figure 4.9). Nevertheless, the SA provides an assignment where the workload level is balanced over the order pickers resulting in a workload level of 44.87% for order picker 1 and workload level of 47.43% for order picker 2.



j	1	2
T_j	10.07	5.82
$\sum_{i=1}^{n} w_i x_{ij} + T_j$	44.87	47.43

Figure 4.12: Final solution toy-problem

4.7 Input of solution approach

This section describes the input that the solution approach requires, which consists of the travel time between depot locations, pick time of fixture, takt time of a fixture, net. production time and maximum workload level. This section provides a partial answer to research question 3f.

Travel distance between depot location of fixtures

The travel times between depot locations determines how long it takes for an order picker to move to another depot location. The travel times between depot locations depend on the distance between the depot location and the speed with which an order picker can walk. The depot locations in SPZ's warehouse are at the front of each picking aisle

The distance between the depot locations can be determined by measuring the distance between the depot locations. However, the exact locations of the depot locations are already determined and can be obtained from a 2d technical drawing program of SPZ. Each depot location in the technical drawing program consist of a x and y coordinate. The x and y coordinates are in millimeters and represent the exact location of the depot location in the warehouse. Let depot location 1 have coordinates (x_1, y_1) and depot location 2 have coordinates (x_2, y_2), then the distance between the depots can be calculated with equation 4.16. In the current situation, all depot locations have the same y-coordinates because the depot locations are at the same height. Therefore, we can simply determine the distance between the depots by $|x_2 - x_1|$. However, if we want to have a model that also provides a solution when the depot locations are not at the same height we need to calculate the y distance between the depots. To access a depot in another picking aisle, an order picker needs to travel via the front or the back side of a picking aisle since the order picker cannot traverse a picking aisle in horizontal direction. The vertical distance (y-distance) depends on the travel direction of the order picker. The order picker can travel via the front side of the picking aisle or via the back side of the picking aisle. We calculate vertical distance via the front and back side with formulas 4.14 and 4.15 where y_{front} represents the y-coordinate of the front of the picking aisle and y_{back} represents the y-coordinate of the back of the picking aisle. The distance that provides the shortest path is chosen as the travel distance.

$$\text{Distance via front side: } d_{front}(x, y) = (y_{front} - y_1) + (y_{front} - y_2) \tag{4.14}$$

$$\text{Distance via back side: } d_{back}(x, y) = (y_1 - y_{back}) + (y_2 - y_{back}) \tag{4.15}$$

$$\text{Distance between depots: } d(x, y) = |x_2 - x_1| + \min(d_{front}(x, y), d_{back}(x, y)) \tag{4.16}$$

Recall from Section 4.3.1 that in reality there are only depot locations at BB12, BG11 and BH11. Order pickers that pick in the BA-aisle or BC-aisle need travel to the BB12 depot location to request and print the order pick list. In addition, order pickers that pick in the BF-aisle need to travel to the BG12 depot location to request and print the order pick list. We take into account this assumption when calculating the travel distance between these depots. For the calculation of the travel distance between depot BA11 and BA11, we use the travel distance between BA11 and BB11. In addition, to calculate the travel distance between BC11 to BC11 we use the travel distance between BB11 and BC11. For the distance between BF12 and BF12 we use the distance between BF12 and BG12. Table 4.5 shows the travel distance between the depot locations of the LB2-warehouse of SPZ.

Table 4.5: Travel distance between depot locations (in m)

Depot	BA11	BB11	BC11	BF12	BG12	BH12
BA11	9.48	9.48	17.48	36.25	43.66	52.16
BB11	9.48	0	9.85	28.62	36.04	44.54
BC11	17.48	9.85	9.85	20.51	27.93	36.43
BF12	36.25	28.62	20.51	9.34	9.34	17.85
BG12	43.66	36.04	27.93	9.34	0	9.82
BH12	52.16	44.54	36.43	17.85	9.82	0

Travel speed between depot locations

When an order picker travels to another depot location, the order picker might face traffic, such as passing reach trucks or tugger trains. Tugger trains drive past the pick-up point at the front of a picking aisle to pick up the fixtures and transport them to the assembly line. Reach trucks drive between the BC and BF aisles to transport incoming goods from trailers to the other warehouses of SPZ. The trailer unload dock is located behind the LB2 warehouse, which means that the reach truckers are obliged to drive through the LB2 warehouse. Figure 4.13 provides a graphical representation of the traffic situation at the LB2 warehouse of SPZ.

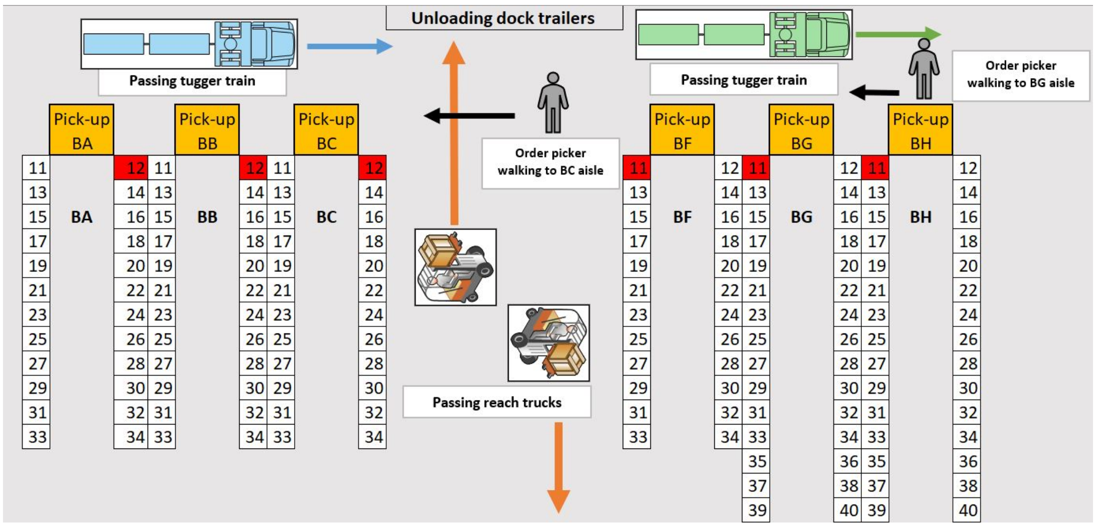


Figure 4.13: Possible congestion areas's

When an order picker faces traffic the order picker has to wait until a tugger train or reach truck has passed. Due to this waiting time, it takes longer for an order picker to reach another depot location. To model the traffic we reduce the travel speed of the order picker. Table shows 4.6 the travel speed of order pickers between the depot locations of the LB2-warehouse. For the travel speed between the depots BA11-BA11 and BC11-BC11 we use the travel speed to depot BB11 because in reality there is no depot at BA11 and BB11. The same reasoning holds for the travel speed between BF12-BF12.

Table 4.6: Travel speed between depot locations (in km/h)

Depot	BA11	BB11	BC11	BF12	BG12	BH12
BA11	4	4	4	2.5	2.5	2.5
BB11	4	5	4	2.5	2.5	2.5
BC11	4	4	4	2.5	2.5	2.5
BF12	2.5	2.5	2.5	4	4	4
BG12	2.5	2.5	2.5	4	5	4
BH12	2.5	2.5	2.5	4	4	5

Pick time of a fixture (P_i)
The pick time of a fixture determines how long it takes for an order picker to replenish a fixture. We determine the pick time of a fixture on the basis of timings in the working standard. Recall from Section 2.3 that the working standard describes a predetermined set of tasks to pick a fixture. All the tasks in the working standard contain timings about the duration of the task. The pick time of a fixture is determined by summing up the durations of these tasks. The pick time of a fixture also includes the administration time for requesting pick lists, printing pick lists and signing off pick lists. Table 4.7 shows the order pick time of the fixtures that are used at the LB2-warehouse of SPZ.

Takt time of a fixture (L_i)
The takt time of a fixture determines how long an order picker has the time to replenish a fixture. Recall from Section 2.2.2 that the takt time of a fixture depends on the demand of the parts that the fixture carries. Due to the assumption in Section 4.3.1 that fixtures arrive and depart exactly every takt time, the takt times of the fixtures are deterministic. Table 4.7 shows the takt times of the fixtures that used in the LB2-warehouse.

Table 4.7: Takt time and pick time per fixture

Fixture	Takt time (hh:mm:ss)	Pick time (in sec.)
LL322-DBP-BA	00:20:16	351
LL336-DBP-BC	00:20:16	290
LL734-LINKS-DBP-BH	00:15:12	262
LR322-DBP-BA	00:20:16	366
LR450-DBP-BB	00:20:16	330
LR734-RECHTS-DBP-BH	00:15:12	262
SL323-DBP-BA	01:31:12	350
SL330-DBP-BC	01:31:12	290
SL393-DBP-BB	01:31:12	330
SL580-LINKS-DBP-BH	00:45:36	262
SR322-DBP-BA	01:31:12	350
SR578-RECHTS-DBP-BH	00:45:36	262
Y07C146-DBP-BF	02:00:00	220
Y07C154-P-DBP-BF	06:00:00	160
Y10A106-PX-DBP-BG	01:31:12	402
Y10A156-DBP-BG	00:20:16	402
Y11B136-BP-BF	05:00:00	256

Net. Production time (PT)
The net production time is the effective working time on a normal working day. The higher the net production time the more replenishment cycles per day (R_i). The net production time is equal to the work time of an order picker minus break times. Recall from Section 2.3 that on a normal working day there are 2 shifts of 8 hours at the LB2-warehouse of SPZ. The last 15 minutes of the 8-hour shift are often used for cleaning up, which leaves 7.75 hours per shift. Furthermore, about 45 minutes per shift are taken into account for small stops. This means that if production takes place without line stops, 45 minutes remain at the end of a shift. Since we are assuming normal production without line stops, we have to deduct this time as well, which leaves a net production time of 14 hours (840 minutes).

Maximum workload level of the order picker (c)
The maximum workload level of an order picker determines how much workload we can assign to an order picker. In the current situation we do not know what the workload of the order pickers is and thus it is difficult to determine what a suitable maximum workload for an order picker is. Figure 4.14 shows the trade-off between maximum workload (% resource busy) and the waiting time (% busy/%idle). If a resource is completely utilized (100% utilization) then waiting times become infinite (Griffiths, 1996). In our research this would mean that a high workload per order picker leads to the situation that order pickers cannot pick the fixtures within the takt time. This is because order pickers who already face a high workload cannot

cope with a workload that varies. Since the number of parts on a fixture and the pick time of a part varies, the workload of a fixture varies as well. Therefore, we need to incorporate slack time so that the fixtures are still picked within the takt time when the workload is sometimes higher than average. Figure 4.14 shows that the waiting time increases dramatically when the utilization/workload level exceeds 80%. We expect that this also applies to our problem, which means that fixtures will more frequently be picked to late when the workload level of order pickers exceeds 80%.

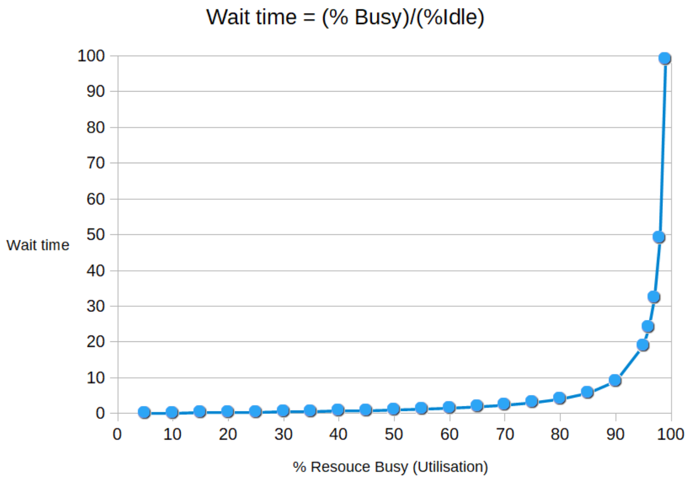


Figure 4.14: Resource utilization versus waiting time (extracted from McNamee (2019))

4.8 Output of solution approach

This section describes the output of the solution approach, which consists of the number of order pickers, assignment strategy and the workload per order picker. Furthermore, it gives the remaining answer to research question 3f

Minimal number of order pickers

The model provides a minimal number of order pickers that are required. The number of order pickers is an important indicator because it indicates how many order pickers SPZ needs to deploy in the LB2-warehouse. The number of order pickers provides SPZ information on the personnel cost for the LB2-warehouse.

Assignment strategy of fixture to order picker

The model provides an assignment strategy that assigns each fixture to an order picker.The assignment strategy is used in Section 5.1.5 as input for the simulation model in order to evaluate the performance of the assignment strategy.

Workload per order picker

The model provides a workload level for every order picker that is used. The workload of an order picker determines how much time an order picker spends on order picking and travelling between the depot locations as percentage of the net. production time (PT). The workload per order picker is an important indicator to determine the performance of the order picking process.

4.9 Conclusion

This section concludes the chapter

In Section 4.1 we investigated the properties of our problem and compared this with the problem characteristics of the VRP, IPMP and BPP. We concluded that a BPP best fits our problem because we prefer finding a minimum number of order pickers over balancing the workload.

In Section 4.2 we stated that we want to develop a future-proof method that determines the required workforce for the LB2-warehouse and is able balance the workload over the order pickers. We choose to use the metaheuristic SA for our solution approach because SA is easy to implement and has a connected solution space, which enables us to find all feasible solutions to the problem.

We developed a general solution approach that consists of two steps. In the first step a best-fit heuristic provides an initial solution to our problem and provides an upper bound on the number of order pickers. In the second step, we use the output of the first step as input for a SA heuristic to search for an improved solution with the use of a multi objective function that minimizes the number of order pickers, minimizes the travel time and balance the workload over the order pickers.

The SA heuristic uses swap and move operators to explore neighborhood solutions. The move operator enables us to explore the entire solutions because the move operator can find neighborhood solutions with more or fewer order pickers. We expect that the swap operator is preferable when we want to balance the workload. The selection of the swap and move operator is based on the performance of the operator in the last 100 iterations.

In Section 4.7 and 4.8 we defined the input and output parameters of our model.

5 Simulation model

In this chapter, we set up a simulation model to test the performance of assignment strategies. An assignment strategy provides an assignment of each fixture to an order picker. Section 5.1 presents a model description, which includes the key performance indicators (KPIs), assumptions and input of the simulation model. Subsequently, Section 5.2 discusses the initial settings of the simulation model such as, the run length, warm-up period, number of replications and the use of common random numbers. Section 5.3 addresses the verification and validation of the simulation model. Section 5.4 elaborates on the experimental design. Finally, Section 5.5 presents the conclusions of this chapter.

5.1 Model description

This section describes the simulation model. Section 5.1.1 introduces the simulation model and describes why we choose to use a simulation model. Subsequently, Section 5.1.2 provides a general overview of the simulation model. Section 5.1.3 elaborates on the key performance indicators that determine the performance of an assignment strategy. Next, Section 5.1.4 discusses the assumptions of the simulation model. Finally, Section 5.1.5 describes the inputs of the simulation model

5.1.1 Introduction

This section introduces the simulation model and describes why we choose to use a simulation model.

In the assignment model of Chapter 4, we assume that fixtures arrive and depart exactly at the end of a replenishment cycle and that fixtures have a deterministic order pick time. Recall from Section 2.6 that order pick times are not deterministic because the order pick time depends on several factors such as the handling complexity of the parts and the order picker that is picking the parts. Furthermore, recall from Section 4.3.1 that the arrival and departure of fixtures is stochastic due to slack time or small delays in the arrival and departure process of the fixtures. Using a simulation model we generate stochastic order pick times for parts and a stochastic arrival and departure process for fixtures with which we can determine the performance of assignment strategies under stochastic conditions.

5.1.2 Overview of simulation model

This section provides an overview of the simulation model and describes how we simulate the order picking process.

The simulation model simulates the order picking activities of order pickers in the warehouse. Therefore, the simulation model generates a request list with fixtures that need to be picked in the warehouse on a day. The request list shows when a fixture arrives and departs in the warehouse. In addition, each fixture on the request list consists of a pick list that includes the parts that need to be picked for that fixture and the storage location of the part. In the simulation model order pickers are instructed to pick the fixtures on the request list to which they are assigned. The number of requests for a fixture is based on the average number of replenishments of a fixture on a normal production day. Section 5.1.5 explains in more detail about the generation of the request list.

The order picking process is simulated as follows. An order picker starts at the depot location where the order picker has to sign off the previous order pick list, request a new pick list and print it. We simulate this activity as "administration time" with the use of a uniform distribution because order pickers indicate that the administration time lies within a range of 50 and 70 seconds. However, sometimes an order picker needs to perform some additional activities as part of the administration time, such as replenishing an empty fixture or scanning an empty storage location. These additional activities need to be performed approximately once every 8 replenishment cycles. The time to perform these additional activities is modelled with a truncated exponential distribution. Section 5.1.5 explains why we use a truncated exponential distribution and how we estimate the parameters of the distribution.

As soon as the order picker has printed the pick list, the order picker travels to the pick-up point of the fixture. The simulation model determines the travel time of this activity by calculating the distance from depot to the pick-up point and divide the distance with the travel speed of the order picker. Subsequently, the order picker travels to the storage locations of the parts that are requested for the fixture. Therefore, the simulation model calculates the travel time between the storage locations the order picker has to visit. Once an order picker arrives at a storage location, the model simulates an order pick time by drawing a value from a truncated normal distribution with as parameters the average pick time of part and the standard deviation of the pick time of a part. We use the normal distribution because values for a normal distribution are fairly constant but with some random variability (either positive or negative) and we expect that the order picking time for a part in the LB2-warehouse is also fairly constant around the average pick time. However, we cannot prove that the average pick time behaves normally because SPZ does not have sufficient measurements of the pick time of the parts. Section 5.1.5 describes how we estimate the parameters of the normal distribution for the order pick time and how we truncate the normal distribution to avoid negative order pick times.

When the order picker has picked the required parts for the fixture, the order picker returns the fixture to the pick-up point. Subsequently, the order picker travels back to the depot location and starts picking with the next fixture on the request list. The simulation model continuously calculates the travel time and order pick time of an order picker. This enables us to measure the daily travel time, order pick time, congestion and workload of an order picker. In addition, the simulation model calculates the service level and tardiness of fixtures. Section 5.1.3 elaborates more in depth about the KPIs of the simulation model. The number of order pickers in the simulation model and the assignment strategy is determined by the assignment model of Chapter 4.

5.1.3 Key performance indicators (KPIs)

This section describes the KPIs of the simulation model

Service level: The service level indicates the fraction of the fixtures that is picked within the takt time of the fixture. If an assignment strategy has a low service level, fixtures are often not ready when they need to be transported. This results in a delay in the tugger train process that transports the fixtures to the assembly line. If the tugger train process is delayed too much, parts may not be delivered to the assembly line on time, which could cause a line stop.

Tardiness: The tardiness of a fixture indicates how much time the picking process exceeds the takt time. An assignment strategy can have a relatively low service level while the pick time of the fixtures only exceed the takt time a few seconds. If the pick time exceeds the takt time only a few seconds, this leads to small delays in the tugger train process. These small delays in the tugger train process do not immediately have major consequences and do not lead to a line stop. However, when the pick time exceeds the takt time with more than 2 minutes, the tugger train process disturbes and parts do not arrive at the assembly line on time, which could cause a line stop. The tardiness of a fixture is calculated with $T_i = \max(0, C_i - L_i)$, where T_i indicates the tardiness, C_i the completion time and L_i the takt time of a fixture.

Workload: The workload measures how much time an order picker effectively spends on order picking activities as a percentage of the total work time. The workload that an order picker faces provides insight in the productivity of the order picker. In addition, measuring the workload of each order picker provides insight into the workload balance over the order pickers.

Travel distance: The travel distance indicates the distance an order picker has to travel on a working day. Travel distance does not directly add value to the order picking process, and thus we want to reduce travel distance as much as possible.

Congestion: We define congestion as when 2 order pickers are in the same picking aisle at the same time. Congestion causes order pickers to block each other, which can delay the order picking process. In the current situation, order pickers do not experience congestion because each order picker is responsible for the picks in its own picking aisle. We only measure how often congestion occurs but do not include extra pick time when it occurs because it is unknown what the effect of congestion is on the pick time is.

5.1.4 Model assumptions and model simplifications

This section describes the modeling assumptions and simplifications

We assume a normal production day without line stops. Line stops lead to a stop in production, which means that fixtures cannot be replenished because there is no consumption of parts.

We simplify our model by assuming that at the front of each pick aisle there is a depot location. However, in reality there are only depot locations at BB12, BG11 and BH11. Order pickers that pick in the BA-aisle or BC-aisle need travel to the BB12 depot location to request and print the order pick list. In addition, order pickers that pick in the BF-aisle need to travel to the BG12 depot location to request and print the order pick list. We take this simplification into account by using the travel distance of the nearest depot location if there is no depot location in the pick aisle.

5.1.5 Input of the model

This section describes the inputs of the simulation model

Request list of fixtures: The request list shows the replenishment requests of fixtures on a day. A replenishment request specifies at which time a fixture needs a replenishment. Furthermore, each replenishment request consists of a pick list with parts that need to be picked to fulfil the replenishment request. The number of replenishment requests on a day is based on the production time and the takt time of the fixture.

Recall from Section 2.5 that an order picker has to visit a variable number of storage locations per replenishment cycle of a fixture. In the simulation model, each replenishment request consists of a unique pick list. Therefore, the storage locations that the order picker needs to visit varies per replenishment request. We generate a unique pick list by selecting a pick list from a data set. The data set consists of pick lists from fixtures that are picked in the past period between February 2021 and November 2021. Table 5.1 shows an example of a pick list from the data set. When a fixture needs a replenishment we pick a random pick list from the data set and instruct an order picker to pick the items on the pick list.

Table 5.1: Example of a pick list from the data set

Part number	Part quantity	Pick list number	Fixture	Storage locations
2355342	1	4334647	LR322-DBP-BA	BA11
2355342	1	4334647	LR322-DBP-BA	BA11
2408708	1	4334647	LR322-DBP-BA	BA13
2608446	1	4334647	LR322-DBP-BA	BA15
2608446	1	4334647	LR322-DBP-BA	BA15
2608446	1	4334647	LR322-DBP-BA	BA15
2608446	1	4334647	LR322-DBP-BA	BA15
2635870	1	4334647	LR322-DBP-BA	BA17
1854878	1	4334647	LR322-DBP-BA	BA19
1488605	1	4334647	LR322-DBP-BA	BA23
2259592	1	4334647	LR322-DBP-BA	BA25
2446961	1	4334647	LR322-DBP-BA	BA25
2407422	1	4334647	LR322-DBP-BA	BA27
2407422	1	4334647	LR322-DBP-BA	BA27
2407422	1	4334647	LR322-DBP-BA	BA27

Arrival time of fixtures: The arrival time of a fixture determines at which time the fixture arrives in the warehouse. Each replenishment request of a fixture contains an arrival time. The generation of arrival times of fixtures is not based on historical data because the data from the ERP-system does not specify the exact arrival times of fixtures in the LB2-warehouse. Recall from Section 4.3.1 that on a normal production day, fixtures do not arrive and depart exactly every takt time because the fixtures are sometimes a bit too early or too late due to slack time or small delays. Therefore, the simulation generates a stochastic arrival process for fixtures, assuming that a fixture arrives every takt time + a small delay. We only take into account the small delays and not the slack time because when a fixture arrives too early the order picker often waits until the replenishment cycle starts before he start picking the fixture. We simulate the small delays in the arrival process of the fixtures using a truncated exponential distribution. We choose to use the exponential distribution because values for an exponential random variable have more small values and fewer large values. The delay in the arrival process is often caused by short delays (small values), which means that there is a very small chance that a fixture will arrive much later (large values). We simulate a small delay in the arrival process by drawing a value from the truncated exponential distribution with parameter $\lambda = 1/\text{mean delay time}$. We truncate the exponential distributions at 200 seconds and estimate that the mean delay time is 60 seconds. These values are based on conversations with order pickers who indicate that the average waiting time is about 1 minute and the waiting time for small delays usually does not exceed 200 seconds.

Assignment strategy: The assignment strategy of fixtures to order picker is generated with the order picker assignment model of Chapter 4. The assignment model assigns each fixture to an order picker. The assignment strategy depends on the settings of the multi-objective function of the assignment model. In Section 5.4 we discuss the multi-objective settings for each experiment.

Coordinates of storage locations, depots and pick-up points: The coordinates of the storage locations, depots and pick-up points are extracted from a Laycad model of the warehouse of SPZ. We use the coordinates of the storage locations, depots and pick-up points to determine the travel times. The travel times between storage locations, depots and pick-up points are calculated with the same method as described in Section 4.7 to determine the travel time between the depots in the assignment model.

Storage locations of parts: The storage location where a part is stored is retrieved from data of SPZ's ERP-system, which indicates which storage location belongs to a part.

Order pick time of a part: The order pick time of a part indicates how long it takes to pick a part. An order pick time of a part is generated by drawing a value from a normal distribution with the mean pick time of a part and the standard deviation of the pick time of a part. Since there is limited data available of the pick times of parts, we do not have a good estimation of the mean pick time and standard deviation of the pick time for each part individually. Therefore, we assume that the pick time of a part that belongs to a fixture is on average the same. Recall from 2.2.2 that a fixture specifically carries a particular type of part, which means that usually the same type of parts are transported on a fixture. Based on conversations with order pickers and our observations, we conclude that the pick time of parts that are picked on the same fixture are roughly the same. We determine an average pick time for each part by dividing the average pick time of a fixture with the average number of parts that are picked on a fixture. As a result, every part that belongs to a fixture has the same average order pick time. Due to the lack of data we cannot estimate the standard deviation of the order pick time therefore we assume that 95% of the order pick times are 5 seconds longer or shorter than the average pick time. This assumption is based on conversations with order pickers who indicate that the average pick time of a part usually lies within this range. Due to this assumption, we can determine the standard deviation of the pick time. Figure 5.1 shows the standard deviations of the mean for a normal distribution. If 95% of the pick times differ +- 5 seconds from the mean, we can observe that this are 2 standard deviations. One standard deviation is then equal to 2.5 seconds. In the simulation model the normal distribution is truncated at zero to avoid negative order pick times.

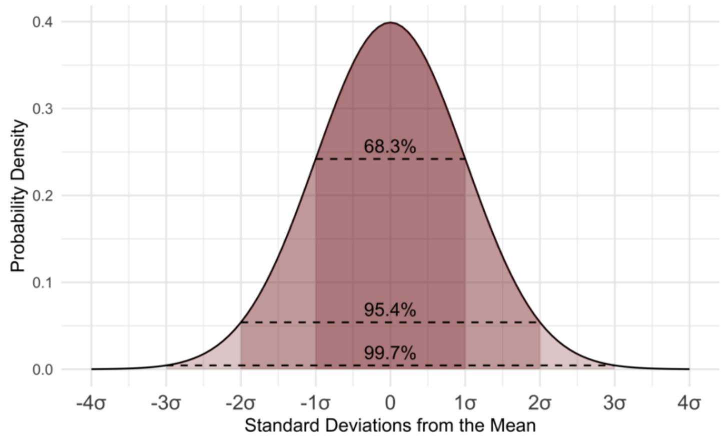


Figure 5.1: Standard deviation from the mean for a normal distribution (Extracted from Wells, 2019)

Since there is limited data available of the order pick times, it is difficult to validate whether the pick times are realistic. It is possible that the actual pick times differ from the pick times that are generated with the normal distribution. Therefore, we perform a sensitivity analysis in Section 6.4 with different order picking times to examine how our assignment model performs under varying order pick times. In the sensitivity analysis, we increase and decrease the pick time up to [-20%;+20%] of the average pick time and examine the effect on the output parameters.

Administration time at depot: Recall from Section 2.3 that a working standard describes a predetermined set of tasks to pick a fixture. The working standard shows that 60 seconds are indicated for requesting, printing and signing off pick lists. Scanning empty locations takes approximate 20 seconds and replenishing an empty pallet takes about 40 seconds. If we sum these times, order pickers have 120 seconds per fixture to complete these activities during a replenishment cycle of a fixture. However, a storage location only needs to be scanned if a storage location is empty and a pallet only needs to be replenished if there is an empty pallet. We do not know how often an empty pallet must be replenished or an empty location need to be scanned. Furthermore, the times on the working standard are an indication of the time that is necessary to fulfill the activities. In the simulation model, we assume that the time that is required for requesting, printing and signing off a pick list is uniformly distributed between 50.0 and 70.0 seconds. In addition, we assume that in 1 out of 8 replenishment cycles a storage location needs to be scanned or an empty pallet needs a replenishment. The time to scan a storage location or to replenish an empty pallet is assumed to be exponentially distributed with a mean duration of 30 seconds. The exponential distribution is truncated at 60 seconds because this is indicated as the maximal duration. The determination of these values is based on conversation with order pickers and observations of the researcher.

Travel speed of order pickers: For the travel speed of order pickers between depot location we use the travel speeds of Table 4.6 of Section 4.7. In a picking aisle we use a travel speed of 5km/h for an order picker.

5.2 Simulation settings

This section elaborates on the settings of the simulation model such as the run length, warm-up period, number of replications and the use of common random numbers.

The simulation model is a terminating system because the simulation model starts at 6 o'clock in the morning and ends at 8 o'clock in the evening when the normal production of trucks has been reached. The run length of the simulation model is equal to 14 hours (net production time on a day) and the simulation model calculates at the end of the day the performance indicators. The simulation does not require a warm-up period because the performance indicators are based on the generated demand per day. For example, if the daily production time decreases the daily number of replenishments of a fixture decreases as well, because the daily number of replenishment depends on the daily production time. The workload of an order picker depends on the number of replenishment requests of fixtures to which the order picker is assigned. If the daily production time decreases the daily number of replenishment requests for a fixture decreases and the workload is calculated based on the decreased production time.

Using the run length of the simulation model, we can determine the number of replications. To calculate the required number of replications we use the sequential procedure of Law (2015). In each replication of the simulation model we determine a point of the mean of an output variable and calculate at which replication we obtain a confidence interval of 95%. As output variable we use the travel distance of the order pickers. To obtain a confidence interval of 95% the simulation model requires 3 replications. The number of replications is low because the variability in the simulation model is also small. Appendix E describes in more detail how we calculate the number of replications.

In the simulation model we implement the common random number (CRN) technique to control the randomness. For each replication of an experiment we use a different random stream. However, each replication number of an experiment uses the same random number stream. E.g., suppose we do two experiments with 3 replication then each replication uses a different random stream but replication 1 in experiment 1 & 2 use the same random stream.

5.3 Verification and validation

In this Section we discuss the model verification and validation. To ensure that interventions or experiments have the same effects in reality as in the simulation model, our simulation model must be a representative reflection of reality. In Section 5.3.1 we describe how we verify the simulation model and in Section 5.3.2 we describe how we validate our simulation model.

5.3.1 Verification

This section elaborates on the verification process of the simulation model.

In the verification process, we check whether our conceptual model matches our simulation model. We created our simulation model in python and use the verification techniques of Kleijnen (1995) to verify the simulation model. The code of the simulation model is checked on programming errors by running and debugging the code every few lines. In the debugging process we place breakpoints in our code and check if variables have the same value as we expect. Furthermore, we applied modular programming which means that we programmed our simulation model in parts and add the parts to the model one by one. When a part is added we run the complete simulation model and check if no errors occur. Moreover, we continuously logged the time and position of an order picker in the model, which enables us to monitor the order pickers location at any time in the simulation model. This allows us to check whether the order pickers picking times and travel times correspond to what we expect. Finally, we adjust the input of the simulation model such as the travel speed of the order picker and check whether it results in the expected outcome.

5.3.2 Validation

This section elaborates on the validation process of the simulation model.

In the validation process, we check if our simulation model is a representative reflection of the current system. We use face validity to check if the simulation model is consistent with the perceived system behavior (Law, 2015). The face validity is performed by the team leaders of the warehouse of SPZ. The team leaders conclude that the simulation model with its assumptions is a good representation of reality.

We validate the results of the simulation model with actual data of April 2020 when was the last time there was a longer period of normal production (output +- trucks). Due to the chip shortage in the automotive sector, it is not possible to compare the model with more recent data as there has not been a longer period of normal production since April 2020. For our model validation, we compare the mean pick time of order pickers, average number of parts per fixture and the average number of replenishments cycles on a day.

In the first two columns of Table 5.2, the mean pick time in the simulation model (SM) and the pick time in reality is shown. The mean pick time in the simulation model reveals a small difference with the pick time in reality. Due to the lack of accurate measurements of the pick time of fixtures in reality we use the timings that are represented on the working standard. The pick time on the working standard is an average of a couple of measurements in the past and gives an indication of the actual pick time of a fixture. However, there is no information available about these measurements that are done in the past. As a result, the actual pick time in reality may deviate from the pick times in the working standard. Since there are no other measurements of the pick times, we use this pick time to validate the average pick times created by the model. The differences between the average pick time in the simulation model and in reality are caused by the stochastic order pick times that are generated with the normal distribution in the simulation model. If we compare the differences in the order pick times, we conclude that the differences between the average pick time in the simulation model and the pick time in reality are small. Since the pick time in reality is based on a couple of measurement that gives an indication of the actual pick time and the pick time of our simulation model is close to this value, we conclude that the pick times of our simulation model are a representative indication of the order pick times in reality.

Table 5.2: Validation data

Fixture	Mean pick time (SM)	Pick time reality	Avg. number of parts per fixture (SM)}	Avg. parts per fixture reality	Avg. replenishments cycles (SM)	Avg. replenishment cycles reality
LL322-DBP-BA	279.94	271	22.02	23.40	42	41.00
LL336-DBP-BC	227.59	210	8.84	10.30	42	41.00
LL734-LINKS-DBP-BH	197.62	182	20.39	21.66	56	54.64
LR322-DBP-BA	288.94	286	15.93	17.91	42	41.00
LR450-DBP-BB	280.79	250	11.16	13.08	42	44.36
LR734-RECHTS-DBP-BH	196.65	182	13.75	17.78	56	54.64
SL323-DBP-BA	285.13	270	21.73	22.81	10	9.00
SL330-DBP-BC	228.13	210	7.86	8.93	10	9.09
SL393-DBP-BB	271.25	250	10.87	10.89	9	9.73
SL580-LINKS-DBP-BH	211.69	182	12.10	12.29	18	18.36
SR322-DBP-BA	281.41	270	14.27	15.95	10	9.00
SR578-RECHTS-DBP-BH	196.79	182	10.50	12.05	19	18.45
Y07C146-DBP-BF	130.09	135	6.00	6.00	7	7.00
Y07C154-P-DBP-BF	116.77	125	4.00	4.00	2	2.00
Y10A106-PX-DBP-BG	333.16	322	12.93	12.42	9	9.18
Y10A156-DBP-BG	343.60	322	10.73	11.00	42	40.91
Y11B136-BP-BF	236.12	260	31.83	Unknown	2	2.00

The average number of parts on a fixture determine how many storage location an order picker needs to visit and how often an order picker needs to pick a part. Consequently, the average number of parts per fixture influences the order pick time and the travel time of an order picker. Therefore, it is important that the average number of parts per fixture corresponds with average number of parts per fixture in reality. The two columns in the middle of Table 5.2 show the average number of parts per fixture in the model and the average number of parts per fixture in reality. Recall from Section 5.1.5 that we select a pick list from a historical dataset to determine which parts an order picker needs to pick for a fixture. We randomly select a pick list that was picked in the period between February 2021 and November 2021. The number of order lines on a pick list determine how many parts and which parts need to be picked for the fixture. To validate if the average number of parts per fixture from the simulation model corresponds with reality, we compare the average number of parts per fixture in the model with the average number of parts per fixture on 10 consecutive production days in April where on average 200.56 trucks are produced. The differences in the number of parts per fixture in the simulation model and the number of parts per fixture in reality is small and usually not more than one or two parts. Therefore we conclude that the number of parts per fixture in the simulation model matches the number of parts per fixture in reality.

In the last two columns of Table 5.2 we compare the average number of replenishments generated in the simulation model with the average number of replenishments cycles in reality. The average number of replenishment cycles in the simulation is calculated by dividing the production time with the takt time of a fixture. Therefore, the daily number of replenishments cycles in the simulation model is fixed. The average number of replenishments cycles per fixture in reality is determined by counting the number of replenishments cycles per fixture in 10 consecutive production days in April where on average 200.56 trucks are produced. When we compare the average number of replenishment cycles of the simulation model with reality we observe a small difference. If we round the number of replenishment cycles in reality the difference in the number replenishment cycles for all fixtures is within 2 replenishment cycles. Therefore, we conclude that the average number of replenishments cycles of the simulation model corresponds with the average number of replenishments cycles in reality.

5.4 Experimental design

This section describes the experimental design that consists of 3 interventions and 4 scenarios. Section 5.4.1 elaborates on the interventions that we test in the simulation model. Subsequently, Section 5.4.2 explains the scenarios on which we test the interventions.

5.4.1 Interventions

This section describes the interventions that we test in the simulation model.

Intervention 1: Optimizing the travel time of order pickers.
In intervention 1, we examine if the travel time between the depots for order pickers can be reduced. Therefore, we set the weight factor of the multi-objective function of the assignment model for minimizing the travel distance to 1 and the weight factor for balancing the workload to 0. The objective of the assignment model is then equal to formula 5.1. In the assignment model we allow order pickers to pick in the same aisle, which leads to possible congestion situations.

$$\min z = 1 * f_{td}^{norm} + 0 * f_{br}^{norm} + 5 * f_{no} \tag{5.1}$$

Intervention 2: Optimizing balancing ratio
In intervention 2, we optimize the balancing ratio. Therefore, we set the weight factor for the balancing ratio to 1 and the weight factor for minimizing the travel time to 0. The objective of the assignment model is shown in formula 5.2. This interventions aims to find the best balancing ratio to distribute the workload evenly over the order pickers. In the assignment model we allow order pickers to pick with multiple order pickers in an aisle

$$\min z = 0 * f_{td}^{norm} + 1 * f_{br}^{norm} + 5 * f_{no} \tag{5.2}$$

Intervention 3: Optimizing the travel time and the balancing ratio
In this intervention, we try to find an assignment strategy where we have a good trade-off between a reduction in travel time for the order pickers and a balanced workload over the order pickers. We adjust the weight for the balancing ratio and for travel time reduction step by step and investigate if we can find an assignment strategy that provides a good trade-off between both factors

5.4.2 Scenarios

This section describes the scenarios on which we test the interventions.

Scenario 1: Current situation
In scenario 1, we test the interventions on SPZ's current LB2 warehouse. We use the existing LB2 warehouse layout, the corresponding fixtures and assume a normal production of trucks per day without lines stops.

Scenario 2: Increased output of trucks
SPZ intends to increase the production of trucks to trucks per day next year. The aim is to produce trucks in the same production time. To increase the production in the same production time, more replenishments of fixtures per day are required. In this scenario, we assume that the takt time of the fixtures increases proportionally to the increase in production output. We calculate the required number of replenishments with an increased output with formula 5.3 and the new takt time with formula 5.4.

PT : Net. production time on a normal day. (in seconds)
O_{cur} : Current production output
O_{new} : New production output
$R_{i,cur}$: Current daily number of replenishments for fixture i
$R_{i,new}$: Daily number of replenishments for fixture i with increased production output
$L_{i,cur}$: Current takt time of fixture i (in seconds)
$L_{i,new}$: New takt time of fixture i with increased production output (in seconds)

$$R_{i,new} = \frac{O_{new} * R_{i,Cur}}{O_{cur}} \tag{5.3}$$

$$L_{i,new} = \frac{PT}{R_{i,new}} \tag{5.4}$$

In this scenario, we investigate if SPZ warehouse requires additional order pickers with the increase in output and what the impact is on the performance. The assignment model of Chapter 4 is used to find suitable assignment strategies for the increase in output.

Scenario 3: Adding extra picking aisles
SPZ plans to expand the LB2 warehouse with additional picking aisles in the near future. The plans for this expansion are already in an advanced stage. SPZ wants to extend the picking aisles of the BB & BC aisles and add an extra picking aisle. This extra picking aisle will be located next to the BC aisle. Figure 5.2 shows the expansion of the LB2-warehouse, where the green colored boxes indicate the extra added storage locations. In the new situation, SPZ's warehouse will have 92 extra storage locations. In addition, there will be placed a depot location at each front of a picking aisle. After the expansion reach trucks will continue to drive between the BD and BF aisle, which means that we have to take this into account by using a lower travel speed when an order picker has to pass between the BD and BF aisles.

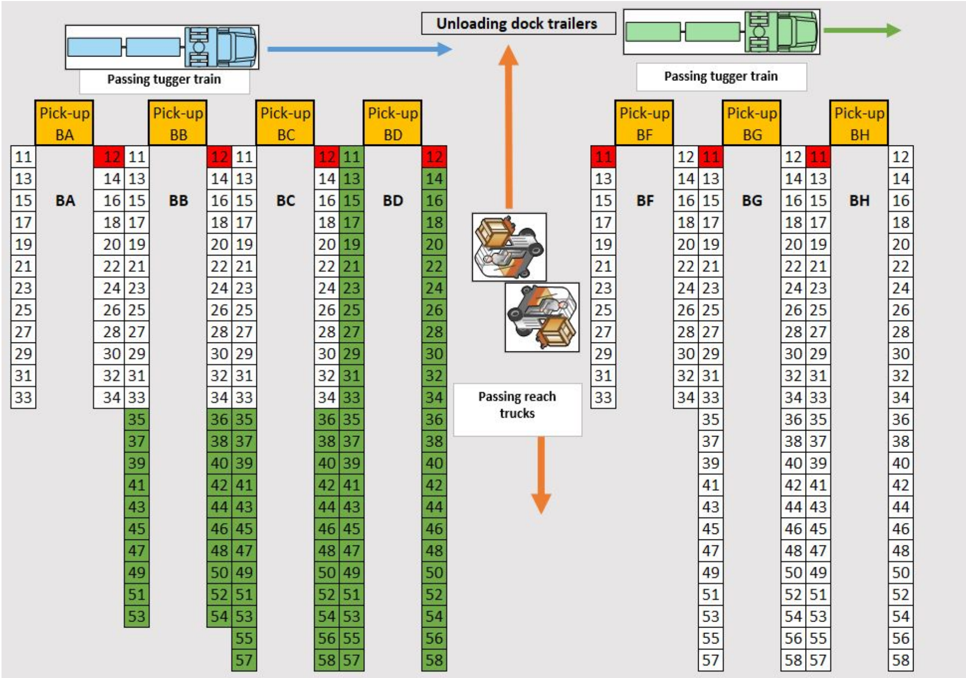


Figure 5.2: Expansion of the LB2-warehouse after construction

The addition of 92 extra storage locations means that more parts are stored in the warehouse and that extra fixtures are picked in the warehouse. Table 5.3 shows the extra fixtures that need to be picked in the (extra) picking aisles with their takt time and pick time.

The fixtures that will be picked extra in the LB2 warehouse are taken away from the HB-warehouse. The fixtures will be moved to the LB warehouse because these fixtures have a relatively high consumption in the HB-warehouse. Since the fixtures are picked in a different way in the HB-warehouse, it is unclear what the pick time per fixture in the LB2 warehouse will be. Therefore, we estimate the pick time by multiplying the average pick time of a part in the LB2 warehouse (approximately 15 seconds) with the average number of parts on a fixture. Since the parts on these fixtures have similar sizes and shapes as the parts that already being picked in the LB2 warehouse, we expect that the pick time of a part on these fixtures will be similar to other parts in the LB2 warehouse.

Table 5.3: Takt time and pick time of fixtures that added to the LB2 warehouse

Fixture	**Takt time (hh:mm:ss)**	**Avg. pick time (in sec.)**
LL662-EB-BB	01:33:20	167.73
LR662-EB-BB	01:33:20	167.73
LL140.1-G-EF-BD	07:00:00	70.96
LL120.1-EF-BD	01:16:22	70.96
LL311-EB-BC	02:48:00	334.82
Z07B116-EF-BB	02:00:00	99.58
Z06L120-KIT-EC-BD	02:15:00	510.07
SL535-EB-BB	03:30:00	167.73
SR122.1-EF-BD	02:48:00	70.96
SR304-EB-BC	07:00:00	334.82
SR486-EF-BB	07:00:00	99.58
Z06L129-P-KIT-EC-BD	04:40:00	510.07

Scenario 4: Increased output of truck and adding extra picking aisles
In scenario 4, we combine scenarios 2 and 3 and examine whether the SPZ warehouse needs additional order pickers when the warehouse is expanded with additional picking aisles and the truck output increases to trucks per day. Furthermore, we want to investigate whether the order pick efficiency improves when combining both scenarios.

5.5 Conclusions

This addresses the main conclusions of this chapter.

In this chapter we set up a simulation model to measure the order pick performance in the LB2 warehouse. The performance of the order picking process is measured with the KPIs Service level, tardiness, workload, travel distance and number of congestion situations. As input for the model we use historical data that contains pick lists of fixtures from the past. In the simulation model we simulate a stochastic arrival process of fixtures, stochastic order pick times and stochastic administration times.

The model uses a run length of 14 hours (net production time in one day) and does not require a warm-up period. To determine the number of replications, we used the sequential method from Law (2015). The method showed that when using 3 replications we obtain a confidence interval of 95%. The number of replications is low because the variability in the simulation model is also small. Additionally, we implement the CRN technique controll the randomness in the simulation model.

In the verfication process of the simulation model we use the verfication techniques of Kleijnen (1995). The code of the simulation model is checked on programming errors by running and debugging the code every few lines. In the debugging process we place breakpoints in our code and check if variables have the same value as we expect. We validate our model using facing validity and by comparing the results of the simulation model with actual data. For our model validation, we compare the mean pick time of order pickers, average number of parts per fixture and the average number of replenishments cycles on a day. We conclude that the average number of replenishments cycles and the number of parts per fixture in the simulation model corresponds with reality. In addition, we conclude that the average order pick time in the simulation provide a representative indication of the order pick times in reality.

The experimental design consists of 3 interventions and 4 scenarios. Intervention 1 focuses on a assignment strategy that minimizes the travel per order picker, intervention 2 focuses on an assignment strategy that balances the workload evenly over the order pickers and intervention 3 on an assignment strategy that has a trade-off between the two. The first scenario evaluates the current situation, the second scenario an increase in the output of trucks, the third scenario an expansion of the LB2-warehouse and the fourth scenario a combination of scenarios 2 and 3.

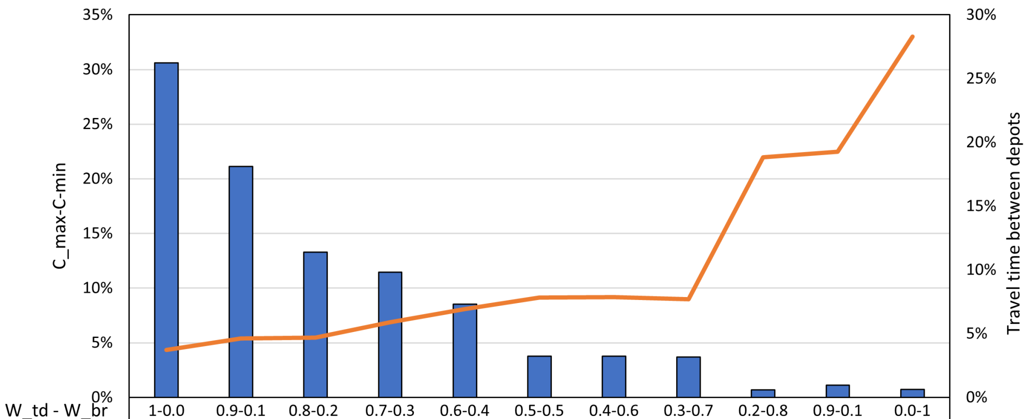
6 Experimental results

In Section 6.1 we determine the assignment strategies of intervention 1,2 and 3 with the assignment model. In addition, we evaluate the balancing ratio and travel time between the depots for each intervention. Section 6.2 compares the performance of the interventions in the simulation model. Section 6.3 compares the performance of the future scenarios with each other and elaborates on the impact of the scenario on the order picking performance. Next, Section 6.4 explains about the sensitivity analysis, where we examine the effect of an increase or decrease of the order pick time on the output parameters. Section 6.5 describes the return on investment of the expansion of the LB2-warehouse with the current output of trucks and with an increased output of trucks. Finally, Section 6.6 concludes the chapter.

6.1 Assignment strategies of interventions in scenario 1

In this section we describe the results of the assignment model at the various trade-off points for the current situation. Thereby, we can vary the weight for the objective minimizing travel time and the weight for balancing the workload. This section answers research question 4a.

Figure 6.1 shows the results of the assignment model at various trade-offs points between balancing the workload and minimizing the travel time of order pickers. The left side of the x-axis focuses entirely on minimizing the travel time (W_{td} = 1 and W_{br} = 0) and the right side of the x-axis focuses entirely on minimizing the balancing ratio (W_{td} = 0 and W_{br} = 1). Step by step, the weight factor for the balancing ratio increases with 10% and the weight factor for the travel time decreases with 10% until the assignment model fully minimizes the balancing ratio. At intervention 1, where the weight value for travel time between depots is 1 (W_{td} = 1) and the weight value for balancing ratio is 0 (W_{br} = 0) we observe a balancing ratio of 30.62%. This implies that in this intervention the workload is unbalanced over the order pickers. However, in this intervention we observe that the travel time between the depots for the order pickers is at a minimum. At intervention 2 (W_{td} = 0 and W_{br} = 1), we observe that the assignment model finds an assignment strategy with a balancing ratio of 0.75%. This implies that the workload is balanced over the order pickers. However, the travel time between the depots in this intervention increases from 3.71% up to 28.28% compared to intervention 1. The increase is a consequence of order pickers needing to pick more often in multiple picking aisles. Appendix F shows the workload per order picker and the travel time per order picker for intervention 1 and 2 provided by the assignment model.



W_td - W_br	1-0.0	0.9-0.1	0.8-0.2	0.7-0.3	0.6-0.4	0.5-0.5	0.4-0.6	0.3-0.7	0.2-0.8	0.9-0.1	0.0-1
cmax -cmin	30.62%	21.11%	13.27%	11.46%	8.53%	3.77%	3.76%	3.71%	0.68%	1.12%	0.75%
tj	3.71%	4.61%	4.68%	5.88%	6.93%	7.83%	7.85%	7.69%	18.83%	19.26%	28.28%

Figure 6.1: Trade-off between workload balance and minimizing the travel time in current situation

For intervention 3, we want to find a good trade-off point where we minimize the travel time and the balancing ratio. Therefore, the points (W_{td} = 0.8 and W_{br} = 0.2) and (W_{td} = 0.5 and W_{br} = 0.5) are interesting. At W_{td} = 0.8 and W_{br} = 0.2, the balancing ratio decreases to 13.27%, and the travel time per order picker is below 5%. At W_{td} = 0.5 and W_{br} = 0.5, the balancing ratio decreases to 3.77% and the travel time per order picker slightly increases to 7.83%. Both points show a good trade-off between the two factors with the first point focusing more on a reduction in the travel time and the second point focusing more on a reduction of the balancing ratio. We choose the point (W_{td} = 0.8 and W_{br} = 0.2) as the trade-off point for intervention 3 because we rather have a slightly larger balancing ratio than a further increase in travel time per order picker. The reason for this is that travel time per order picker does not add value to the order picking process. At the point (W_{td} = 0.8 and W_{br} = 0.2), the balancing ratio reduces with 17.35% and travel time per order picker only slightly increases with 0.97% compared to intervention 1.

Table 6.1 shows the assignment strategies of the three interventions. Intervention 1 provides the same assignment strategy as the one currently in use. This was expected because in the current situation, the travel time per order picker is already reduced by assigning all the fixtures that belong to a picking aisle to one order picker. In addition, order pickers are assigned to entire aisles that are adjacent to each other, which reduces the travel time between depots. Therefore, we conclude that it is not possible to further minimize the travel time between depots for order pickers. Intervention 2 provides an assignment strategy where order pickers are assigned to many different picking aisles. For example, order picker 1 is assigned to fixture in the BA, BC and BG aisle. Assigning order pickers to multiple fixtures in different aisles enables a more even distribution of the workload over the order pickers but increases the travel time per order picker. The assignment strategy of intervention 3, looks similar to the assignment strategy of intervention 1 except that order picker 1 has to pick one fixture less and order picker 4 has to pick two fixtures less. These fixtures are now picked by order picker 2 and 3 resulting in a better workload balancing ratio and a slight increase in travel time per order picker.

Table 6.1: Assignment strategies for interventions 1,2,3 (I1,I2,I3)

Fixture	Assignment I1	Assignment I2	Assignment I3
LR322-DBP-BA	O1	O4	O1
SR322-DBP-BA	O1	O3	O2
LL322-DBP-BA	O1	O1	O1
SL323-DBP-BA	O1	O1	O1
LR450-DBP-BB	O2	O3	O2
SL393-DBP-BB	O2	O3	O2
SL330-DBP-BC	O2	O2	O2
LL336-DBP-BC	O2	O1	O2
Y07C146-DBP-BF	O3	O3	O3
Y07C154-P-DBP-BF	O3	O3	O3
Y11B136-BP-BF	O3	O2	O3
Y10A156-DBP-BG	O3	O2	O3
Y10A106-PX-DBP-BG	O3	O1	O3
LR734-RECHTS-DBP-BH	O4	O4	O4
SL580-LINKS-DBP-BH	O4	O3	O3
SR578-RECHTS-DBP-BH	O4	O3	O3
LL734-LINKS-DBP-BH	O4	O2	O4

6.2 Comparison of interventions

In this section we answer research question 4B: what is the impact of interventions on the order picking performance? The interventions in this section are applied on the current situation (scenario 1). Based on the performance of the interventions, we will choose the best intervention which we use in the other scenarios.

Service level of order picker

The service level of an order picker indicates the percentage of the total number of replenishments an order picker picks a fixture within the takt time. A high service level is desirable because picking a fixture too late can lead to line stops. Figure 6.2 shows the average service levels per order picker of the three interventions for the current situation (scenario 1). If we look at the three alternatives, we observe that for each alternative the average service level per order picker is above 95%. This is as expected because the assignment model assigns the workload up to a maximum workload of 80%. Due to the 20% slack, a high service level can be maintained when the pick time of a fixture is larger than average. Based on the high service level in all interventions, we conclude that in all alternatives order pickers are able to pick the fixtures within the takt time.

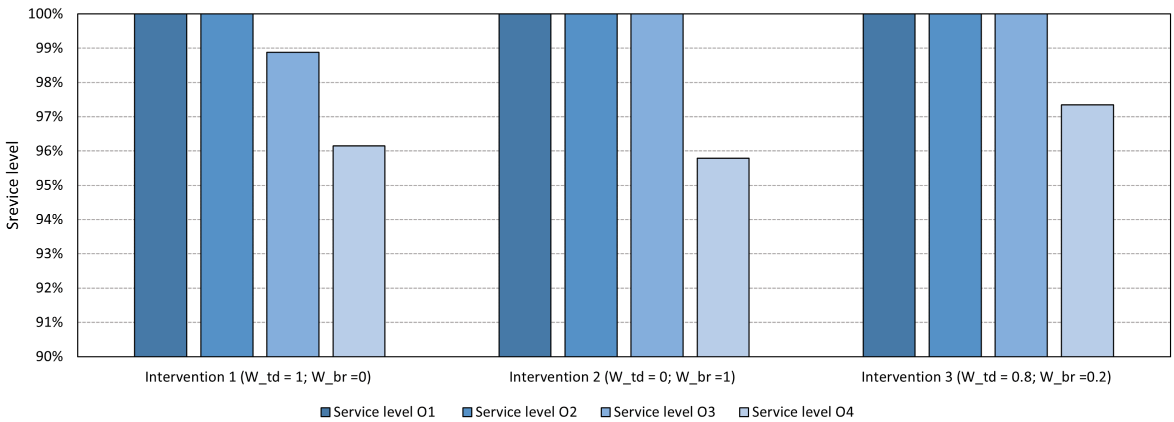


Figure 6.2: Comparison of service level per order picker at interventions

Tardiness

The tardiness of a fixture indicates how much time the picking process exceeds the takt time. A high tardiness of a fixture leads to long delays in the tugger train process and a possible line stop. A low tardiness indicates that the fixtures are picked a few seconds after the takt time, causing small delays in the tugger train process. A small delay does not immediately have major consequences and do not lead to a line stop. From conversations with order pickers, it appears that a tardiness of more than 2 minutes can lead to a major disruption in the tugger train process and possibly to line stops. Table 6.2 shows the tardiness of the fixtures that do not have a 100% service level. We observe that for all interventions the tardiness of a fixture remains below 2 minutes. We conclude that the tardiness for the three interventions remains within the boundaries of a small delay and that the interventions do not result in line stops.

Table 6.2: Tardiness (in sec.) of fixtures per intervention that do not have a 100% service level

Fixture	Intervention 1	Intervention 2	Intervention 3
SR578-RECHTS-DBP-BH	3.37	0.00	0.00
SR322-DBP-BA	63.70	0.00	35.50
Y10A156-DBP-BG	0.00	10.93	0.00
Y11B136-BP-BF	0.00	30.22	0.00

Workload per order picker
The workload of an order picker indicates what percentage of the net production time an order picker effectively spends on order picker activities. Ideally, we want to have an evenly distributed workload over the order picker. Figure 6.3 shows the workload levels of the order pickers per intervention. The order pickers per intervention are ranked in descending order of workload. The difference in workload between the order picker with the highest workload and the order picker with the lowest workload is equal to 29.14% at intervention 1, equal to 3.86% at intervention 2 and equal to 13.35% at intervention 3. We conclude that intervention 1 creates a huge unbalanced workload compared to intervention 2 and 3. Intervention 2 definitely performs the best on the KPI workload distribution and is recommended when SPZ wants to distribute the workload over the order pickers as much as possible.

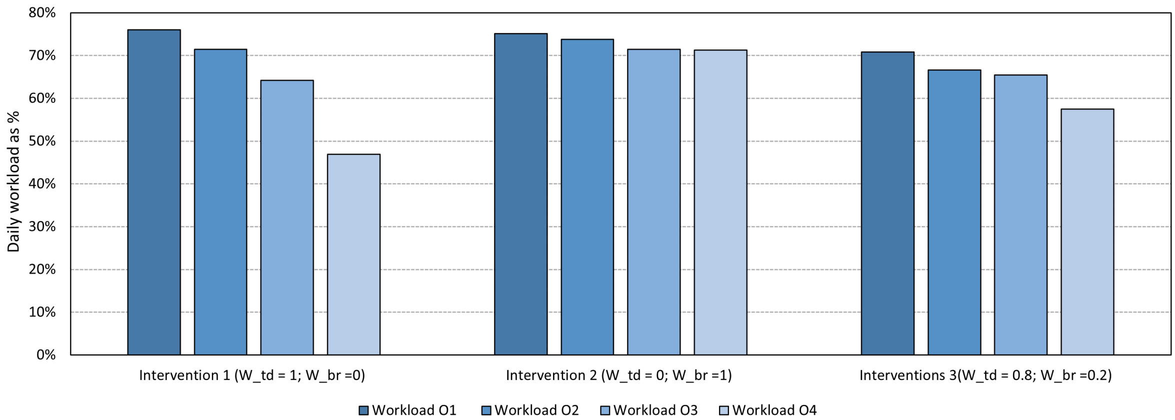


Figure 6.3: Comparison of workload per order picker at interventions

Travel Distance
In Figure 6.4 we compare the travel distance of the order pickers in the simulation model. The order pickers per intervention are ranked in descending order of travel distance. The figure shows that the travel distance for intervention 2 compared to intervention 1 almost doubles for each order picker. The sum of the travel distances in scenario 1 equals 11506 meters, in intervention 2 equals 22087 meters and in intervention 3 equals 12478 meters. The difference in travel distance between intervention 1 and 3 is relatively small and equal to 972 meters. If SPZ wants to reduce the travel distance as much as possible, we recommend to apply intervention 1. However, intervention 3 is also a good alternative for minimizing the travel distance.

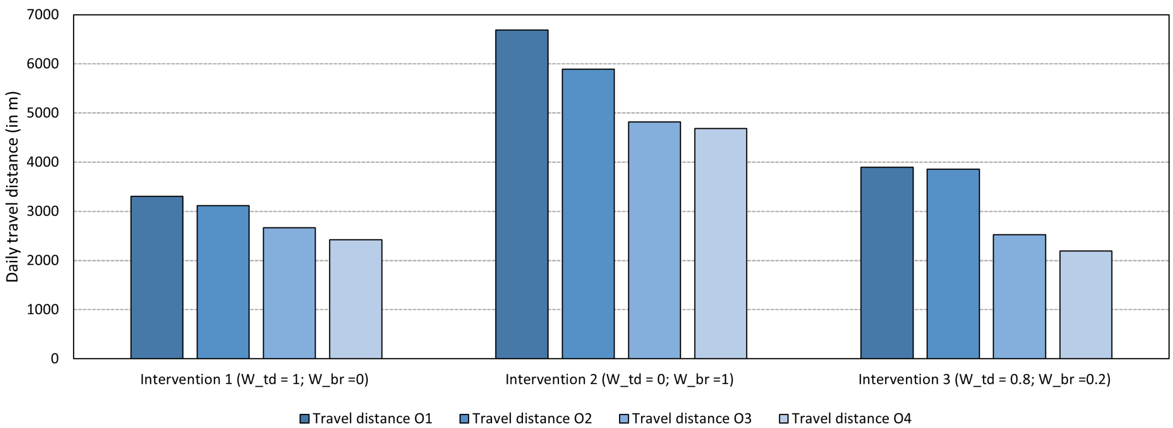


Figure 6.4: Comparison of travel distance per order picker at interventions

Number of congestion situations
The number of congestion situations measures how much congestion occurs in the picking aisles. Congestion causes order pickers to block each other, which can delay the order picking process. Table 6.3 shows the number congestion situations per aisle. As mentioned earlier, at intervention 1 there is no congestion because the order pickers are assigned to fixed set of picking aisles and responsible to pick the fixtures in the aisles to which they are assigned. By balancing the workload in intervention 2, order pickers are more often assigned to multiple picking aisles. This creates a lot of congestion in the picking aisles. At intervention 2, it sometimes happens that three order pickers are picking at the same time in an aisle, which raises the chance of congestion strongly. If SPZ allows multiple order pickers in an aisle, intervention 3 offers a good alternative because congestion is relatively limited in this scenario. However, if SPZ mainly wants to reduce congestion as much as possible, it is recommended to apply intervention 1.

Table 6.3: Comparison of congestions situations at intervention 1,2,3

Aisle	BA	BB	BC	BF	BG	BH	Sum
Congestions situations I1	0	0	0	0	0	0	0
Congestions situations I2	751	0	22	0	54	439	1266
Congestions situations I3	123	0	0	0	0	141	264

6.3 Comparison of scenarios

This section provides an answer on research question 4c: How will the order picking performance change in the future? First, we provide the assignment strategies per scenario and than we compare the performances of the assignment strategies using the KPIs of the simulation model

To obtain an assignment strategy for each scenario, we use intervention 3 in our assignment model. We choose this intervention because we concluded in Section 6.2 that this intervention is preferable if SPZ wants an improved workload ratio. When the assignment model has obtained an assignment strategy for each scenario we test the performance of the assignment strategy in the simulation model. Recall from Section 5.4 that we test the following scenarios.

Scenario 1: Current warehouse situation
Scenario 2: Current warehouse situation with increased truck output of trucks per day.
Scenario 3: Warehouse after expansion with current output of trucks per day.
Scenario 4: Warehouse after expansion with truck output of trucks per day.

Table 6.4 show the assignment strategies for the four scenarios. In scenario 2, 3 and 4 it is not possible to pick the fixtures with four order pickers and thus an extra order picker needs to be deployed in the warehouse. It is remarkable that in scenario 3 and 4 order pickers are much more often assigned to fixtures in multiple pick aisles. This is caused by the extra fixtures that need to be picked in the warehouse after the expansion. The extra fixtures that need to picked have relatively few replenishments per day and therefore have a relative low workload ($w_i \approx 0$) and low travel time between depot ($T_j \approx 0$). Due to the low workload and low travel between depots of the fixture, assigning these fixtures to an order picker has almost no impact on the total workload of an order picker.

Table 6.4: Fixture to order picker assignment per scenario

Fixtuur	Scenario 1	Scenario 2	Scenario 3	Scenario 4
LL322-DBP-BA	O1	O1	O1	O1
LR322-DBP-BA	O1	O1	O1	O1
SL323-DBP-BA	O2	O5	O4	O2
SR322-DBP-BA	O1	O2	O2	O3
LL662-EB-BB	-	-	O2	O1
LR450-DBP-BB	O2	O2	O2	O2
LR662-EB-BB	-	-	O1	O2
SL393-DBP-BB	O2	O2	O3	O2
SL535-EB-BB	-	-	O1	O1
SR486-EF-BB	-	-	O2	O4
Z07B116-EF-BB	-	-	O2	O2
LL311-EB-BC	-	-	O4	O2
LL336-DBP-BC	O2	O5	O2	O3
SL330-DBP-BC	O2	O5	O3	O2
SR304-EB-BC	-	-	O5	O2
LL120.1-EF-BD	-	-	O4	O2
LL140.1-G-EF-BD	-	-	O4	O2
SR122.1-EF-BD	-	-	O4	O2
Z06L120-KIT-EC-BD	-	-	O4	O3
Z06L129-P-KIT-EC-BD	-	-	O5	O3
Y07C146-DBP-BF	O3	O5	O3	O5
Y07C154-P-DBP-BF	O3	O3	O3	O5
Y11B136-BP-BF	O4	O4	O5	O2
Y10A106-PX-DBP-BG	O4	O4	O3	O3
Y10A156-DBP-BG	O4	O4	O4	O5
LL734-LINKS-DBP-BH	O3	O3	O5	O4
LR734-RECHTS-DBP-BH	O3	O3	O3	O4
SL580-LINKS-DBP-BH	O4	O4	O5	O3
SR578-RECHTS-DBP-BH	O4	O4	O5	O5

Service level of order picker

Figure 6.5 shows the service level per order picker for each scenario. We observe that for scenarios 1, 2 and 3 the service level is above 95%. Therefore, we conclude that order pickers in these scenarios are able to pick the fixtures frequently enough within the takt time. In Scenario 4, we observe a service level of 80.85%, which means that an order picker cannot replenish a fixture within the takt time in 1 out of 5 replenishments. The drop in service level could lead to possible delays in the tugger train process and thus in possible line stops. However, it might be that this drop in service level arises because an order picker is only a few seconds late in some replenishment cycles (low tardiness). However, when the tardiness in this scenario is high, this scenario leads to too much disruptions in the tugger train process, which results in line stops. The tardiness in this scenario will determine whether the assignment strategy that belongs to this scenario is feasible.

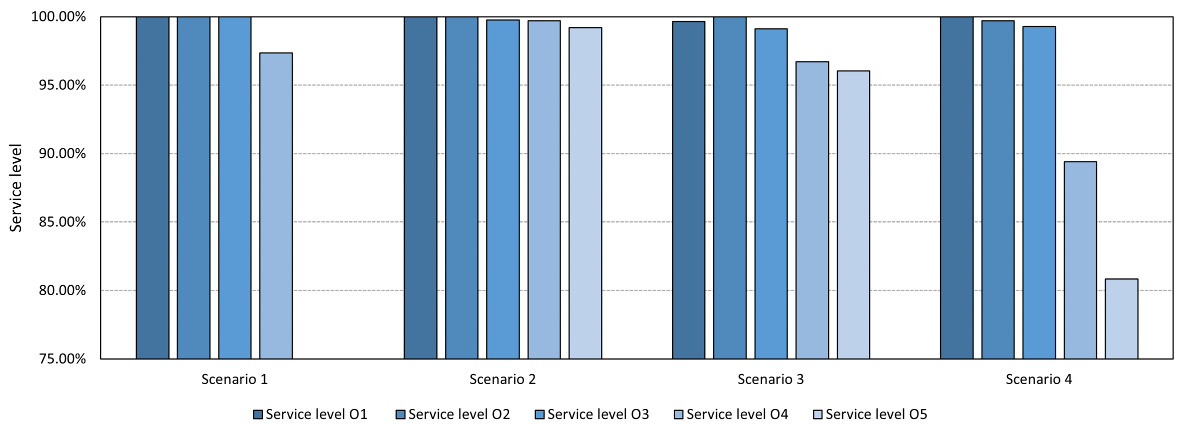


Figure 6.5: Comparison of service level per order picker in scenarios

Tardiness

Table 6.5 shows the tardiness of the fixtures that do not have a 100% service level for a particular scenario. We observe that for all scenarios the tardiness of a fixture remains below 2 minutes, which means that the tardiness is within the boundaries of a small delay (0-2 minutes). In scenario 3, we observe a relatively high tardiness for fixture Z06L129-P-KIT-EC-BD. The high tardiness is created because this fixture needs only a few replenishment per day (R_i = 3) but has a relatively high pick time (P_i = 510.07 sec.), which has a major impact on the tardiness. For example, suppose an order picker is assigned to two fixtures. The first fixture needs 56 replenishments per day (takt time = 15 minutes) with a pick time of 300 seconds and the second fixture needs one replenishment per day (takt time = 420 minutes) with a pick time of 1800 seconds. The workload of the first fixture then equals ((56 * 300) / 50400) * 100 = 33.33% and the workload of the second fixture equals ((1 * 1800) / 50400) * 100 = 3.57%. If both fixtures are assigned to the same order picker, this results in a total workload of 36.9% for the order picker (without counting the travel time between depots). Adding the second fixture to the order picker has a relatively low impact on the total workload of the order picker. However, that one time on a day when the order picker has to pick the second fixture the order picker cannot replenish the other fixture that has a takt time of 15 minutes. As a result, the other fixture is picked way too late which results in high tardiness. A high tardiness for a fixture with a low takt time and a high pick time is mainly a theoretical problem because in the simulation model an order picker needs to pick a complete fixture before the order picker can start picking another fixture. In reality, a fixture with a high pick time and a low takt time will not be picked in one go, but will be picked in pieces.

Table 6.5: Tardiness (in sec.) of fixtures per scenario that do not have a 100% service level

Fixture	Scenario 1	Scenario 2	Scenario 3	Scenario 4
SR322-DBP-BA	35.50	0.00	0.00	5.56
LR734-RECHTS-DBP-BH	0.00	0.16	0.00	0.00
SL330-DBP-BC	0.00	4.14	0.00	0.00
LL734-LINKS-DBP-BH	0.00	0.00	5.49	0.00
Y10A156-DBP-BG	0.00	0.00	2.82	0.00
Z06L120-KIT-EC-BD	0.00	0.00	63.21	0.00
Z06L129-P-KIT-EC-BD	0.00	0.00	108.44	0.00
Z07B116-EF-BB	0.00	0.00	14.00	0.00
SL580-LINKS-DBP-BH	0.00	0.00	28.26	0.00
LL120.1-EF-BD	0.00	0.00	2.22	0.00
SL323-DBP-BA	0.00	0.00	2.97	0.00
LL662-EB-BB	0.00	0.00	0.00	22.79
LR662-EB-BB	0.00	0.00	0.00	47.36

Workload per order picker

Figure 6.6 compares the workload levels of the order pickers per scenario. We observe in scenario 2 that the workload is more unbalanced compared to scenario 1. The workload per fixture increases proportionally with the extra truck output. As a result, the increase in the workload for the fixtures that already have a high workload is much higher than the fixtures that have a low workload. This enlarges the workload differences and makes it more difficult to balance the workload over the order picker. We observe a similar situation between scenario 3 (truck output =) and scenario 4 (truck output =) where the workload imbalance also increases. The workload for an order picker in scenario 4 equals 85%. This is slightly higher than the maximum workload of 80%. However, the tardiness of scenario 4 does not exceed the maximum value, which means that this assignment does not lead to delays in the tugger train process and possible line stops. In scenario 4, the same number of order pickers are required as in scenario 2 and 3. Additionally, scenario 4 is a combination of scenario 2 and 3, which means that SPZ's order picker capacity is used more efficient when both scenarios are implemented together (scenario 4) instead of separate.

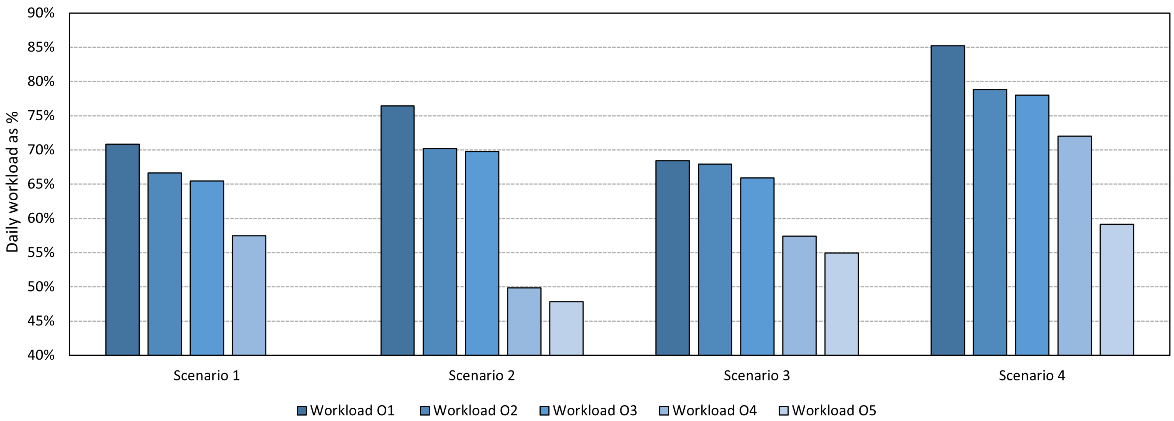


Figure 6.6: Comparison of workload per order picker in scenarios

Average travel distance
Figure 6.7 compares the travel distances of the order pickers per scenario. The average travel distance in scenario 1 equals 3119.68 meters and in scenario 2 it equals 2954.26 meters. The increase in output to trucks (scenario 2) requires an additional order picker. Due to the use of the extra order picker, the average travel distance per order picker in scenario 2 is approximately the same compared to the current situation. However, when the extra picking aisles and fixtures are added to the warehouse (scenario 3) the average travel distance increases to 3817 meter. The extra picking aisles increase the average travel distance per order picker with approximately 700 meters compared to the current situation, despite one extra order picker in scenario 3. Due to the increase in the output of trucks and the extra picking aisles the average travel distance per order picker in scenario 4 increases to 4262.52 meters.

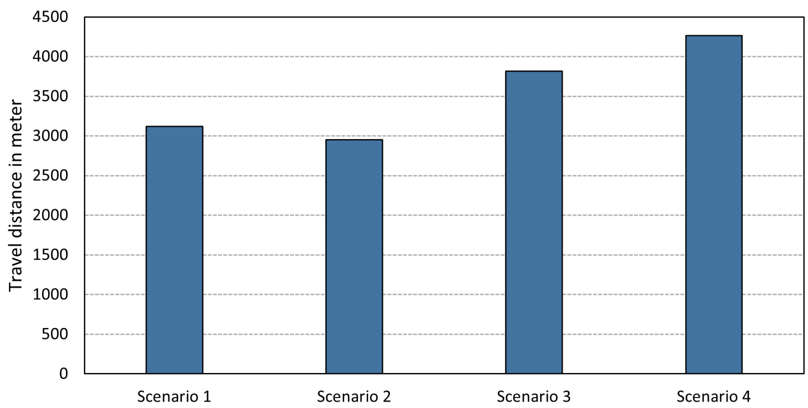


Figure 6.7: Comparison of average travel distance per order picker in scenarios (in meters)

Congestion
Table 6.6 shows the congestion in the picking aisles for each scenario. Congestion mainly occurs in the BA and BH aisles. This is because the number of replenishments of fixtures in these picking aisles is much higher than in the other picking aisles. A higher number of replenishments increases the chance of congestion. When the output equals trucks per day, congestion can be avoided by assigning one order picker to all the fixtures in the BA aisle and one order picker to all the fixtures in the BH aisle. However, when the output increases

to trucks per day it is no longer possible to pick all the fixtures in the BA or BH aisle with one order picker. Consequently, with an output of trucks per day, congestion will be inevitable.

If we look at the differences between scenarios 1 and 2, we observe that the congestion is more than doubled due to the increase in output. If SPZ increases its truck output in the future, this is a important factor to consider as congestion can delay the picking process. By adding an extra pick aisle with fixtures, order pickers have to pick more often in multiple picking aisles, which increases congestion as well.

Table 6.6: Comparison of congestions in scenarios

Aisle	**BA**	**BB**	**BC**	**BD**	**BF**	**BG**	**BH**	**sum**
Scenario 1	123	0	0	0	0	0	141	264
Scenario 2	489	0	0	0	0	0	309	798
Scenario 3	216	129	56	35	3	94	511	1044
Scenario 4	425	55	86	86	0	77	324	1053

6.4 Sensitivity analysis

To determine which input parameters have the greatest effect on the output parameters, we perform a sensitivity analysis. In this sensitivity analysis, we change the average order picking times of the fixtures and examine how sensitive the performance of the assignment strategy is to the change in input.

Recall from Section 5.3.2 that no accurate measurements are made of the average order pick time. Therefore, we examine the effect of a deviating average order pick time on the output parameters in a sensitivity analysis. We vary the average pick time of a fixture from -20% up to +20% of the current pick time and examine the effect on the average congestion per order picker, average travel distance per order, average service level per order picker and the balancing ratio. We use the weight ratio W_{td} = 0.8 and W_{br} = 0.2 of scenario 3 and the current output of trucks. We let the assignment model create an assignment strategy when the picking time is -20%, -10%, 0, +10%, +20% and then we put this assignment strategy into the simulation model where we adjust the average picking time of a fixture with the same factor.

Figure 6.8 shows the sensitivity analysis where we observe three colored areas. The colored areas indicate the number of order pickers needed. A change in the average pick time affects the required number of order pickers. In the orange area, when the average order pick time of a fixture is 20% lower than the current average pick time, the assignment model assigns the 17 fixtures to three order pickers. In the green area when the average pick time is between -10% and +10% the assignment model assigns the fixtures to four order pickers and in the blue area when the average pick time of a fixture is +20% the assignment model assigns the fixtures to five order pickers.

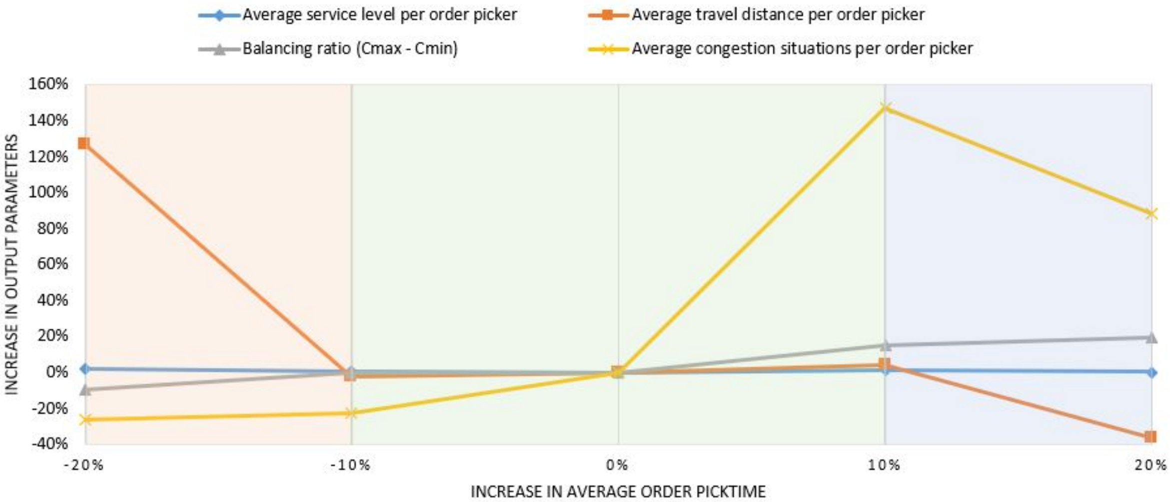


Figure 6.8: Sensitivity analysis

Average travel distance per order picker
At an average decreased picking time of -20%, we observe an increase of 126.5% in the average travel time per order picker. The main reason for this is that with a -20% average picking time, 3 order pickers are used. As a result, the order pickers have to travel a much larger distance to pick all the fixtures. In the green area with 4 order pickers, the average travel time per order picker already decreases considerably and remains constant up to an increase of +10% in the average pick time. When the average pick time per fixture increases to +20%, the average travel time per order picker decreases with 36.5% because 5 order pickers are used and the order pickers are assigned more frequently to a single picking aisle, which reduces the average travel distance.

Average service level per order picker
In Figure 6.8 we observe that the average service level per order picker is constant. This is because we use the maximum workload level of 80%, which means that any delays in the picking process or arrival process can be handled and do not immediately lead to a lower service level. In addition, the number of order pickers increases when the total workload of the fixtures exceeds the workload that the order pickers can handle, which maintains a high service level.

Balancing ratio
If we look at the balancing ratio, we observe that it slowly increases from -10% to +15% with a weight. The increase arises because in the orange area we can distribute the workload of 17 fixtures over 3 order pickers, which gives more possibilities to distribute the workload more evenly, while in the blue area we have to distribute the workload of 17 fixtures over 5 order pickers, which gives less possibilities to distribute it more evenly over the order pickers.

Average congestion per order picker
If we look at the average congestion per order picker, we observe a fluctuating line that goes from -26% with an average order pick time of -20% up to +147% with an average order pick time of +10%. The huge increase in the number of congestion situations at an increase of +10% average order picking time arises because the workload of the fixtures belonging to a pick aisle becomes too high, forcing multiple order pickers to pick in the same picking aisle. Since multiple order pickers are assigned to fixtures in the same picking aisle, more congestion situations arise. However, in the blue area with five order pickers, we observe that the average number of congestion situations decreases. In comparison with the situation in the orange area where four order pickers are deployed in the warehouse, the order pickers are less frequently assigned to

multiple picking aisles. This means that an order picker in the blue area is more often responsible for a single picking aisle, which reduces the number of congestion situations.

6.5 Return on investment of expansion of LB2-warehouse

SPZ wants to know what the return on investment is for the costs of expanding the LB2-warehouse. By transferring parts from the high-bay warehouse to the LB2-warehouse, where order picking is more efficient, it may be possible to save one order picker.

The expansion of the LB2 warehouse is planned to have sufficient warehouse capacity for an output increase to trucks per day. Due to the increased output, SPZ needs to store more parts and thus needs to add extra storage locations. SPZ chooses to expand the LB2-warehouse because in the LB2-warehouse there is still some space left for expansion and because picking in the LB2-warehouse is more efficient compared to picking in the HB-warehouse.

If SPZ increases to an output of trucks per day without expanding the LB2-warehouse, it would need an extra order picker in the HB-warehouse because the fixtures that are picked there require more replenishments per day. If SPZ finishes the expansion of the LB2-warehouse without an output increase, fixtures with a relatively high workload in the HB-warehouse are transferred to the LB2-warehouse. As a result of this transfer, one order picker is saved in the HB-warehouse. However, due to the transfer of the fixtures from the HB-warehouse to the LB2-warehouse an extra order picker is required in the LB2-warehouse. Therefore we do not save an order picker at an output of trucks but only transfer the order picker from the HB-warehouse to the LB2-warehouse.

When SPZ finishes the expansion of the LB2-warehouse and increases the output to trucks per day, SPZ needs 5 order pickers in the LB2-warehouse, which means that we save 1 order picker in the HB-warehouse. For one Full Time Employee (FTE), SPZ calculates an annual salary of . Since SPZ works in shifts we can assume annual costs of 2x per year. The estimated total cost of expanding the LB2-warehouse is , which means that the return on investment of the expansion of the LB2-warehouse is = 4.55 years in case the truck output equals trucks.

Except the saving of one FTE for the picking process, the expansion of the LB2-warehouse also results in additional bulk storage (above ground level). Furthermore, the expansion of the LB2 warehouse ensures that SPZ has sufficient storage capacity to scale up to an output of trucks per day and the additional output of the number of trucks will lead to higher turnover for SPZ.

6.6 Conclusions

In this section we summarize the main conclusions of this chapter

This chapter discussed the results of the interventions and scenarios using a simulation model. We determined the KPIs of the interventions and compared the performance of the interventions with each other. In addition, we analysed scenarios and provide a sensitivity analysis to show what the effect is of changing the average picking time on the output parameters. Finally, we provided a financial analysis on the return on investment of the expansion of the LB2-warehouse.

We tested three interventions on the current situation (scenario 1). The first intervention focuses on minimizing the travel time per order picker, the second on balancing the workload over the order pickers and the third on a trade-off between the two. If we implement the three proposed interventions, this will not lead to disturbances in the tugger train process and possible line stops because all intervention show a high service level and a tardiness within the boundaries of a small delay. Intervention 1 and 3 showed promising results, whereas intervention 2 looks not desirable. Table 6.7 show a summary of the results of the interventions.

Table 6.7: Key performance indicators per intervention

Key Performance Indicator	Intervention 1	Intervention 2	Intervention 3
FTE	4	4	4
Average service level per order picker	98.76%	98.95%	99.34%
Maximum tardiness of a fixture	63.70 sec	30.22 sec	35.50 sec
Balancing ratio	29.15%	3.86%	13.35%
Average travel distance per order picker	2876.68 m	5521.94 m	3119.69 m
Congestion situations in aisles	0	1266	264

We applied intervention 3 to three near future scenarios and compare the performance with the current situation to provide future proof recommendations. The first scenario evaluates the current situation with a daily truck output of , the second an increase in the daily truck output to , the third an expansion of the LB2-warehouse with extra picking aisles and a daily output of trucks, and the fourth an expansion of the LB2-warehouse with extra picking aisles and a daily output of trucks. Table 6.8 shows a summary of the KPIs per scenario.

Table 6.8: Key performance indicators per scenario when applying intervention 3

Key Performance Indicator	**S1: Current situation**	**S2: Daily truck output:**	**S3: Expansion of LB2-warehouse**	**S4: Truck output: & Expansion of LB2-warehouse**
FTE	4	5	5	5
Average service level per order picker	99.34%	99.73%	98.30%	93.85%
Maximum tardiness of a fixture	35.50 sec	4.14 sec	108.44 sec	47.36 sec
Balancing ratio	13.35%	28.58%	13.54%	26.08%
Average travel distance per order picker	3119.69 m	2954.26 m	3817.85 m	4262.52 m
Congestion situations in aisles	264	798	1044	1053

We conclude that in all scenarios the assignment model provides an assignment strategy that is feasible. Moreover, we conclude that the order pick capacity is better utilized in scenario 4 compared to scenario 3 because both scenario require 5 order pickers, whereas the output in scenario 4 is 40 trucks higher. When we look at the number of congestion situations in the picking aisles we conclude that we cannot avoid congestion with an truck output of trucks because it no longer possible to pick all the fixtures in the BA or BH with 1 order picker. Adding an extra picking aisle with fixtures results in more congestion situations because order pickers have to pick more often in multiple picking aisles.

In the sensitivity analysis we showed how sensitive the output parameters are on a change in the pick time. We observe that with a pick time between -10% and +10% the assignment model assigns the fixtures to 4 order pickers. Above or below this change the number of order pickers alters. Moreover, we conclude that the travel distance is sensitive to a change in pick time. If we look at the sensitivity of the service level, we observe that it is not sensitive to a change in the picking time because the number of order pickers increases with an increase of the picking time and because the order pickers have a maximum workload of 80% in the assignment model. Furthermore, we noticed that the balancing ratio is slightly sensitive to an increase in picking time. Due to an increase in picking time, more order pickers are needed in the model, which makes it more difficult to balance the workload over the order pickers.

We conclude that the expansion of the LB2-warehouse cannot be regained with a saving in the number of FTE's if the current output of trucks is maintained. However, when SPZ increases the output to trucks after the expansion, an order picker in the HB-warehouse can be saved. As a result, the return on investment of the expansion of the LB2-warehouse becomes years.

7 Conclusion, recommendations and discussion

This chapter presents the conclusions, recommendations and discussion of this research. Section 7.1 draws a conclusion about the current workload distribution in the LB2-warehouse, the order pick performance of the various interventions and the order pick performance in the future. Section 7.2 provides recommendations to improve the current and future capacity utilization in the LB2-warehouse. Finally, Section 7.3 provides the discussion of this research.

7.1 Conclusions

Order pickers in the LB2-warehouse face a varying workload throughout the day, which lead to overcapacity and undercapacity in the LB2-warehouse. The cause of this problem is that SPZ does not have an appropriate method to assign the workload to the order pickers. We examined whether a method could be developed that assigns the workload in the LB2-warehouse to a minimal number of order pickers and take into account the travel time and workload distribution of order pickers.

Currently, SPZ uses the forecast on the number of picks per day to estimate the workload. The forecast on the number of picks does not provide any information about the workload that is required to pick these items. Therefore, the forecast on the number of picks is inadequate to predict the required workforce in the LB2-warehouse.

We investigated the properties of our problem and compared this with the problem characteristics of the VRP, IPMP and BPP. We conclude that a BPP best fits our problem because we prefer finding a minimum number of order pickers over balancing the workload. We formulated a mathematical problem that is based on a BPP formulation. To solve the mathematical model, we developed a general solution approach that consists of two steps. In the first step, a best-fit heuristic provides an initial solution to our problem and provides an upper bound on the number of order pickers. In the second step, we use the output of the first step as input for a SA heuristic to search for an improved solution with the use of a multi-objective function that focuses on minimizing the number of order pickers but also includes the balancing ratio and the travel time of order pickers.

To test the performance of our assignment model under stochastic conditions we set up a simulation model. The simulation model simulates a stochastic arrival process of fixtures, stochastic administration times and stochastic order picking times for parts. The performance of an assignment strategy is determined based on the KPIs: service level, tardiness, balancing ratio, travel distance and congestion.

We tested three interventions on the current situation. The first intervention focuses on minimizing the travel time per order picker, the second on balancing the workload over the order pickers and the third on a trade-off between the two. We conclude that all interventions provide an assignment strategy that results in a tardiness below 2 minutes, which means that the interventions do not lead to any disturbances in the tugger train process or line stops. Intervention 2 performs well on the balancing ratio KPI but leads to a travel distance that almost doubles and much congestion in multiple aisles. Therefore, we do not recommend to implement intervention 2. We advise SPZ to implement intervention 1 when SPZ wants to minimize the travel distance per order picker as much as possible or reduce congestion as much as possible. We advise SPZ to implement intervention 3 when SPZ wants an improved workload balancing ratio and is willing to allow order pickers to travel a bit more.

We applied intervention 3 to three near-future scenarios and compare the performance with the current situation (scenario 1) to provide future proof recommendations. The first scenario evaluates the current situation with a daily truck output of , the second an increase in the daily truck output to , the third an expansion of the LB2-warehouse with extra picking aisles and a daily output of trucks, and the fourth an expansion of the LB2-warehouse with extra picking aisles and a daily output of trucks. Scenarios 2,3 and 4 require an additional order picker in the LB2-warehouse. We conclude that all scenarios provide an assignment strategy that results in a tardiness below 2 minutes, which means that the scenarios do not lead to any disturbances in the tugger train process or line stops. In scenarios 2 and 4, where the truck output increases, we observe a more unevenly distributed workload over the order pickers than in scenarios 1 and 3. We conclude that a workload increase makes it more difficult to balance the workload over the order pickers. Despite an extra order picker in scenarios 3 and 4, the average travel distance per order picker increases due to the increase in output of trucks. In addition, the number of congestion situations rises as well, because order pickers need to be in the same picking aisle more often. In Scenarios 2 and 4 congestion is inevitable because the workload of the fixtures in the BA and BH aisle is too high for a single order picker.

We conclude that the expansion of the LB2-warehouse cannot be regained with a saving in the number of FTEs if the current output of trucks is maintained. However, when SPZ increases the output to trucks after the expansion, an order picker in the HB-warehouse can be saved. As a result, the return on investment of the expansion of the LB2-warehouse becomes 4.55 years.

We conclude that this research provides a future-proof assignment model for the LB2-warehouse of SPZ that finds an assignment strategy with a minimal number of order pickers and takes into account the travel time and workload distribution of the order pickers. The assignment model is future-proof because it can be used regardless of LB2-warehouse size or truck output. In this research at SPZ, we could not save an order picker in the current situation (scenario 1) because the currently used assignment strategy is an appropriate assignment strategy to minimize the number of order pickers and because the LB2-warehouse is a relatively small warehouse with few picking aisles. We expect that when we use the assignment model in a warehouse with more picking aisles and more fixtures, the assignment model provides more promising results.

This study contributes to theory since we are the first who developed a method to assign the workload to a minimal number of order pickers and can make a trade-off between minimizing the travel time and balancing the workload of order pickers. What makes our research unique is the method to calculate the travel time between the depots for an order picker. We expect that the developed method to assign the workload to order pickers is generic applicable to other warehouses. However, we expect that the method to determine the workload and travel time for an order picker in this research is company-specific, which means that this is not directly applicable in other warehouses.

7.2 Recommendations

This section provides the recommendations of this research

7.2.1 Recommendations on the proposed model

- We recommend SPZ to use the assignment model of this research to assign order pickers to the workload. Assigning pickers with the assignment model prevents over and under capacity in the LB2-warehouse. Since the assignment model uses a maximum workload level of 80% a high service level is maintained.

- We advise SPZ to implement intervention 1 when SPZ wants to minimize the travel distance per order picker as much as possible or reduce congestion as much as possible. We advise SPZ to implement intervention 3 when SPZ wants an improved workload balancing ratio and is willing to allow order pickers to travel a bit more. We do not advise SPZ to implement intervention 2 because the travel distance almost doubles and there is much congestion in multiple picking aisles

- We advise SPZ to speed up to an output increase of trucks as soon as the expansion of the LB2-warehouse has been finished because the cost of the expansion of the LB2-warehouse cannot be regained with a saving in the number of FTEs when the current output of trucks is maintained. However, when SPZ increases the output to trucks after the expansion, an order picker in the HB-warehouse can be saved and the return on investment of the expansion of the LB2-warehouse is 4.55 years.

7.2.2 Other recommendations

- We advise SPZ to gather more data about the picking process. In the assignment model, the picking times of the work standards are used which only give an indication of the actual picking time. More accurate measurements of the picking time enable a better estimation of the workload. A better estimation of the workload in the assignment model provides a more accurate assignment strategy.

- Our model does not take into account the safety of the order pickers. We advise SPZ to study the effects on the safety of the order pickers when the assignment model is used. The study should focus on which possible unsafe situations can occur and what the probability of these unsafe situations will be. If this study shows that the use of the assignment model leads to more unsafe situations, additional rules and safety requirements must be drawn up to reduce the unsafe situations. A possible safety risk that may arise is congestion between order pickers in the picking aisles. However, we expect this safety risk to be minimal because order pickers travel at a low speed. Another possible safety risk arises when order pickers have to overpass between the BC and BF aisle more frequently because the chance of a collision between an order picker and a reach truck driver increases. This safety risk is much higher because reach trucks move through the warehouse at a much higher speed, which increases the impact of a possible accident.

- We advise SPZ to investigate the effect of congestion on the picking time. The current assignment strategy does not allow order pickers to pick together in a picking aisle. Therefore, the effect of congestion on the picking time is unknown. The expectation is that a high level of congestion will lead to significantly higher picking times. In addition, we showed that SPZ cannot avoid congestion if the truck output increases to trucks per day, which makes this study relevant for the future.

- There are some practical issues that SPZ should take into account when implementing an assignment strategy generated by the assignment model. First, SPZ needs to investigate whether fixtures are not too wide to pass each other when congestion arises in a picking aisle. Second, SPZ needs to take into account that order pickers may have to wait for each other at a depot location. In the current situation, each order picker is assigned to a fixed set of picking aisles with a single depot location. Using the assignment model, multiple order pickers might be assigned to a picking aisle and want to use a depot location at the same time. As a result, order pickers may have to wait for each other.

7.3 Discussion

In this section, we discuss the research limitations and suggestions for further research.

7.3.1 Research limitation

- In the assignment model of Chapter 4, we use the best-fit heuristic to find an initial solution. The outcome of the best-fit heuristic is used as input for the SA. In the SA, we use move and swap operators to improve the solution. The move operators moves 1 item and the swap operators swaps 2 items with each other. When there are many items in a solution (large solution space) a performed move or swap makes a relatively small change to the solution. As a result, many swaps and moves are required to search for a good solution, which is obviously very time-consuming. By giving the SA multiple initial solutions at the start of the heuristic the SA can find a good solution more quickly and the solution quality may increase.

- In the SA we do not temporarily accept infeasible solutions. For example, when a neighborhood solution exceeds the maximum workload of an order picker we do not accept the solution and do not count the iteration. By temporarily accepting a neighborhood solution that exceeds the maximum workload, a feasible and improved solution can be found in the subsequent iterations, which is exactly the strength of SA. Since we did not apply this in this research, the solution quality may be reduced. We could solve this problem by adding an extra penalty function in the multi-objective function that charges a penalty cost when the maximum workload of order pickers exceeds.

- As explained with the example in Section 6.3 the tardiness of a fixture can be very high due to fixtures that require only a few replenishment per day but have a relatively high order pick time. Fixtures with these properties have a relatively low impact on the total workload of an order picker in the assignment model. However, in the simulation model the fixtures with these properties often result in a high tardiness. This is due to their long pick time that only occurs a few cycles per day. As a result, an order picker cannot pick the other fixtures to which he is assigned within the takt time. The assignment model cannot cope with fixtures that have these properties, because the assignment model does not take into account the possible tardiness of a fixture.

7.3.2 Suggestions for further research

- In the current situation, order pickers need to travel to a depot location at the start of a replenishment of a fixture. Subsequently, the order picker needs to request a pick list, print it and sign off after picking. This process takes about 60 seconds on average and has a significant impact on the workload of an order picker. Since these activities do not add value to the order picking process, we advise SPZ to conduct further research on reducing the so-called administration time. SPZ should investigate the implementation of online pick lists that are displayed on a portable device such that order pickers no longer need to travel to a depot location and pick lists no longer have to be physically printed.

- In our assignment model, travel time increases when we want to improve the balancing ratio. This is because order pickers are more frequently assigned to multiple fixtures in different picking aisles, which results in more travel distance. However, this method of balancing the workload is not preferred because more travel distance does not add value to the order picking process. SPZ should investigate how they can distribute the workload in the picking aisles by moving fixtures and their corresponding parts. For example, the workload in the BF aisle is currently relatively low and the workload in the BA aisle is relatively high. By swapping fixtures + parts from the BA-aisle with fixtures + parts from the BF-aisle, the workload in the BA-aisle can be reduced and the workload in the BF-aisle can be increased, which results in a more balanced workload. By balancing the workload in this way and maintaining the current assignment strategy where the travel distance is minimized, an order picker does not have to travel more distance for a more balanced workload

- At SPZ, the usage of real-time data can optimize the picking process in the LB2-warehouse. Currently, SPZ uses an offline planning model, which makes it difficult to deal with stochasticity. For example, one of the assembly lines might stop, which means that fixtures arrive with a delay in the LB2-warehouse. As a result, order pickers wait until the fixtures to which they are assigned arrive and then start replenishing the fixtures.

However, if SPZ would use an online planning model where we can monitor the arrival progress of fixtures, SPZ can deal with the stochasticity by real-time assignment of arriving fixtures to order pickers. When there is a delay in the arrival process of a fixture, order pickers can be temporarily assigned to other fixtures that are not delayed, so that the order picker does not have to wait.

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Appendices

A Supply methods

This section describes the internal supply methods at SPZ.

The supply of parts to the assembly line is called part feeding. The part feeding process consists of two types of supply methods: Factory Feeding (FF) and Line Feeding (LF). The FF-flow directly transports parts to the assembly without intermittent storage in a warehouse, while in the LF-flow incoming parts are first stored in an (on-site) warehouse before the parts are transported to the assembly line. The FF-flow consists of one supply method, whereas the LF-flow consists of six different supply methods. Parts in the LF-flow are stored in four warehouses which are shown in Figure A.1. The selection of a particular supply method is based on the available inventory space on the assembly line, the consumption rate of a part, and the size of a part.

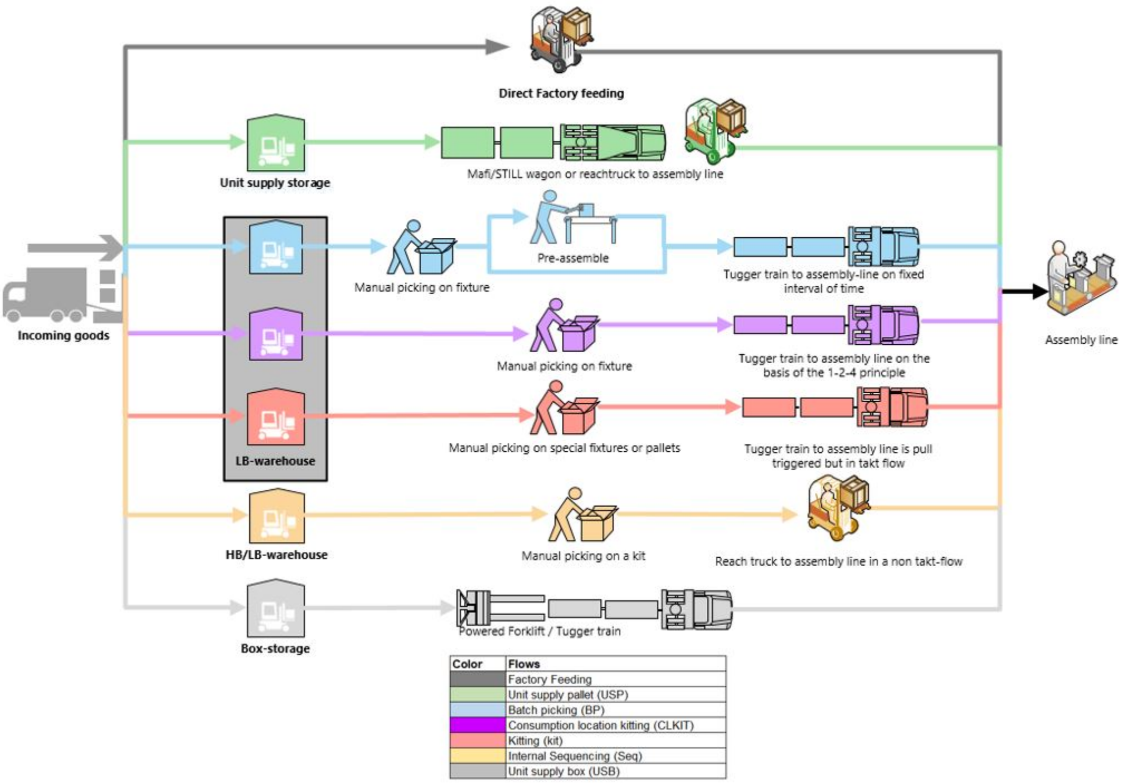

Figure A.1: Supply flows at SPZ

Factory feeding (FF) The factory feeding or external sequencing method is typically used for heavy, complex or fragile items such as cabins, engines and axles. The parts are supplied to the assembly line in the sequencing of when the parts are required on the assembly-line.

Unit Supply Pallets (USP): Parts with a high demand use the USP as its supply method. The transport of parts on pallets to the assembly line is facilitated by tugger trains with pallet wagons according to the two-bin principle. The replenishment of USPs on scheduled times on fixed routes every couples of minutes is based on the takt time of the assembly line. The USP storage is in the unit supply storage warehouse (marked in green in Figure A.1).

Batch Picking (BP): In the BP supply method, an order picker picks multiple times the same part on a fixture. Tugger trains with fixture wagons facilitate the replenishments on a fixed interval of time. In case of replenishment, a tugger train driver swaps a complete (almost) empty fixture at the assembly line for a filled one. If not all parts have been consumed before the replenishment, the fixture is refilled to a predefined up-to-order level (UOL). The BP supply method is marked blue in Figure A.1 and uses the LB-warehouse as its storage location.

Consumption location kitting (CLKIT): Parts in the CLKIT supply method are dedicated to a specific chassis and are supplied to the assembly line in a hybrid form of a takt flow and a non-takt flow with low frequency parts. Since the demand of parts is not as high as in the USP-flow, the supply of parts is organised in a 1-2-4 principle. Every train, alternating on a train run or one in four train runs a tugger train with fixture wagons transports the fixtures to the assembly line.

Kitting (KIT): An order pickers places parts necessary for a replenishment on a fixture or pallet. All the parts together form a kit and are dedicated to one chassis number. Replenishment is facilitated with tugger trains and pull triggered but with a takt flow, which means that a replenishment is carried out when the parts in a kit are consumed. Kitting is commonly used for low volume parts.

Internal Sequencing (SEQ): Parts in the internal sequencing supply method are supplied to the assembly-line in a non-takt flow carried out by reach trucks. Parts that are picked in this supply method are offered to the assembly-line based on the truck sequencing and are stored in the LB-warehouse and in the HB-warehouse.

Unit Supply Boxes (USB): Small parts in boxes are transported to the assembly line on picking carts. A two-bin system regulates the replenishment of a USB and tugger trains facilitates the transport from the box-storage warehouse to the assembly line. This supply method is usually used for low value parts, such as nuts and bolts. The USB flow (marked in grey) uses the box-storage warehouse as its storing location. The box storage warehouse is the only warehouse that is not an on-site warehouse. The box-storage warehouse is located nearby SPZ within walking distance.

B Example of replenishment orders

The storage locations that an order picker needs to visit for a fixture often succeed each other and often contain the same storage location. To emphasize this, Table B.1 shows the storage locations that need to be visited for 5 randomly chosen replenishment orders of the LR322-DBP-BA fixture. The storage locations in the replenishment orders show a lot of overlapping storage locations.As a result, the routing and the travel distance in a replenishment cycle for a fixture is approximately the same for every cycle.

Table B.1: Storage locations of 5 random replenishment orders of the LR322-DBP-BA fixture

Order-1	**Order-2**	**Order-3**	**Order-4**	**Order-5**
BA11	BA11	BA11	BA11	BA11
BA13	BA13	BA13	BA13	BA13
BA15	BA15	BA15	BA15	BA15
BA17	BA17	BA19	BA19	BA17
BA19	BA19	BA23	BA25	BA19
BA23	BA25	BA25	BA27	BA25
BA25	BA27	BA27		BA27
BA27				BA31

C Flowchart best-fit heuristic

This appendix shows a flowchart of the best-fit heuristic that we described in Section 4.6.2

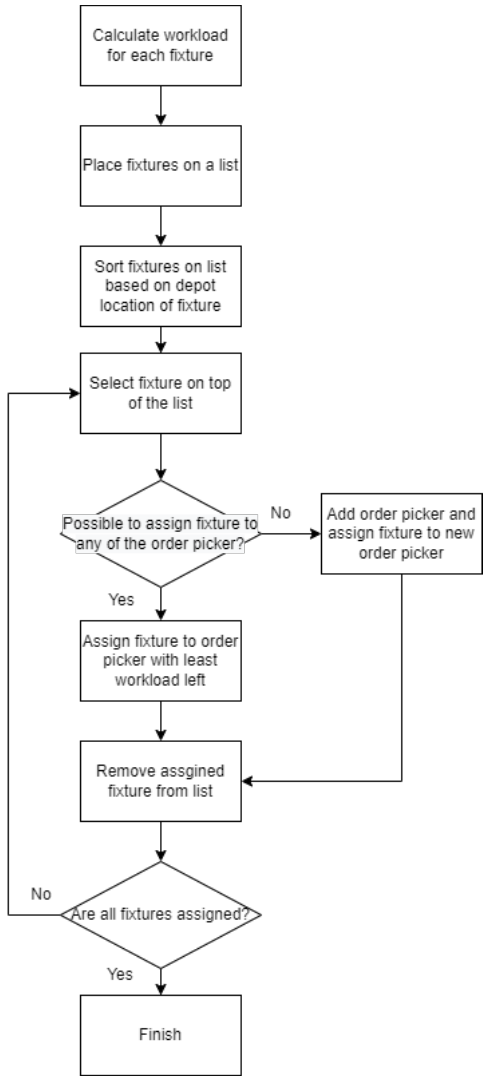

Figure C.1: Flowchart of best-fit heuristic

D Flowchart simulated annealing

In this section, we describe how the SA heuristic works using a flowchart

As explained in Section 4.6 we use the SA metaheuristic to improve the initial solution from the best-fit heuristic. SA searches for a global optimum by using diversification at the beginning of the heuristic and intensification at the end of the heuristic. Figure D.1 shows a flowchart of the SA heuristic, the numbers indicate the step number in the flowchart.

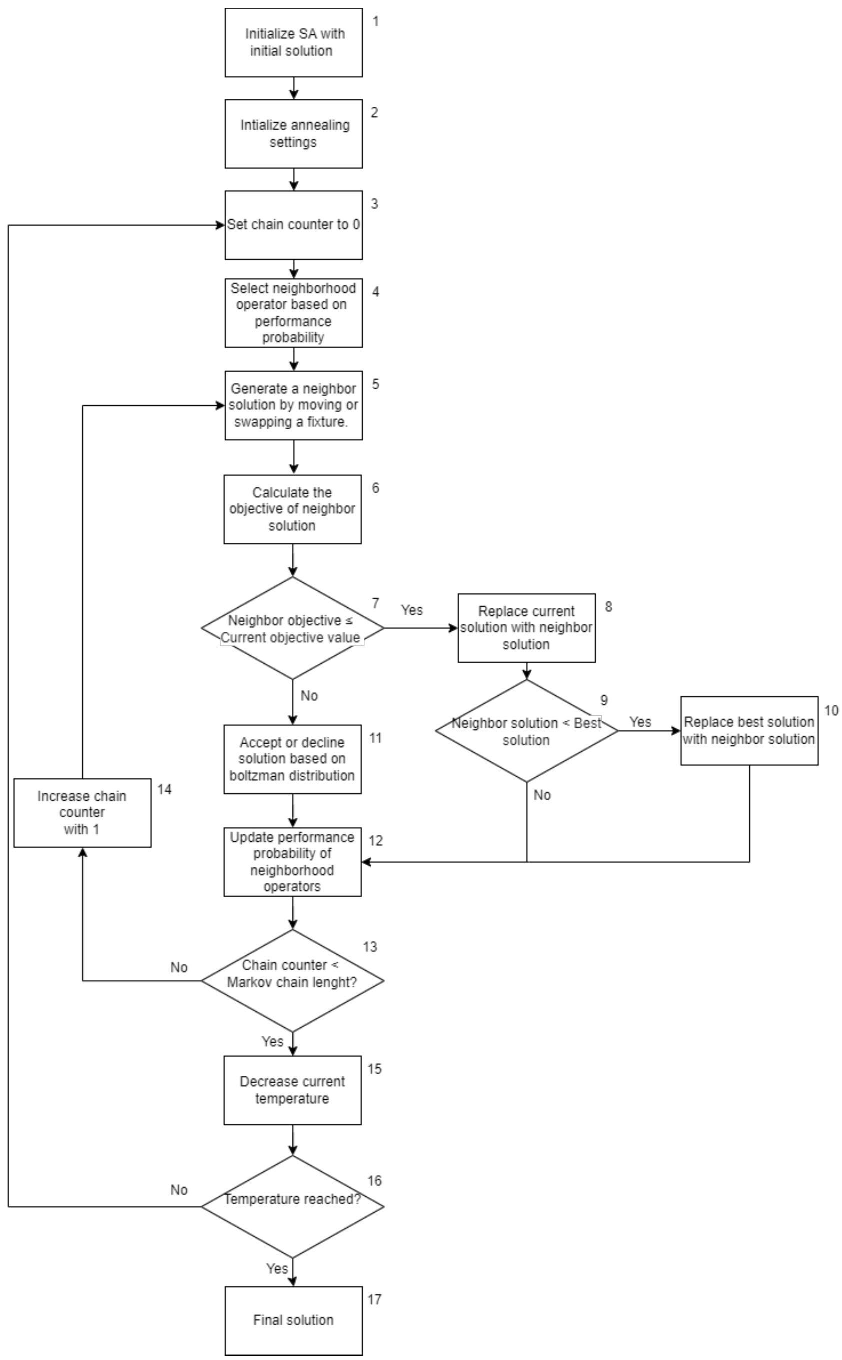

Figure D.1: Flowchart of SA

E Statistical tests

This appendix provides the statistical tests that we use to determine the number of replications

As explained in Section 5.2 we use the sequential procedure of Law (2015) to determine the required number of replications. Using a sufficient number of replications we can obtain a confidence level 95%. Formula E.1 describes how we calculate the confidence interval.

$$\left[\bar{X} \pm t_{n-1,1-\alpha/2} * \sqrt{S^2/n}\right] \tag{E.1}$$

$\bar{X}$ = sample mean
S^2 = sample variance
n = number of replications
α = confidence level
$t_{n-1,1-\alpha/2}$ = t-value from Student's t-distribution

We simulate multiple replications and measure the output variable. Subsequently, we list the results of the output variable and calculate at which replication we obtain a confidence interval of 95%. To determine at which replication we have reached a confidence interval of 95, we use the relative error. The relative error is the confidence interval half-width relative to the mean and is calculated with the following formula eq. (E.2).

$$\frac{t_{n-1,1-\alpha/2}\sqrt{S^2/n}}{\bar{X}} < \gamma' \tag{E.2}$$

$\gamma' = \frac{\gamma}{1+\gamma}$ = the adjusted relative error
γ = the actual error

According to Law (2015) the relative error should be lower than 0.15. However, we use a relative error of 5% (γ = 0.05) and a confidence interval level of 95% (α= 0.05) to calculate the number of replications.

F Output of assignment model

This appendix provides the output of the assignment model for intervention 1 and 2

F.1 Output assignment model for intervention 1

Figure F.1 shows the output of the assignment model where we observe that the travel time between the depots (T_j) for each order picker is very small. The travel time between the depots is calculated as a percentage of a working day. For example, order picker 1 spends 1.71% of his day on travelling between the depots. Moreover, order picker 1 has a fixed workload of 71.76%, which is the sum of the workload of the fixtures assigned to an order picker ($\sum_{i=1}^{n} w_i x_{ij}$). If we add up the travel time between depots and the fixed workload, we obtain a total workload ($\sum_{i=1}^{n} w_i x_{ij} + T_j$) of 71.36 + 1.76 = 73.52%.

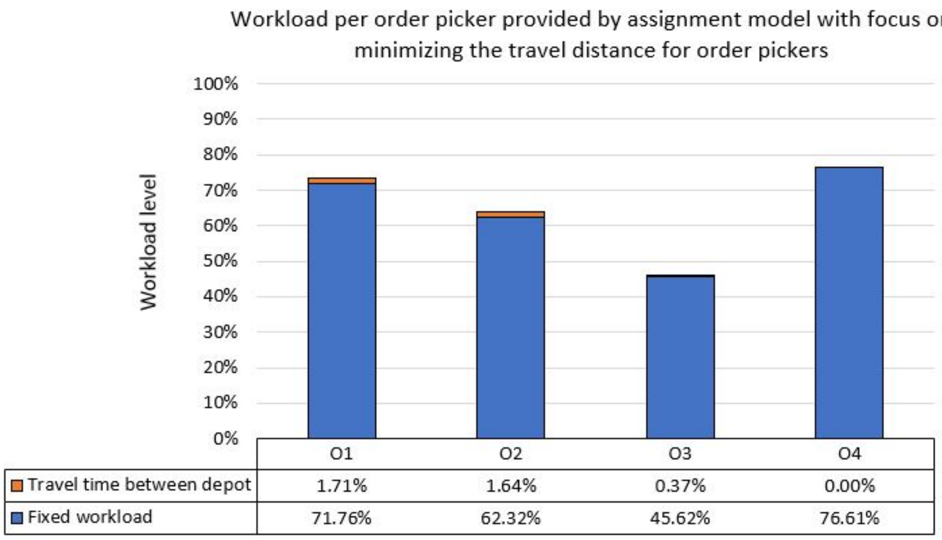

Figure F.1: Workload distribution provided by assignment model with focus on minimizing the travel time per order picker

F.2 Output assignment model for intervention 2

Figure F.2 shows the workload calculated by the assignment model. We observe that the workload is evenly distributed over the order pickers because the difference between the order picker with the highest workload (order picker 2 with a workload of 71.52) and the order picker with the lowest workload (order picker 1 with a workload of 70.78) is 0.75%. We conclude that the assignment model is able to find an assignment strategy that distributes the workload evenly over the order pickers. Despite an assignment strategy has been found that balance the workload over the order pickers, the travel time per order pickers increases significantly. In scenario 1, where we minimize the travel time, the sum of the travel time between depots for the order pickers is 3.71%, while in this scenario it has increased to 28.28%. As a result, order pickers spend 24.57% more time on a working day on travelling between depot locations.

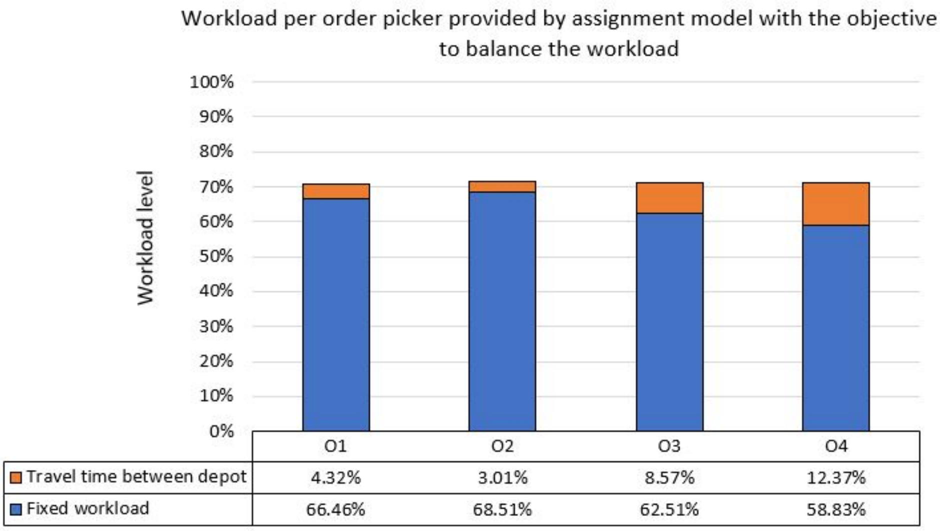

Figure F.2: Workload distribution provided by assignment model with focus on a balanced workload