Improving the outbound performance of a newly built semi-automated production and spare parts warehouse

A Simulation Study

MASTER'S THESIS AT TERBERG BENSCHOP

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TERBERG BENSCHOP
MANUFACTURER OF SPECIAL VEHICLES

Preface

This thesis is the result of my graduation assignment to finalize my Master's degree in Industrial Engineering and Management at the University of Twente. The host company for this assignment, Terberg Benschop, offered me a close look at their manufacturing and warehouse logistics. Although at first sight the warehouse did not seem very large, the product flows and warehouse operations were surprisingly complex, with many exceptions. Therefore, it was both a challenging and an interesting assignment to understand the current warehouse operations and find solutions for improving the warehouse productivity.

Luckily, I was warmly welcomed and actively supported by the Logistics department of Terberg Benschop, that provided me with my own workspace were I carried out the research. Despite the Covid-19 outbreak, which lasted during the entire research period, the management of Terberg Benschop found ways to allow my presence at the warehouse. They understood the importance of me being able to observe the process and interact with the employees to really understand the operations. I am sure that being able to go to the office has paid a huge contribution to the outcomes of this research.

I would like to thank Jorrit, Ilya and Gerrit-Jan for their active support and input during the days at Terberg Benschop. Furthermore, I would like to thank the graduation committee members Peter and Martijn for their advice and guidance throughout the research. Last but not least, I would like to thank my girlfriend, who was willing to make the step of moving to an apartment together to both work hard on our graduation assignments.

It has been a great, educational and entertaining experience for me and I am happy to present the results to you with this thesis. I hope you enjoy reading it.

Management Summary

Terberg Benschop, a manufacturing company of specialized vehicles like the Yard Tractor, is facing outbound performance issues within their recently built central warehouse. The central warehouse stores SKUs that are requested for production of new vehicles in two different assembly halls, or as spare parts for existing customers. The storage system inside the warehouse is a combination of an automated storage and retrieval system (AS/RS) and nine narrow pallet aisles. The warehouse was built with the purpose of expanding the storage space and increasing the throughput, to keep up with the growing production numbers that are the result of larger demand in new vehicles. More vehicles sold results in a larger active fleet which also results in larger need in spare parts.

Although the expectation was that the new warehouse was able to keep up with the expected growth in demand until 2027, the warehouse started to face outbound performance issues in 2018. Outbound performance is determined by throughput as well as the On-Time pick completion rate. The goal of this research is to evaluate the outbound performance of the current warehouse operations and find ways to increase the throughput and pick efficiency to deal with higher demand. Expansion of the newly built central warehouse is not possible. Therefore the main research question we try to answer in this research is:

"How can Terberg arrange the warehouse operations and resource allocation within the central warehouse to increase the outbound performance, to deal with the growing production numbers and spare part sales?"

The focus of this research is mainly on the outbound activities of the warehouse. For the analysis of the current outbound performance, we used historic pick data containing pick time, SKU number, unit load, storage location and pick deadline data of each order line. This data showed us that the number of order lines and shipments is unequally divided over the different pick areas of the warehouse. Especially the difference between pick lines at the AS/RS (named OSR at Terberg) and the pallet aisles is substantial, about seven times larger at the OSR. However, orderliness are not a completely representative measure to compare the workload at each pick area, because of the difference in pick methods or SKU characteristics that might require different handling effort. Therefore, the pick data was translated to a workload in time (utilization) measure per pick area.

Since we do not only want to evaluate the current performance but also find possible long term improvements, it is important that we find an approach to generate and test possible solutions in future situations. For this research we focus on the output of the warehouse as a whole, not the individual storage areas separately. The pick process in the central warehouse is based on dedicated zone picking. Each area, OSR pick station or narrow pallet aisle, has a dedicated order picker. Orders might require SKUs to be picked from different areas, which results in consolidation effort before shipping the goods out of the warehouse. This dedicated zone picking and consolidation process, results in interdependence of the different picking areas. This interdependence of picking areas makes the optimization a complex problem that is not solvable with an exact mathematical approach. Therefore, we have selected simulation as the research approach to evaluate the systems performance and test possible process improvements. We have used discrete event simulation to model the warehouse outbound operations.

After constructing and validating the current situation in the simulation model, the following eight interventions were designed and tested in different experiments:

1. Variable end of working day based on work left in queue;
2. Switching the priority rules on sales orders and the logistics time;
3. Relocating the SKUs over the pick areas based on the outcome of simulated annealing;
4. Outsource the supply of 2Bin materials;
5. Malaysia orders picked only on Friday afternoons when the activities at the assembly halls are stopped;
6. Splitting the outbound flow of the OSR and the pallet aisles, making the consolidation independent of the part of the shipments picked at the OSR;
7. Increasing the production numbers at the HVA (High Volume Assembly) from 26 vehicle to 40 vehicles a week
8. Extend the working day of the OSR with 1.5 hours;

We have designed ten different simulation runs to test a single intervention or a combination of interventions. The table below shows an overview of which interventions and combinations are tested in each of the ten experiments.

Experiment Nr.	Interventions
1	1
2	1, 2
3	3
4	4
5	4, 5
6	4, 6
7	4, 7
8	4, 6, 7
9	4, 6, 7, 8
10	3, 4, 5, 6, 7, 8

One of the interventions tested is the relocation of SKUs over the different pick areas, with the purpose of optimally dividing the workload over the areas to improve pick efficiency. Analysis showed that on average 76% of the total order completion time is wating time on each area to finish its share. Two slotting methods, MILP and Simulated Annealing, are explored to relocate the SKUs over the storage areas to improve the pick efficiency and decrease the waiting time. The MILP was not able to find a solution to the total problem in polynomial time because of the hard complexity of the problem. Therefore, we used the local search heuristic, Simulated Annealing, to find alternative SKU to area allocations. The Simulated Annealing heuristic was able to reduce the total picking routes required to pick the same orders by 10%. The effect of this SKU re-allocation based on the outcome of the Simulated Annealing slotting heuristic is tested as intervention 3 in the simulation experiments.

Besides the ability to evaluate the warehouse outbound performance and interrelations of the different storage aisles, the simulation model provides additional information to evaluate the warehouse system, compared to the historical data. Currently the performance of the warehouse is mainly based on the On-Time score, which is the rate of shipments that are completed before the pick deadline over a given time period. A shipment is the total of SKUs that are requested within a Phase or Sales order. We have added four main performance measures based on data provided by the simulation model: Maximum lateness (max difference between order completion and deadline), Orders still in queue (orders in queue at the end of a simulation run), full occupation of consolidation area rate (percentage of total operational time in which all consolidation areas are occupied) and Waiting time rate (percentage of total operational time in which the full occupation of consolidation areas causes waiting time). The tables below show the results of the most important performance indicators for the base simulation and each experiment.

	26 vehicles per week at HVA						
	Base	1	2	3	4	5	6
% On-Time Phase	99.798%	99.977%	92.735%	99.899%	99.946%	99.977%	100%
Max Lateness Phase (hh:mm:ss)	(08:05:28)	(01:19:04)	(03:27:34)	(02:42:46)	(04:30:54)	(01:18:40)	00:38:13
% On-Time Sales	99.613%	99.544%	96.346%	99.361%	99.982%	99.927%	99.988%
Max Lateness Sales (hh:mm:ss)	(06:48:43)	(04:11:30)	(04:42:39)	(06:33:48)	(04:01:04)	(04:04:07)	(00:03:19)
% On-Time 2Bin	2.66%	100%	100%	0.00%	96.380%	98.19%	97.739
# Still in Queu	115	0	0	165	0	0	0
% Full Occupation Consolidation	26%	17%	22%	30%	13%	17%	4%
% Waiting time	19.34%	15.23%	19.81%	23.39%	10.44%	11.84%	2.31%

	40 vehicles per week at HVA			
	7	8	9	10
% On-Time Phase	98.298%	100%	99.994%	100%
Max Lateness Phase (hh:mm:ss)	(08:08:21)	00:03:27	(00:03:51)	01:59:26
% On-Time Sales	97.640%	99.360%	99.977%	99.965%
Max Lateness Sales (hh:mm:ss)	(04:03:25)	(01:17:18)	(00:09:50)	(00:14:34)
% On-Time 2Bin	10%	34.00%	98.643%	99.095%
# Still in Queu	1	2	0	0
% Full Occupation Consolidation	10%	4%	4%	2%
% Waiting time	9.30%	3.37%	2.91%	2.36%

The outcomes of the different simulation runs with 26 vehicles per week at the HVA, show that the On-Time performance of Phase and Sales orders is very strong, except for the experiment with a changed priority rule. The operational improvements become visible by looking at the On-Time 2Bin and Waiting Time performances. Experiment 6 shows a very strong overall performance. This is the result of a combination of two interventions; reducing the workload at the OSR by outsourcing 2Bin and reducing the waiting time at consolidation by separating the OSR outbound flow from the pallet aisles outbound flow.

Experiment 8, shows that the same combination of interventions with increased production numbers still yields a strong performance for Phase and Sales orders, but the 2Bin performance at the OSR is falling behind again. Increasing the operational capacity at the OSR by extending the working day with 1.5 hours at the OSR is sufficient to increase the On-Time score of 2Bin over 98%. Experiment 10 shows that some additional changes in SKU allocation and pick sequencing improves the system performance even a bit more.

The simulation outcomes in this research show that the central warehouse of Terberg Benschop is able to deal with demand growth after implementing the combination of three interventions:

1. Decreasing the workload at the OSR by outsourcing the 2Bin
2. improving the outbound efficiency by separating the outbound flow of the OSR from the narrow aisles
3. Increasing the operational capacity of the OSR by increasing the working day with 1.5 hours.

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Glossary

Term / abbreviation	Explanation	Definition on Page
2Bin	Two bin or 2Bin is a supply and local storage system that contains two bins filled with multiple of the same parts.	26
Aisle Master	Crane used to pick goods within the narrow pallet aisles	34
Consolidation	Process of combining parts of the same shipment picked at different storage areas	36
CPS	Carriers per Shipment	92
Exit Scan	The point an order is released to exit the warehouse	39
FTE	Full Time Equivalent	34
HVA	High Volume Assembly	27
Logistics time	Pick deadline before each shipment needs to receive the Exit Scan	33
LVA	Low Volume Assembly	27
Max Lateness	largest lateness score of all orders of a specific order type in a simulation run	79
MILP	Mixed-Integer Linear Programming	73
On-Time score	Percentual share of shipments that receive the Exit Scan before the pick deadline	39
Order line	Part of a picking route for a single or multiple units of a single SKU from a specific location	25
OSR	OSR is the name of the AS/RS system used in the central warehouse of Terberg Benschop. OSR is short for Order Storage and Retrieval.	14
Phase order	Production order with SKUs needed for a specific vehicle phase combination for one of the two assembly halls	23
Picking route	Route within a single storage area that contains all location that need to be visited to complete the order	26
RC	Roll-Container	33
Sales order	Spare part orders for existing customers	25
Simulated Annealing	Local search heuristic method	74
SKU	Stock Keeping Unit	23
Tote	Crate used in the OSR to store smaller SKUs and transport them to the pick stations	35
Utilization	Indicator of how much of the pickers operational capacity is used	44
VPL	NL: Voorraad Productie Lijn. Which means inventory at the production line	25
WMS	Warehouse Management system	37

1 | Introduction

In the framework of finalizing my Masters study Industrial Engineering and management, this research was conducted of which this thesis is the final report. The purpose of this thesis is to present Terberg Benschop opportunities to improve the warehouse operations, with the ultimate goal to increase productivity so that the output levels can meet the growth prospects. The research is conducted for the central warehouse located at the assembly facility of Terberg Benschop. This warehouse is used for storage and distribution of parts both for the assembly of new vehicles as for sales of spare parts directly to existing customers. Both the demand for new vehicles as for spare parts is growing while the warehouse is struggling to meet the service levels for the current demand. Therefore, the Logistics department of Terberg Benschop is eager to find out ways to improve warehouse operations and increase the output.

1.1. Royal Terberg Group

Terberg Benschop is part of the Special Vehicles division of the parent company Royal Terberg Group. The Royal Terberg Group is a family business that originally was a forge founded in 1869 in Benschop. In 2019 the company existed 150 years and as part of the celebration Terberg Group received the Royal Warrant from the king of The Netherlands. After the second world war Terberg started modifying abandoned army vehicles into agricultural vehicles. That is the basis of Terberg's current business. Today the company is active in 12 countries with over 3000 employees and generating a revenue over 1 billion euros. Customers of Royal Terberg Group are spread over more than 130 different countries.

Royal Terberg Group is divided in six divisions: Special Vehicles, Environmental Equipment, Modification Cars & Vans, Modification Trucks, Truck Mounted Forklifts and Leasing.

1.2. Terberg Benschop

Terberg Benschop is the headquarters of the Special Vehicles division. The Special Vehicles division of Terberg produces, as the name predicts, vehicles with a specialized purpose. At the facilities of Terberg Benschop different types of tractors and trucks are assembled with different usage purposes. Examples are the Yard Tractor and the Body Carrier. The Yard Tractor is a terminal tractor that is designed for quickly coupling and decoupling of trailers, with the purpose of quicker distribution of the trailers in for example port terminals or large distribution centers. The Body Carrier is designed to carry a container on top of the back of its own chassis, equipped with a hook arm to load and unload containers without the need of a crane. Figure 1 shows images of the six different vehicle types that are offered by Terberg Benschop Special Vehicles.

Figure 1: Vehicle types offered by Terberg Benschop

1.3. Central Warehouse

Terberg Benschop is an assembly location and not a parts manufacturer, meaning that all parts and components are ordered at many different suppliers. To control this process of ordering and processing parts needed for assembly, Terberg Benschop has its own local warehouse and logistics department. At Terberg Benschop the entire process from single parts coming in until a completely ready and operational truck riding out of the factory is organized.

Figure 2: Terberg facility grounds

Figure 2 shows the layout of Terberg Benschop. For this research the main focus is on the operations within the walls of the warehouse. Since Assembly is directly related to the warehouse as being its largest client, we cannot completely rule out the operations at Assembly for this research. The relationship between Assembly and the Warehouse will become more clear throughout this thesis.

1.3.1. Warehouse Layout

The storage space of the central warehouse is divided in three different areas: An AS/RS (Automated Storage and Retrieval System) section and nine parallel narrow pallets aisles, of which one is fully devoted to heavy and oversized goods. The AS/RS system of Terberg is called the OSR (Order Storage and Retrieval). In the remainder of this thesis the abbreviation OSR will be used to refer to the AS/RS system.

The warehouse space is fully utilized with the current layout, offering no flexible options for adding storage systems without the need of extending the warehouse building. Figure 3 shows the warehouse floor plan with colors highlighting the three storage sections. The blue section highlights the OSR, yellow the pallet aisles for hand picking and orange the pallet aisle for heavy goods that need machine supported handling.

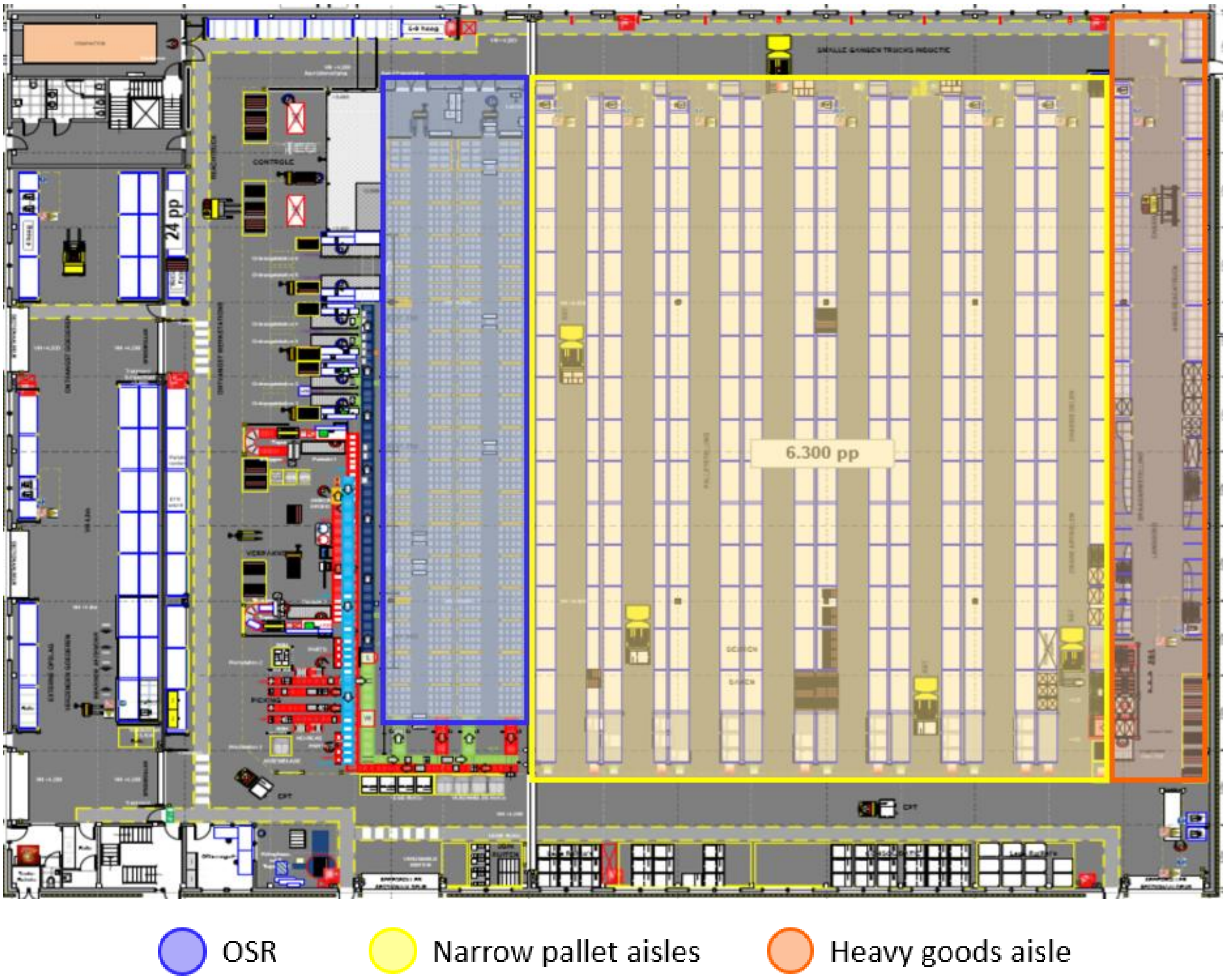


Figure 3: Central warehouse floor plan

1.3.2. Warehouse Operations and resources

The central warehouse is a production warehouse, meaning that its main purpose is supplying the assembly halls with the parts needed for the production of the special vehicles. Terberg Benschop has two different production halls in which different types of vehicles are produced. The production manager of each assembly hall is responsible for placing the orders at the central warehouse. The process of item requests and supply is explained in more detail in Section 2.1.5.1.

Next to supplying the assembly halls the warehouse is also used for the flow of spare part units. Existing customers or the maintenance engineers of Terberg can order spare parts at the central warehouse that are needed to repair vehicles at the customer. Because of the double purpose of the warehouse and the large variety in vehicle types, over 15,000 SKUs are stored in the central warehouse.

The orders that enter the warehouse are separated in different pick assignments for each warehouse area. In this case an area is not just the distinction between OSR and pallet aisles but the OSR and each individual aisle is a separate area. Pickers therefore do not navigate through the different aisles but move up and down a single aisle to collect the items of a shipment. The pick areas are numbered. The OSR is area 0 and the pallet aisles are numbered from 31 to 39, starting with 31 that is the aisle closest to the OSR.

At the OSR there are two pick stations installed. At each pick station a single operator collects the items from the crates, which we refer to as totes, that are brought to the picker via the conveyor belt system of the OSR. After collecting the items requested they are placed on a tray in a roll container.

In the narrow pallet aisles the picker uses an aisle crane to move between pick locations. The aisles are flanked at both sides by single depth pallet racks with up to nine levels of pallet locations in hight. Depending on how the pallets are stored, the total number of pallet positions in the narrow aisle is around 6,250. The aisle cranes can move up and down and back and forth at the same time. Using a fork just as a regular forklift the aisle crane can carry a roll container or pallet together with the picker to a pick location. The picker takes the items requested from the pallet in the shelves and places them in the roll container. After the pick is complete the picker navigates back to the front of the aisle and drops off the filled roll container.

In the heavy goods pallet aisle a forklift is used to pick a pallet with goods from the shelves and take it to the front of the aisle. Another picker uses weight lifting support tools to pick the heavy goods from the pallet and place it on another carrier. The original bulk pallet is returned by the forklift operator to the storage location. A detailed explanation of the pick activities in the warehouse is given in Section 2.1.5.3.

Since an order is split in pick assignments per area the order needs to be consolidated after picking. Twelve consolidation areas are created to which the production orders can be assigned to. The roll containers carrying the items from the different aisles are placed in these consolidation areas and designated workers move items over from one carrier to another to reduce the total number of carriers needed for an order. This is the final step before the carriers can be taken to production. The consolidation process is explained in more detail in Section 2.1.5.3.

1.4. Problem Cluster

In 2017 the build of the Central warehouse was realized at the premisses of Terberg Benschop. This new warehouse gives room to more storage space and the space of the former warehouse is attracted as additional production space. This additional production space was needed since Terberg Benschop is expecting vehicle demand to have grown over 50% by the end of 2027 based on results over 2016. Besides the production growth, spare part sales is expected to grow with three to eight percent each year. The new warehouse was designed to handle this growth in demand but started facing throughput capacity issues in 2018. The warehouse was built just a few years before and logistics management wants to know if and why the warehouse is capable of handling the increase of the product flow through the warehouse or not. The build of the new semi-automated warehouse required a large investment and the size of the warehouse is maximized within the limits approved by the municipality. Therefore, the goal of this research is to find ways to increase the throughput of the warehouse relying on the current infrastructure and resources.

To gain a better understanding of the problem structure, a problem cluster can be created to identify cause-effect relationships of activities that lead to the core problem. The logistics department presented the original problem as the challenge to increase the output of the central warehouse for future demand growth. This problem is the so called action problem (Heerkens H. *Geen probleem* (pp. 22)). An action problem is when the result of activities is not equal to a desired outcome.

The action problem is presented at the top of the problem cluster and colored in orange as showed in Figure 4. To come to the core problems, underlying problems and reasons are found and analyzed until a problem is found that has no underlying cause. The importance of each core problem and whether or not it can be influenced should be evaluated to determine the focus of the research. The core problems that are subject of this research are colored blue in the problem cluster. The core problems that cannot be influenced within the scope of this research are colored red in the problem cluster. Section 1.4.1. explains that the problem can be structured in three main branches. Section 1.4.2 reflects on the core problems found in the problem cluster. A larger more readable version of the problem cluster can be found in Appendix 1.

1.4.1. Problem structure

Looking at the problem cluster helps us to see that the problem can be divided in three main branches: Physical Capacity Constraints (starting at 1), Poor Operations Efficiency (starting at 2) and Increasing Demand Levels (starting at 3 & 4).

1. Physical Capacity constraints

The output levels of the warehouse are partly limited by the physical warehouse capacity. Calculations made for the build of the new warehouse showed that all items could fit the new warehouse, but reality shows differently (5). Goods are stored at an external storage location as well which is 2.5 kilometre further up the road from Terberg Benschop.

The newly built warehouse is built to the limits allowed by the municipality. So, even if Terberg is willing to invest in expanding the warehouse just a few years after the completion, it will probably not be allowed by the municipality or require heavy negotiation. Therefore the physical warehouse capacity is a problem that is beyond our power to influence and out of scope for this research.

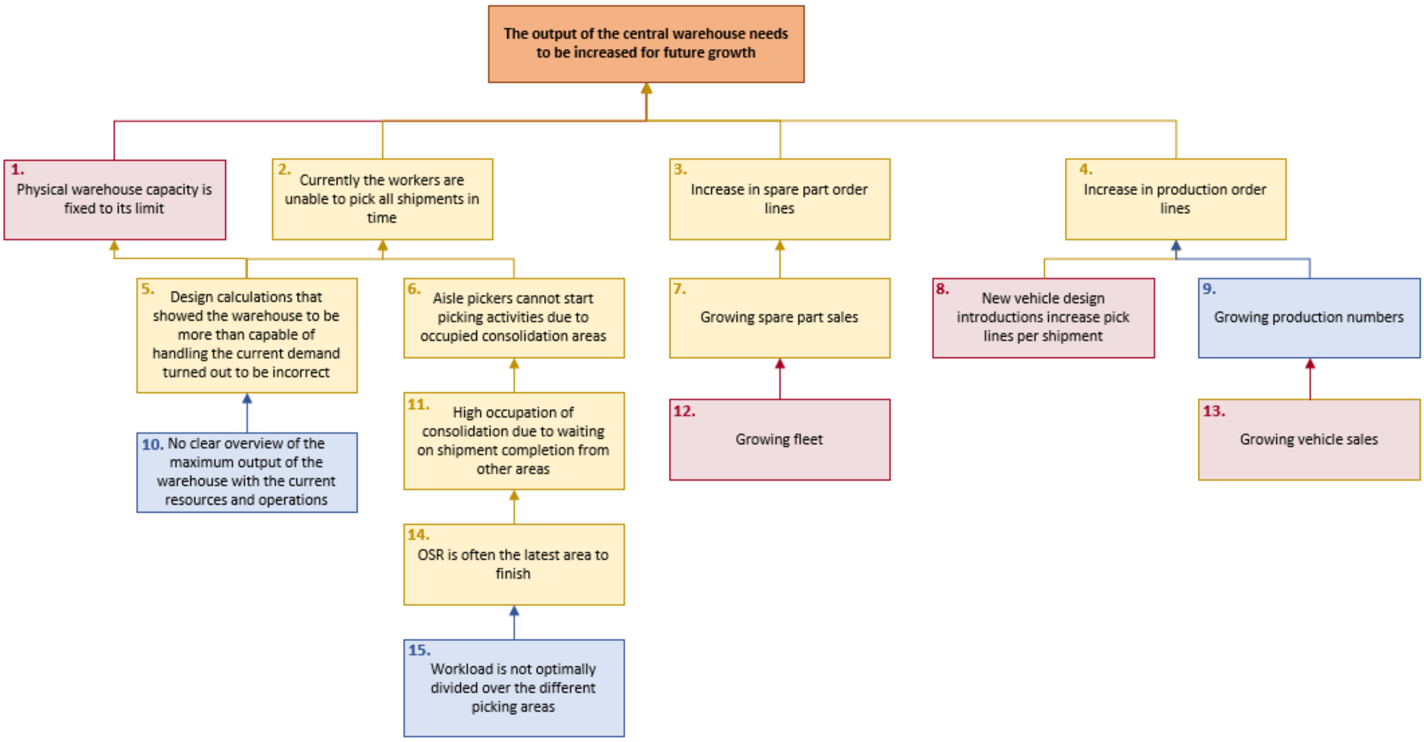


Figure 4: Problem Cluster

2. Poor Operations Efficiency

With the current demand levels, the pickers are at times unable to pick all shipments in time. The On-Time Exit Scan performance measure is the one used to measure to on-time performance. This is explained in detail in Section 2.3.2. The green line in Figure 5 shows that during three weeks in august the on time score was just above 80%.

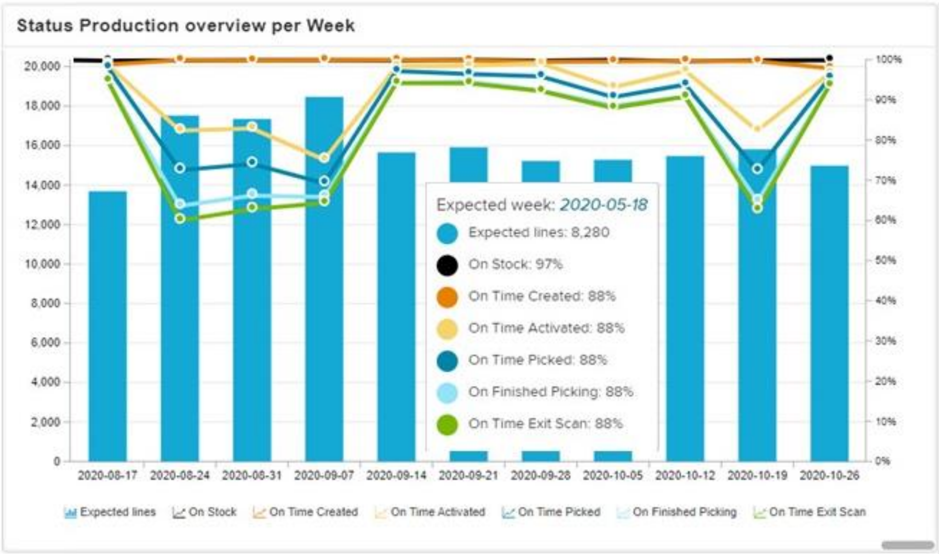


Figure 5: Warehouse performance production orders

The aisle pickers indicate that they often need to wait before they can start picking a new order because the consolidation areas are all occupied. The consolidation areas are full because they are awaiting each area to finish its pick assignment. Pickers mention that the wait is often on the OSR to finish. The high occupation of consolidation areas indicates that the workload is not optimally divided over the different areas.

3 & 4. Increasing demand levels

The number of order lines per week, the blue bars in Figure 5, also shows a negative relation with the pick performance. This indicates that the current warehouse operations cannot keep up with these high levels of demand. It is important to require understanding of which elements of the warehouse operations influence the output performance of the warehouse, to be able to deal with even higher future demand.

The increase in demand, both in new vehicle as in spare part demand, should be considered a positive trend for Terberg Benschop. This is the goal for the sales department. However more sales leads to more pick activities in the warehouse. The increase in vehicle and spare part sales is considered a core reason for the capacity issues in the warehouse but is not within the power of the logistics department to influence. It is also something that in the eyesight of the company as a whole is not desired to be influenced. Therefore the spare part and vehicle sales growth are coloured red in the problem cluster.

Although the warehouse performance is not scoring 100%, operations are not overflowing and still a large number of vehicles can be produced every week. The question however is what will happen if production numbers further increase. With this research, insights should be gained to understand which operation inefficiencies can be improved to deal with demand increase.

1.4.2. Core Problems

10. Uncertain maximum output

One of the core problems that was identified is the fully used physical capacity of the central warehouse. The physical capacity can be considered to be a fixed parameter in the calculations to determine the potential output. It is a parameter that needs to be worked with in the most efficient way. In this case however the physical capacity turned out to be lower than the design calculations predicted. In combination with a lower pick output than expected, the logistics management is left in uncertainty. The historic calculations that were made in the design phase showed the expectancy of the warehouse to be future proof until 2027 with the growth plan considered. Reality differs from these calculations, which puts the management back to an uncertain position.

Information about the maximum output, with the current resources and operations, is very valuable to understand if the warehouse is able to reach the desired output and if not, how big the gap is that needs to be bridged. The maximum output and therefore the size of the problem is unknown (10).

Providing the management of Terberg with a maximum output level is one of the core problems this research is focusing on to solve and therefore coloured in blue in the problem cluster.

15. workload division

One of the reasons mentioned for the poor operations efficiency was the high occupation of the consolidation areas. The high occupation of consolidation areas results in delays in the pick operations. This is the result of non-optimal workload division that results in non-parallel pick activities of multi-aisle shipments. Non-parallel picking means that aisles that have a pick assignment for the same order do not start or work on this same order at the same time. In Section 3.1.3, the problem of this non-optimal workload is explored in more detail.

This non-optimal workload division is considered one of the core problems that is within the power of the warehouse logistics management. Therefore, the workload division is one of the core problems that is considered in this thesis and coloured blue in the problem cluster.

9. growing production numbers

The growing production is a result of the growing demand for new vehicles. To keep up with the growing demand, Terberg Benschop wants to increase production numbers from 36 to 54 new vehicles per week. Although the growing demand is a core problem that is not desired to be discouraged, increased production numbers can only be successfully met when the whole supply chain is able to handle these production numbers. The warehouse is expected to be the bottleneck of this supply chain given the performance issues with the current demand levels. Therefore it is important to choose production levels that can be met by the warehouse.

Optimizing warehouse productivity that ensures the warehouse to be able to deal with higher production level is considered one of the core problems of this research.

1.5. Research Goal

In this section we will present the research questions that are formulated to solve the core problems of this research. In Section 1.5.1 the main formulation of the main research question is presented. In Section 1.5.2 the main research question is divided in multiple sub-questions.

1.5.1. Main Research question

Terberg Benschop is enjoying a period of growth and still has much growth potential. The logistics management of Terberg identified that the warehouse is currently holding back production scale up decisions because warehouse operations cannot keep up with higher production demand. The increasing demand levels in combination with the capacity issues explained in the previous section are reasons for the management to initiate a quantitative analysis to explore solutions to improve the warehouse output. This section formulates the research goal and the multiple research questions in which the main question is divided to provide an answer to the main research question:

"How can Terberg arrange the warehouse operations and resource allocation within the central warehouse to increase the output levels, to deal with the growing production numbers and spare part sales?"

1.5.2. Research questions

Just as with the problem cluster, the research questions are divided in three topics: physical capacity, operations efficiency and demand levels.

1. **Physical capacity**

(a) *Section 1.3.1:* What is the layout of the central warehouse?
(b) *Section 1.3.2:* How many storage locations does the central warehouse have?
(c) *Section 1.3.2:* How many SKUs are stored inside the warehouse?
(d) *Section 2.1.5.4:* How are storage location decisions made?

2. **Operations Efficiency**

(a) *Section 2.1:* What does the current warehouse operation look like?
(b) *Section 2.3.2:* Which KPIs are currently in place?
(c) Section 6.2: Can we define additional KPIs to create a better understanding of the systems performance?
(c) *Chapter 3:* Which inefficiencies can be identified in the current warehouse operations?
(d) *Section 6.2:* What is the maximum output with the current operations?
(e) *Section 5.1:* What existing theory can be used to formulate possible solutions?
(f) *Section 4.1:* How can we test suggested solutions against the expected growth in demand?
(g) *Chapter 6:* What changes in operation result in higher output levels?

3. **Demand**

(a) *Section 2.1.1:* Which type of products run through the central warehouse?
(b) *Section 2.1.5.1:* How is demand created?
(c) *Section 1.4.2:* What is the expected growth in demand?
(d) *Section 4.2:* How can the maximum demand levels that the central warehouse can manage be determined?

1.6. Research Approach

The research approach can be formulated as the problem solving approach. The core problems are formulated in Section 1.4.2. The main goal of the research is to increase the operations efficiency of the warehouse as a whole. Terberg has done analysis on capacity and output levels within areas of the warehouse, but has no information on the potential output of the total warehouse. Due to the operations design decisions made, all areas within the central warehouse are connected as explained in Section 2.1.5.3. It is therefore of great value for Terberg to understand how all operations interact and the warehouse as a whole can increase output levels.

The processes in the warehouse have shown to be complex and therefore difficult to analyse pure mathematically with an analytical study. The many interrelations of activities give endless possibilities of states the warehouse can be in. Therefore simulation was selected to be the most suitable research method to evaluate the warehouse total operations (Law, A. M. (2015)). In this section the definition of simulation is given. In Chapter 4, a more detailed explanation of the structure of a simulation study and which software is used for modelling is given.

Simulation

Simulation is not an unknown concept anymore and used in many different situations, like weather forecast models (Parker W.S., (2014)) or in gaming technology. For this research simulation is used as a numerical tool to find answers to the main research question and improvements for a logistics process. Therefore, this study relies on the definition and terminology of frequently quoted books from Robinson (2014) and Law (2015).

Robinson (2014) formulated the following definition for simulation:

> *Experimentation with a simplified imitation (on a computer) of an operations system as it progresses through time, for the purpose of better understanding and/or improving that system.*

Law (2015) uses a slightly different formulation:

> *In a simulation we use a computer to evaluate a model numerically, and data are gathered in order to estimate the desired true characteristics of the model.*

Both clearly mention the use of a computer based model that can be used to simulate a real system or process to learn more about its nature. Robinson (2014) hints on the interaction with a simulation by using the term "Experimentation", which for this research is believed to be a crucial element in the simulation study. The goal is to find out which changes in the process have a positive effect on the output levels of the warehouse. By conducting experiments with the model by simulating different interventions, the simulation can be used as a Decision Support System as is explored by Robinson (2011). In chapter 4, the design of the simulation model used for this research is explained. The designed experiments are presented in Section 6.4.

1.7. Scope and Assumptions

The warehouse is in the heart of the supply chain of Terberg Benschop. On one hand there are the incoming goods from suppliers and on the other hand there are the outbound streams for assembly and spare parts. Warehouse operations are therefore triggered by the demand and relying on supplier reliability. For this research we solely focus on the outbound activities of the warehouse and how they are triggered. To be able to focus solely on the outbound process, the following two main assumptions needed to be made:

1. All items that have been located inside the warehouse given the historic records, are located in the area based on the latest pick record and do not change location;
2. There is infinite stock, meaning that stockouts do not occur.

More assumptions and system simplifications where necessary to construct a suitable simulation model, which will be explained in detail in Section 4.3.2.

1.8. Deliverables

The final and most important part of the research is presenting the outcomes to the problem owners at Terberg Benschop. To provide the problem owner with a good overview of the recommended changes and how these recommendations were found, multiple deliverables will be provided to Terberg Benschop.

Report

The first and largest deliverable is a full report in the structure of this final Master's thesis. This thesis includes an extensive explanation of the problem identification, problem analysis, generation of solutions and the recommendation of possible operational changes.

Simulation model

For the generation and analysis of possible solutions, simulation models are used. The results of the simulation and the basic design principles are presented in this thesis but a more extensive and detailed model explanation on how to adjust parameters will be provided to Terberg Benschop together with the model itself. The model could potentially form the basis for future research of another student or someone that is already employed by Terberg.

Mathematical models

Outcomes of mathematical models and statistical analysis provide the input distributions for the simulation model. These models form an important basis for the outcomes of the research. These models together with the statistical analysis reports will be shared with Terberg. An example is the simulated annealing model, which is presented in Section 5.3, that was used to generate an optimal item allocation within the narrow pallet aisles.

The research approach and outcomes are presented to all stakeholders at Terberg during two presentation sessions. As an addition to this thesis, the slide deck of both presentation sessions are shared as well.

2 | Current Situation

As will be explained in Section 4.1, understanding the current system is an important step in the simulation study. In this chapter answers are given to some of the research questions regarding the current warehouse layout and operations. Section 2.1 explains the operations and processes within the warehouse, in Section 2.2 attention is given to the available data structure and Section 2.3 explains the current performance measurement.

2.1. Warehouse Layout and Operations

In this section the current warehouse product flow, resources and operations of the central warehouse of Terberg Benschop are presented and evaluated.

2.1.1. Demand classification

Different types of SKUs (Stock keeping unit) flow through the central warehouse. The term SKU is used to indicate a unique type of item stored inside the central warhouse. SKUs differ not only in physical characteristics but in the purpose for which they are requested as well. Pick orders are classified according to this demand purpose. Classification can be one of five options: Phase, Sales, Two bin, VPL and Malaysia. Sales and Malaysia orders are picked for direct sales to the customer. Phase, Two bin and VPL are internal demand for assembly. In the list of definitions the classifications are briefly explained, this section will explain the different demand classifications in more detail.

2.1.1.1. Phase order

Items that are requested for assembly are defined as Phase orders. The assembly process is divided in stages named phases. In Section 2.1.3. the design of the assembly process is explained and visualized. The exact items that are needed to complete a certain assembly phase for the specific vehicle are requested and delivered as one batch order, which explains the name Phase order. The items of a phase order are delivered directly at the assembly line in roll containers. Figure 7 shows an example of a roll container at the assembly line. These roll containers form a local storage location, which are so called supermarkets (Emden. 2016, Faccio et al. 2013). This way of replenishment of supermarkets directly at the assembly line was chosen for two reasons. One is that supplying the assembly staff with exactly the items they need to complete their job, saves them time for sorting out the items needed. The second reason is that it provides a visual check, since the assembly is not complete until all items from the supermarket are used.

A down side of delivering items per phase for each vehicle is that it results in many repetitive pick activities in the warehouse. This is presented in more detail in Section 2.1.2.

2.1.1.2. Two bin

Two Bin is an application of the Kanban lean manufacturing approach (Bugajenko. 2020). Two bins with materials are placed near the assembly phase where they are needed. If one bin is empty it is sent to the warehouse for resupply. A visual card or sticker on the bin shows the materials needed for this bin. While the one bin is refilled the second bin is still being used in assembly. Figure 6 shows an example of a Two Bin rack in the assembly hall. The bill of materials of vehicles includes many small products like bolds and nuts that are required for almost every vehicle. The two bin system must prevent a stockout for these smaller and frequently used products at assembly, and at the same time lower the pressure on the warehouse operations for these goods by picking large numbers at once.

Figure 6: Two Bin & VPL rack

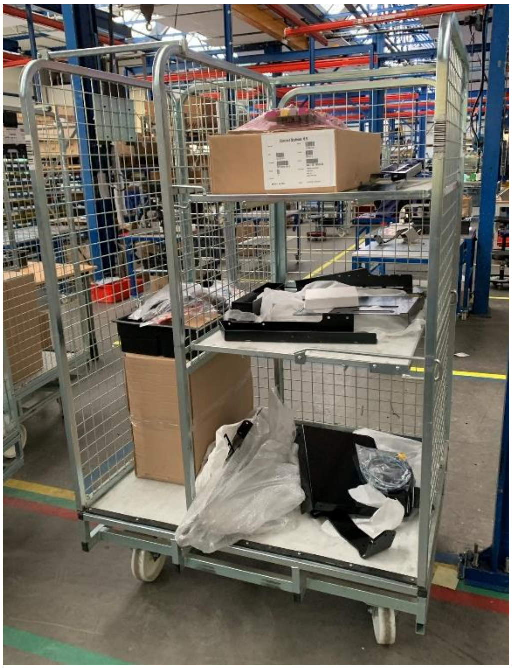


Figure 7: Phase shipment Roll Container

Figure 8: VPL pallet with hydraulic lifting cylinders

2.1.1.3. VPL

With VPL, inventory at the production line is indicated. VPL (NL: voorraad aan de productielijn) is a local stock for parts that are often needed at a certain production phase for more than one vehicle type, or parts that are requested often in phase shipments but are difficult to handle for manual picking from the pallet aisles.

VPL products are shipped to the assembly hall in full pallets or blue bins. This inventory is booked and managed locally. A reorder point for each VPL product is determined. If the local inventory position drops to a level lower than the reorder point, a VPL order is created for the warehouse. Figure 8 shows an example of a VPL pallet with six lifting cylinders. The blue bins in the rack in Figure 6 are VPL bins.

The difference between the Two Bin and VPL system is that for VPL each individual part is scanned when used on an assembly to register stock levels, while Two bin parts are not scanned and stock levels are managed visually as explained in the previous section.

2.1.1.4. Sales

Terberg Benschop values a strong after sales service. One of these services is that customers that use Terberg tractors can request every part of the tractor as a spare part at Terberg Benschop. Sales orders are orders that can consist of just a single part for an existing customer. Terberg strives to reduce the idle time of their trucks at the customer and therefore gives a high priority to spare part orders.

2.1.1.5. Malaysia

Terberg has an external production facility in Malaysia that serves the Asian market. Most products for the assembly are supplied by local suppliers but for some products it is difficult to find suppliers for Malaysia. Therefore production kits with parts that are used in the Dutch assembly as well are shipped from the central warehouse of Terberg Benschop to Malaysia. The central warehouse acts as a distribution center in a way for Malaysia. These Malaysia orders are often larger orders containing items that can be used for the assembly of multiple vehicles.

2.1.2. Demand breakdown

Section 2.1.1. explained the different demand types the warehouse is receiving. VPL, Two bin and Phase orders are the different production order types. The production orders can be considered as internal demand since the production orders are requested by the assembly line of Terberg Benschop. The internal demand is depending on the production numbers at the assembly halls. The more vehicles produced the higher the requests in pick assignments for phase shipments. The other demand types can be classified as external demand, which Terberg has no control over other than anticipating to it by making forecasts based on historic demand.

Phase orders are linked to a vehicle and phase combination and contain all parts needed to assemble the vehicle. The parts needed are not requested all at once as one large bulk order. The production order is divided in shipments for the warehouse. Phase orders and VPL orders are examples of these shipments. These shipments can be subdivided in order lines. Order lines are the actual pick orders containing the product, location and amount information that the picker needs to fulfill the assignment. An order line can contain a single unit or multiple. For example, a VPL shipment is a shipment order with a single order line, but the order line contains multiple units. A phase shipment can include multiple order lines and each order line can be a single or multiple unit request. The group of orderliness that request SKUs from the same pick area form the picking route.

For sales orders the break down is similar. Sales orders are not linked to a vehicle in production but are shipments that can be divided in order lines and units. Parts orders can be a single unit, single order line shipment. Malaysia orders are shipments that contain multiple order lines from different storage areas often requesting multiple units.

The order lines are currently used as the most important indicator for the warehouse. The number of order lines picked on a day is used as the output measure. Order lines are also used as demand indicators and to determine the workload division over the different storage areas. It should be noted that not all order lines are the same. Not only the number of units that need to be picked but product characteristics like size and weight determine the handling time of a pick. Therefore it could be interesting to evaluate whether the order lines are the correct indicator to use for warehouse operations evaluation. In Section 2.2.3 more attention is given to the measurement of the workload for each area.

Currently demand figures show clear peaks in production demand at certain times during the week and in more detail during the day, causing the warehouse to reach its max throughput capacity at certain times. Figure 5 in Section 1.2.1.1. shows demand in order lines per week. Production orders are the largest share of the demand. Historic data from 25-01-2021 till 19-03-2021 illustrates that 83% of all order lines are lines of a production order. Table 1 shows the demand distribution over the different demand types. As already predicted in Section 2.1.1.1, the large majority of the order lines result from phase shipments.

Table 1: distribution of demand classifications

	Production				
	Phase	VPL	2Bin	Sales	**Total**
Order lines	746,682	14,357	54,949	161,862	**977,850**
Percentage of total lines	76.36%	1.47%	5.62%	16.55%	-
Units picked	1,259,855	545,530	15,461,481	1,472,892	**18,739,758**
Percentage of total units	6.72%	2.91%	82.51%	7.86%	-
Average Units per line	1.69	38.00	28.38	9.10	**19.16**

2.1.3. Assembly halls

Terberg Benschop produces different vehicles with differing complexities. Therefore, the assembly halls are split into two production halls. The largest hall is the assembly hall for the more popular and common vehicles like the DT and the YT. This hall is called the High Volume Assembly (HVA). The other hall is equipped for the production of the less demanded and more customized special vehicles like the BC, CC, RT and RR. Because of the higher variation in vehicle types and sizes, lower numbers are produced in this hall per week than in the HVA, which is the reason why it is named the Low Volume Assembly LVA. Production within both halls is arranged differently resulting in different demand distributions.

Both in the HVA as the LVA, production is divided in main assembly phases pre-assembly phases. The difference between main phases and pre-assembly phases is that, at the main assembly phases work is done on the chassis, while at pre-assembly phases sub-systems are being pre-assembled before mounted to the chassis at one of the main phases.

The HVA contain six main assembly phases and eleven pre-assembly phases. At each main assembly phase in the HVA, work is done on two different chassis at the same time. Figure 9 shows the floor plan of the HVA with each assembly phase indicated and two chassis per phase. The production is directed by the movement of a pull chain in the floor to which the vehicles are attached when entering the hall. The chain pulls the vehicles after a fixed amount of time to the next phase, starting as an empty chassis and exiting the hall as a running vehicle. Because of this line-oriented operation, each phase has an equal amount of time to complete its tasks. The time from the start of one phase and the start of the next phase is called takt time. Work is done at each phase during this takt time on a total of twelve different chassis. The parts for all these chassis need to be available at the start of the takt time over the entire line. Because of the takt times, the demand is somewhat predictable.

If goods are not delivered in time for a phase, that phase has less time to finish their job when the goods arrive. This can result in lateness. If it is impossible to move the vehicle to the next stage, the entire production line has to wait on that single phase. This shows the importance of in time delivery from the warehouse for the HVA.

Demand distribution for the LVA hall is different. Vehicles are not produced on a line that advances after a given period of time. However, just as in the HVA the assembly of the vehicles is divided in main assembly phases and pre-assembly phases. Figure 10 shows the shop floor layout of the LVA. Assembly in the LVA is divided in three main phases and nine pre-assembly phases. At each main phase, work can be done on three chassis at the same time.

In the LVA, production times differ for each of the chassis at each phase. The chassis do not advance to the next phase all at the same time. Because of the vehicles not moving synchronously, buffer zones are introduced in the LVA where chassis are stored when there is no place available at the next main phase. There are two buffer zones between the three main phases. At each buffer zone two chassis can be placed to wait at the same time. Furthermore, due to the different times of vehicle advancement to the next stage, the demand of goods for the next phase is not requested for all vehicles at the same time. This makes the demand for parts for LVA a lot harder to predict.

At busy times for the warehouse, priority is often given to the delivery of goods for HVA to prevent the line from stalling. The result is that delays for a single vehicle in LVA can be substantial.

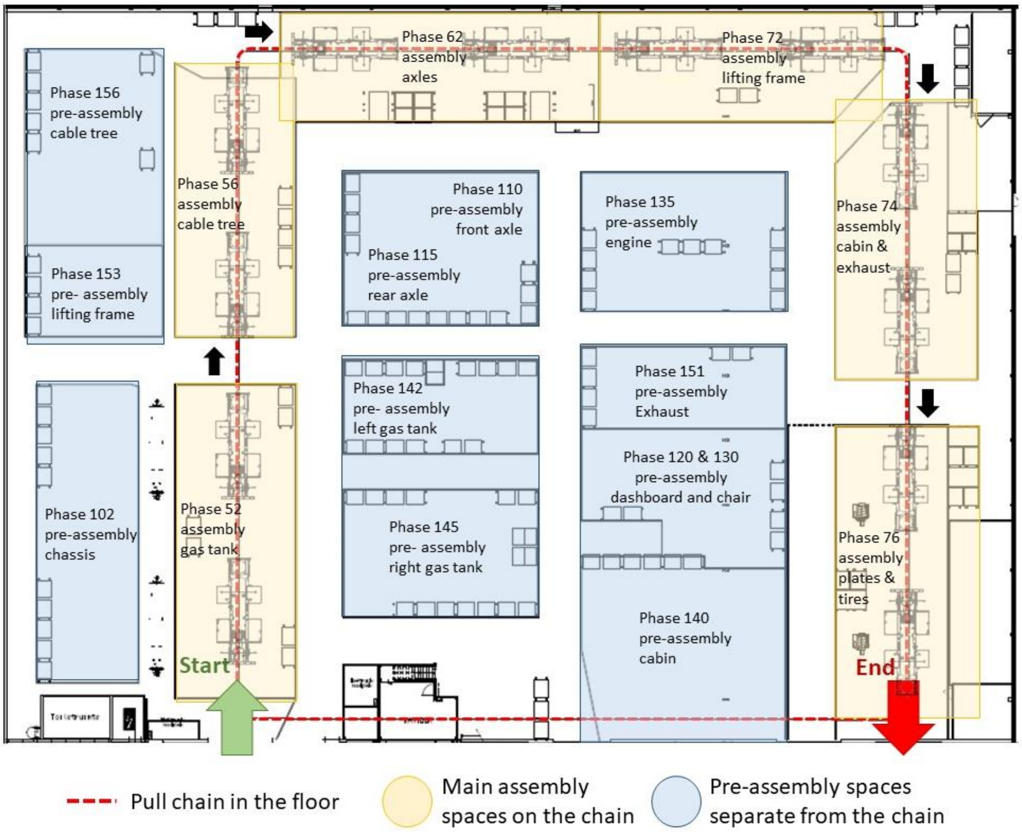


Figure 9: Shop floor layout HVA

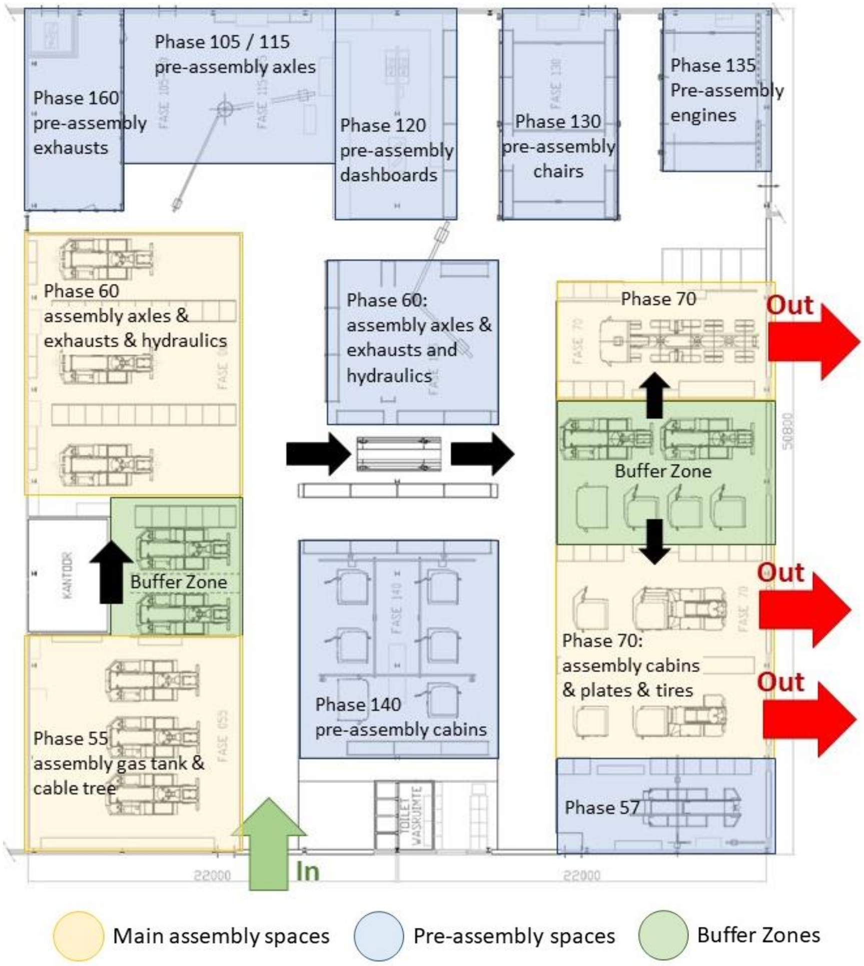


Figure 10: Shop floor layout LVA

2.1.4. Warehouse Logistics Layout

In Section 1.2.1.1 the layout of the storage zone of the central warehouse is explained. This section shows how all activities are fitted inside the warehouse.

The central warehouse can be separated in the three familiar sections: *inbound*, *storage locations* and *outbound*. Figure 11 shows how these three sections are arranged within the warehouse. The yellow area represents the space allocated to *inbound* activities, blue represents the *storage and picking* area, and orange highlights the *outbound* areas. The colored planes show that the warehouse is clearly structured without overlap in areas and each area is an uninterrupted whole.

Inbound is the process that a product is undergoing from the moment it is dropped at the door of the warehouse until it is placed at the allocated storage location.

Picking entails all operations in the warehouse that are required from the moment a shipment is activated until all parts of the shipment are picked and placed at the outbound section of the warehouse. Decisions about the picking resource allocations and picking strategies are considered to be part of *Picking*. Picking is done at the OSR and within the pallet aisles. Each aisle and the OSR are numbered as an individual pick area as mentioned before in Section 1.2.1.2. The OSR is area 0 and the aisles are numbered from 31 to 39 starting from the aisle closest to the OSR, as can be seen on Figure 3 in Section 1.2.1.1. The picking process is explained in more detail in Section 2.1.5.3.

Outbound are all activities needed to make sure that products leaving the warehouse are going to the correct location in time. The warehouse has different types of outgoing orders (Section 2.1.1.). Part of the outbound process is the consolidation of Phase shipments that is done in the consolidation area on the south side of the warehouse that is colored orange in Figure 11. The consolidation process is explained in more detail is Section 2.1.5.3.

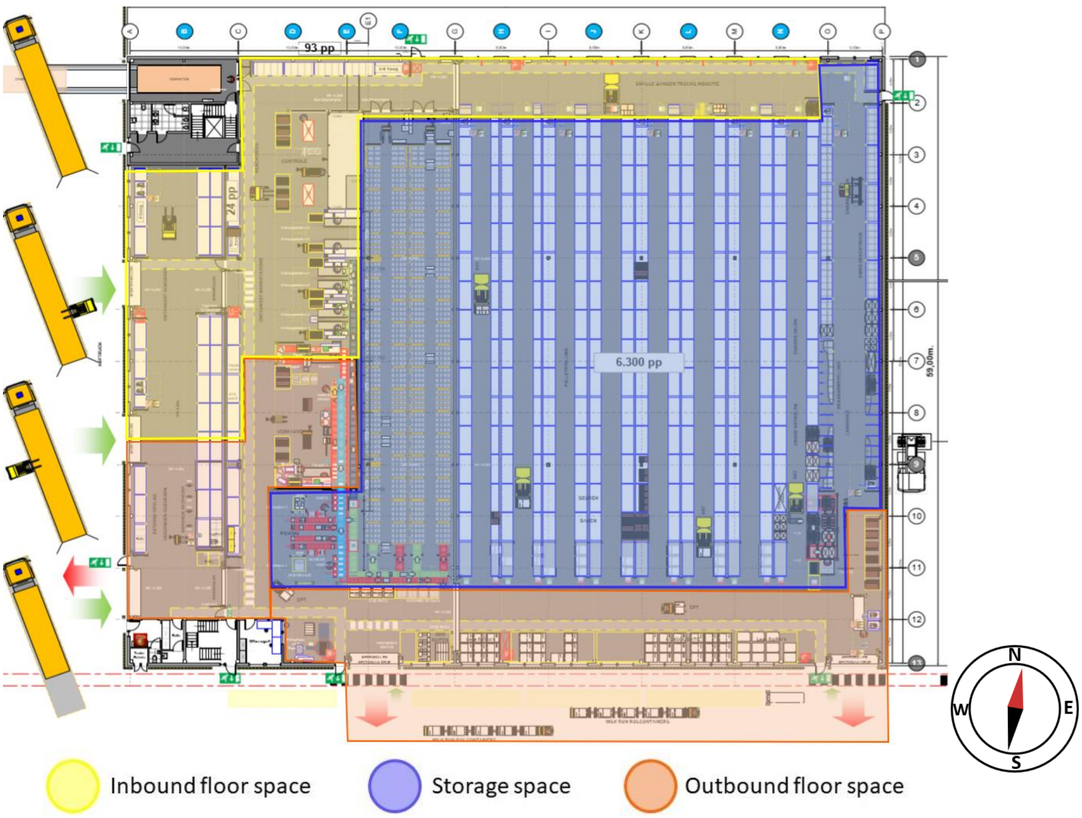


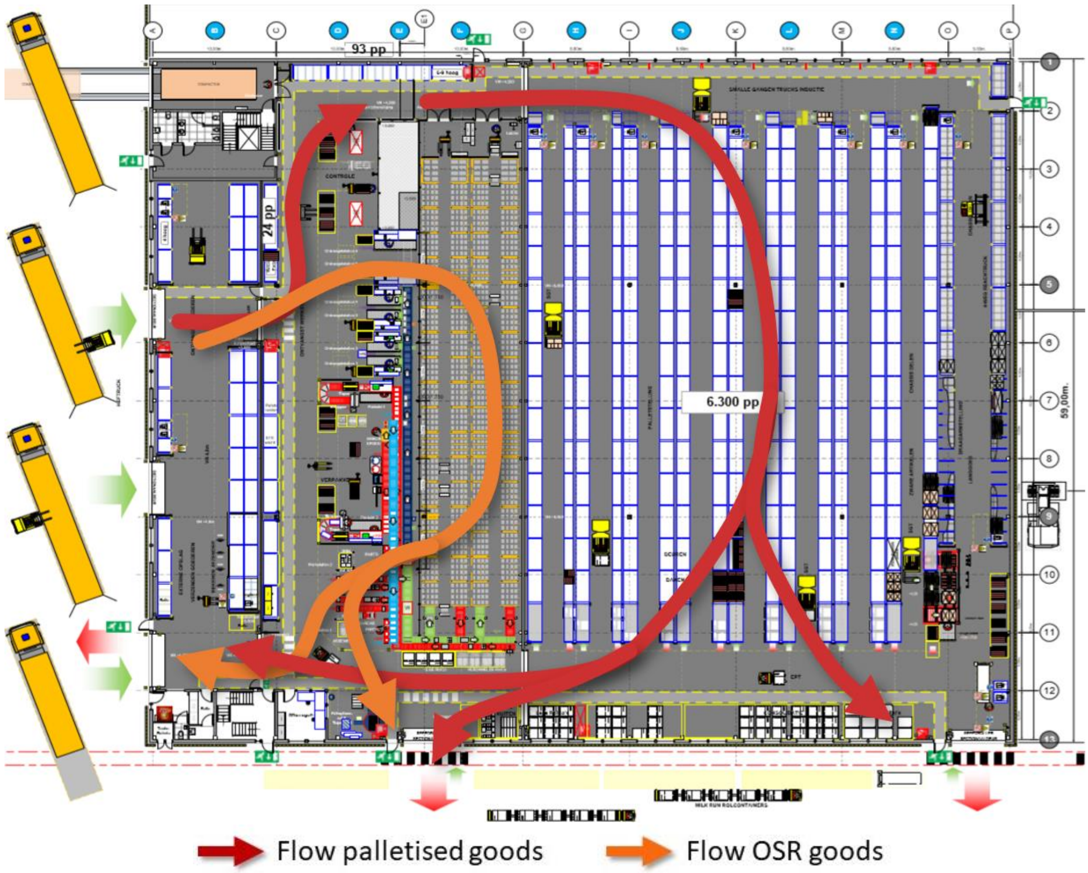
Figure 11: Warehouse logistics sections highlighted

2.1.4.1. Flow of goods

The flow of goods in the warehouse can be drawn by following the sections of the warehouse design of Figure 11. Figure 12 shows the flow of goods using two colored lines. Following the warehouse sections layout is a good initial indicator of the flow. Movement of goods through the central warehouse is controlled by the strict use of aisles resulting in a simple and clear one way flow. Products are not moved within the aisles or between lanes. Goods flow in at the top of the aisles and out at the bottom. The one way flow is an important criterion for an efficient flow (Walker 2020). The flow is fairly simple and clear, the only distinction made is between the flow of pallet goods and small goods. The red line resembles the pallet goods and the orange line resembles the smaller goods that are processed using the OSR.

2.1.4.2. Layout shape

The warehouse layout is a mixture of a U-shaped and L-shaped layout. Three regular warehouse product flow types are presented in Figure 13 (Icograms, 2020). The decision of this combined layout is partly driven by the position of the warehouse but mainly driven to optimize the logistics flow. The U-shaped warehouse is a commonly used layout that offers benefits in the shared utilization of dock resources such as personnel and material handling products. Furthermore, it offers the possibility of cross-docking (RED Storage Systems International, 2020).



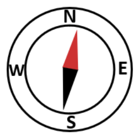


Figure 12: Flow of goods within the warehouse

As mentioned before, the warehouse at Terberg has a mixed purpose. Spare parts and Malaysia kits are shipped out of the warehouse on the west side, that is illustrated by the compass in Figure 12. Before shipment, all sales orders are prepared at the packing area located next to the inbound control section. Receiving and shipping are organized in the same section at the west side of the warehouse. Some of the larger and heavier goods are stored at an external warehouse a little further down the road in Benschop called Rietveld. If these goods are requested as spare parts or for Malaysia, this receiving and shipping section is a solution for cross docking. Another benefit of this layout is that the trucks stay at one side of the warehouse. The rest of the terrain is therefore less busy. Figure 2 in chapter 1 shows on the left the large area that is now designated to ready vehicles, supply and outbound logistics activities that do not interfere with the internal transport flows from the warehouse to the assembly halls.

The reason for the mixture with an L-shaped design is the other purpose of the warehouse, parts supply for assembly. The second exit on the south side is dedicated to the orders that are picked for assembly. Products of a phase shipment are picked from different locations and are combined in the designated consolidation area. Consolidation of production orders is separated from spare part shipment for clarity purposes. It is easier to control the consolidation, which is labor intensive and error sensitive, in this designated area. Furthermore, the exit on the south side of the warehouse is closer to the assembly line, which is located south east from the warehouse. By having two exits, the transportation flows outside the warehouse for the internal and external customer are separated.

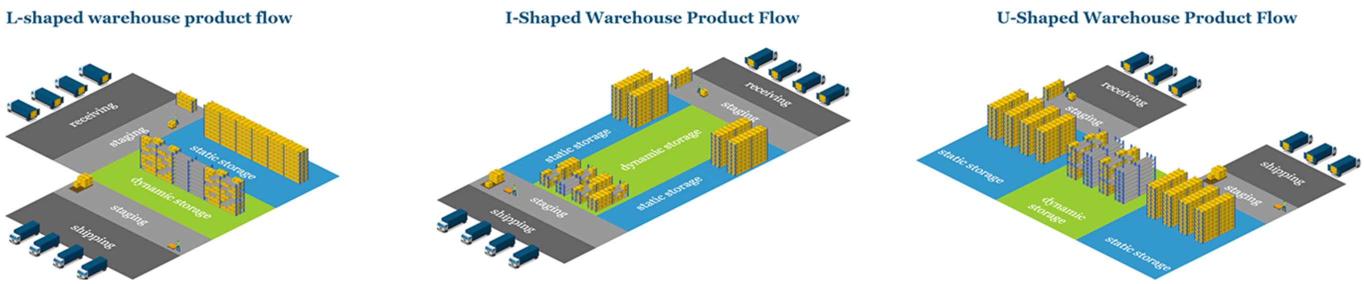


Figure 13: warehouse layout design options (Icograms 2020)

2.1.5. Warehouse operations

In the previous section the warehouse layout has been discussed in detail. In this section the current operations are explained within the warehouse. The warehouse operations can be divided in subsections. For this research we mainly focus on the picking and outbound operations that directly contribute to the output of the warehouse.

2.1.5.1. Shipment generation and activation

The pick process starts with the activation of shipments. Before shipments can be activated these shipments need to be created and offered for picking to the warehouse. Therefore, the process of shipment creation is explained as part of the outbound activities in this section as well. The different demand types as explained in Section 2.1.1. are generated and activated in different ways.

Phase

The phase orders are requested by the production managers of both production halls. The production manager of the HVA orders the shipments three takt times in advance. Based on the production schedule, the production manager knows which vehicle arrives at which phase three takt times ahead. At the advancement of the line the phase orders are placed at the warehouse.

The production at the LVA is arranged differently as explained in Section 2.1.3. Advancement of vehicles from one phase to another does not happen simultaneously for each vehicle, therefore a different order system is used for the LVA. Every day between 08:00 and 08:30 a.m. the production manager orders all shipments that he anticipates to need at least eight hours ahead, giving the warehouse enough time to prepare the shipments. This means that all shipments needed between 16:00 p.m. the same day and 16:00 p.m. the next day are ordered.

Due to the order process of phase orders, a few times a day a large number of shipments is requested at the warehouse at the same time. All these shipments are not directly activated. To gradually offer work to pickers, a pick coordinator is made responsible for the activation of shipments. The pick coordinator is provided with workload information per pick area on which the decision for activation of certain shipments can be based.

Two bin

For the refill request of the Two Bin system the empty bins are the trigger for pick activities. Two bin does not require the input of a replenishment order. Empty bins are brought to the warehouse and placed at the area where the goods are stored with which the bin needs to be filled.

Activation of two bin is not done by the pick coordinator but relies on the initiative of the picker. The picker can decide to take the empty bin, scan it and start the replenishment pick.

VPL

As explained in Section 2.1.1.3, VPL is a local storage at the assembly line for which orders are triggered based on the defined reorder point. Twice a day, around 10:30 and 14:30, VPL items are ordered for which the stock levels are below the reorder point. Just as with the phase orders the VPL orders are activated by the pick coordinator.

Spare parts

Spare part shipments are ordered by the customer at their convenience, which means that they occur at any time during the day. Spare part shipments enter the company at the sales department. The sales representatives directly enter the orders in the WMS (Warehouse Management System). The WMS is the IT system that directs and supports all storage and pick activities within the central warehouse.

Spare part orders are activated directly without the interference of the pick coordinator.

Malaysia

The orders for the external assembly location in Malaysia are also placed at the sales department. Since these orders are often large, containing many order lines requesting multiple items, the sales representatives cut these orders in smaller pieces before activating them in the WMS.

Just as with the regular spare part shipments the Malaysia shipments are activated automatically after the order is placed by the sales representative.

The entire process of shipment generation for the different order types and the activation of picking routes is graphically presented in Appendix 2.

2.1.5.2. Priority rules

The sequence in which all shipments are picked is based on two qualifiers. The first qualifier is the priority score. The shipment with the highest priority is placed in the front of the queue. Spare part orders have the highest priority scores. VPL and Phase shipments have an equal priority score which is lower than sales. 2Bin orders are not managed by the WMS so they cannot receive a priority score. The decision to start picking two bin relies on the initiative of the picker.

The second qualifier is the logistics time. Each shipment receives a logistics time when it is created. The logistics time is the ultimate time before the shipment should be picked to be in time. In time means that the shipment receives the exit scan before the Logistics Time (Section 2.3.2.)

For the phase orders the logistics time is two hours before the start time of the phase for which the shipment is requested. This two hours is based on the time needed for the so-called milk-run trucks to bring all shipments from the warehouse to the assembly halls. For most spare part orders, the logistics time is the end of the day on which it is ordered. Some customers come to collect the parts themselves at Terberg Benschop. This is planned with the sales representatives who determine the logistics time for the sales pick based on the time the customer plans to collect the parts. Other spare parts are needed by the service team of Terberg who have maintenance jobs planned and need parts for it. Logistics times for these spare part orders are based on the departure times of the maintenance engineers.

VPL orders receive a logistics time which is around three hours later than the time on which they are generated. The 2bin orders do not receive a logistics time for the same reason as why they do not receive a priority score.

2.1.5.3. Picking

Picking entails all activities related to fetching the right products at the right time and place them in the right product carrier ready to be taken to their destination. Pickers are supported by the warehouse management system (WMS) and warehouse resources like forklifts, aisle masters and roll containers (RC).

Picking is done differently at the OSR and pallet picking areas. At the OSR picking is done according to the goods to person principle while for pallet picking the operations are person to goods (Manzini et al., 2004).

Person to goods

In the pallet aisles, pickers operate cranes, called aisle masters, that carry both the picker and product carrier to the pick location. For eight narrow aisles seven aisle masters are operational and seven FTE (Full Time Equivalent) to operate them. Only one crane can enter an aisle at once. Since there are more narrow aisles than aisle masters, it is possible for a picker to move a crane to an empty aisle. Pickers are instructed by a handheld RF scanner showing the pick location and the number of items to pick at the location. The location is scanned when the pick is fulfilled to book the pick and request the next location. The picking algorithm for phase picking is based on two basic principles: start from the back of the aisle and move forward, and start high and move upwards as less as possible.

Pick orders that are finished are, depending on the classification of the order, either placed at the front of the aisles ready to be taken outside, or placed in the consolidation area.

On the wall of the warehouse above the consolidation area, multiple screens are mounted, which present order line information and outstanding workload per aisle. This information is used by the pickers to start a new pick order and bring the correct product carrier for the pick assignment. The start of a new order is initiated by the picker. Pickers can only start picking a shipment when the shipments are activated by the coordinator as explained in Section 2.1.5.1.

Figure 15: Aisle Master

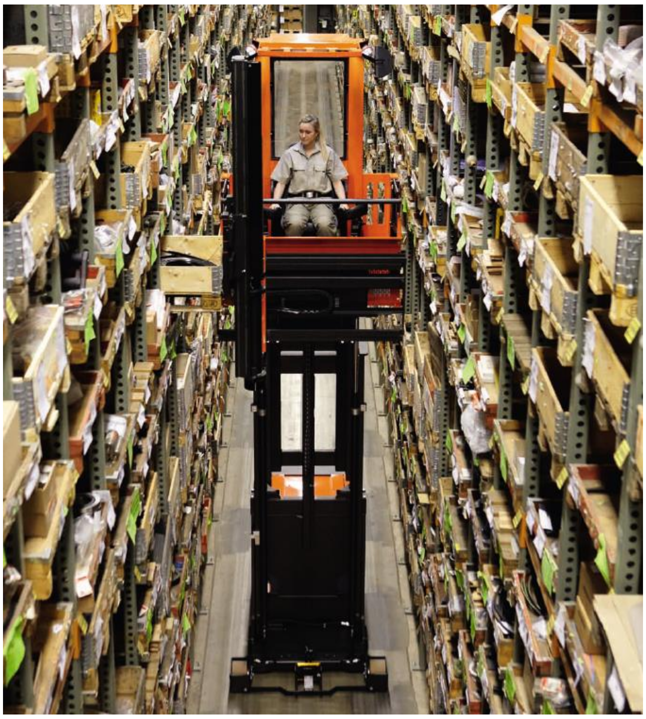


Figure 14: Person to goods picking in narrow aisle

Goods to person

The OSR is an AS/RS system meaning that the transportation of the goods both for storage and for retrieval is automated by the system. The picker stands at a pick station and the goods are transported in crates, which we refer to as totes, on conveyors to the pick station. Figure 16 shows the two pick stations of the OSR and how the crates are transported to the picker. The green arrows indicate the entering movement of the totes to the part of the conveyor that is called the buffer. The buffer can hold up to eight totes. On the end of the buffer the totes switch lanes and move in the opposite direction, as indicated by the red arrow. On their way back the totes enter one of the two collect locations. At that moment, all the picker has to do is pick the correct number of items from the totes and place it on another product carrier like an RC, as indicated by the blue arrow. When the picker finished the pick from a tote, the system will move the tote back to a free storage space inside the system.

The OSR has two pick stations that can be operational at the same time. Each pick station can be used in four different configurations: Sales, Production, Two Bin and Combined. Sales means that only spare part orders and sales orders for direct sales to customers are send to the pick station. The Production configuration sends only products for production shipments. Two Bin is used for filling the empty bins and Combined is sales and production orders but not two bin orders.

Before an operator can start picking at the OSR he or she first needs to prepare an RC by taking an empty RC from the buffer and place it at the filling station. A fill tray is added to the RC to prevent small goods from moving around in the RC. The picking is guided by a display showing the number of items to be picked and from which tote. Production orders are prepared in the RC and brought to consolidation after picking.

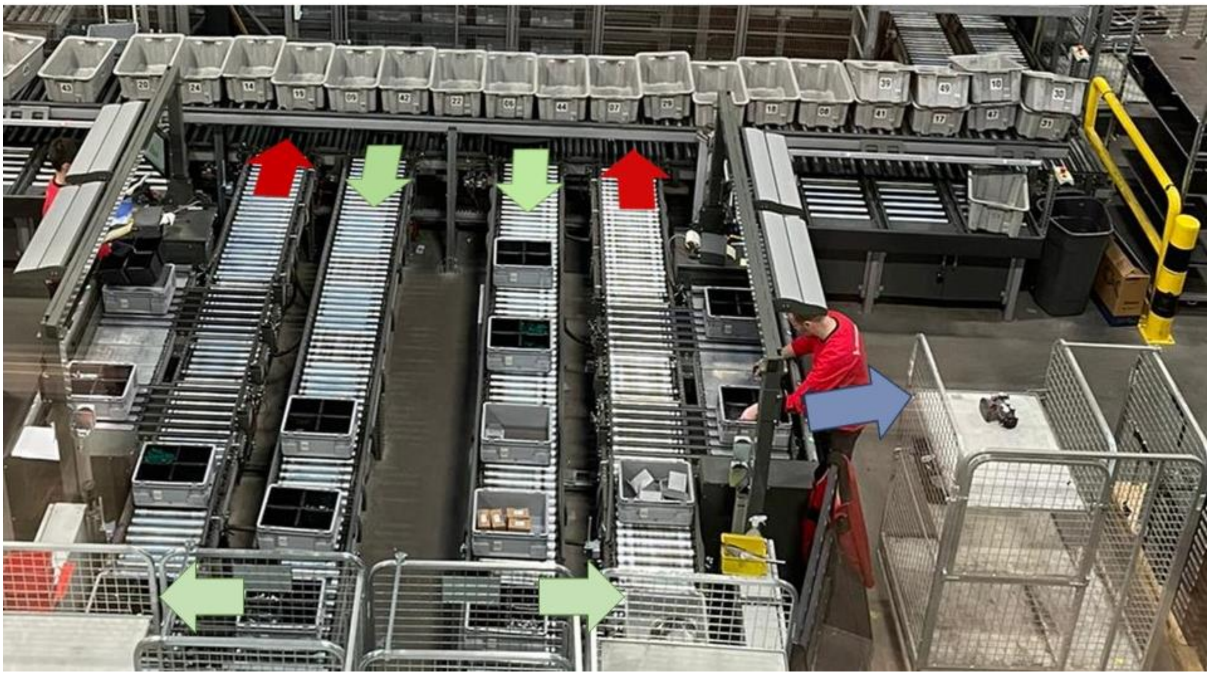


Figure 16: Picture of the OSR pick stations in the central warehouse of Terberg

2.1.5.3. Consolidation

At the bottom side of the narrow pallet aisles a space of twelve consolidation areas is located. The consolidation areas are introduced to structure the combining of pick orders for different aisles that are part of the same shipment. A consolidation area is reserved for a shipment and RCs with parts coming from different areas are brought to this area to be consolidated. At the assembly line limited space is available for the RC with the parts needed. These spaces are visualised as squares in Figure 10 and 11. Therefore, a maximum number of RCs that can be placed at the line is defined. Shipments that are picked in more areas than this maximum need to be consolidated to a number of RCs equal or lower than the maximum. Minimizing the number of RCs that need to be transported from the warehouse to the assembly halls also reduces the number of trips the milk-run needs to make to move all RCs. Each Phase shipment is completed in the consolidation area before it receives the exit scan.

2.1.5.4. Storage Decisions

The storage of goods inside the OSR is an automated process. Goods are booked in and placed in the crates at four inbound stations. After booking in the goods, the systems will transfer the crates to a storage location. The operations within the OSR are managed by KNAPP therefore it is difficult to track goods inside the OSR. Terberg is not able to influence the storage algorithm of KNAPP and therefore the OSR is considered as a single storage location containing all items stored inside the OSR.

The placement strategy of goods in the pallet aisles is more interesting for this research. The pickers in the pallet pick area, are free to place incoming goods on the shelves in their aisle where they want to. First the pallets are placed in the buffer shelves at the back of the aisle, called backpacks, by the forklift operator. The decision in which backpack to place the pallet is based on information on which aisle the product was placed latest. The result is that goods are always stored in the same area they were placed originally but the exact shelve within the aisle can still differ. It is not regularly evaluated whether the goods are optimally distributed over the aisles.

The aisles operators are free to decide on which location to store the goods. They do understand the logic of the pick algorithm and anticipate to it, by trying to store goods that are requested regularly together in the same shipment in one horizontal line. The larger less fragile products in the back and the smaller and fragile products, like visual parts, in the front. The crane operators prefer the horizontal movement over vertical because it is easier and quicker to aim for the right position.

2.2. IT Infrastructure

Operations inside the warehouse are supported by an IT system. At Terberg Benschop an ERP system named Microsoft Dynamix AX is implemented. A warehouse management system (WMS) module is designed and integrated with AX so that in- and outbound movements of goods in the warehouse are directly registered as transactions in the ERP system.

The WMS system is an important element in the traceability of the SKUs in the warehouse. Besides the storage area, each storage location on the shelves in the pallet aisles is registered in AX. Each pallet is linked to one of these locations when stored inside the warehouse. The pickers, that are also responsible for storing the goods inside the pallet aisles, are equipped with a handheld scanner that is connected to the WMS. By scanning the barcode of the location and the barcode of the pallet containing the goods, the goods are connected to the location and this allocation information is registered in the WMS. With this information registered it is always possible to trace the goods inside the warehouse.

The storage location information is essential for the system to support the pick activities. As explained in Section 1.2.1.2. a shipment is divided in pick assignments for each aisle. For the system to be able to make this division it needs the location information of each item that is requested in the shipment. Another important element in this system design is the information of the items required per assembly phase for each vehicle. Production routings are defined in AX for each vehicle and the Bill of Materials, which is also registered per vehicle in AX, is divided over the production phases. This information is the input that the WMS needs to translate the production schedule to pick assignments in the warehouse.

The WMS is connected to the handheld scanner that provides the pickers with the location item and amount information that is needed to fulfill the pick action. By scanning the pick location, the picker registers the pick and the number of items picked are withdrawn from the stock level for that location. The scanning actions are therefore very important both for assigning stock to a location as for reducing stock levels after a pick action is fulfilled.

Next to the items per phase that are needed for a certain vehicle, the information about the maximum number of RCs that can be placed at the production line per phase is stored in AX. This information is leading for the consolidation efforts that are needed for each shipment.

For the goods in the OSR the system is slightly different. The OSR is registered in the WMS just as a single storage location, meaning that the storage area and location are one and the same. The WMS knows which goods are stored inside the OSR but is not aware of the exact location. The OSR is driven by its own software and a black box for Terberg. This OSR software is linked to the WMS. When a shipment is activated containing items that are stored inside the OSR, a message is sent to the OSR with the pick information. The OSR translates this information to placing the totes containing the items needed in the queue for picking. From all assignments that the OSR receives, the system decides on the sequence in which the totes are brought to the pick stations.

2.3. Performance data

In this section, the current performance measurement and data availability at the central warehouse are explained and evaluated.

2.3.1. Data availability

As explained in Section 2.2. the warehouse operations are supported by a WMS module and handheld scanners are used to scan product movements and transactions. These transactional records are all stored in AX. Royal Terberg Group has its own data science department that is able to export the data from AX and use it for their own evaluation.

The data that was provided for this research was historic data of each order line that was executed over a period of one year and a half. This data contained production information, shipment data and pick records.

Production data contains all information about which vehicle is made in which assembly hall and passing through which phases. This production data contains information like: Production order ID, Vehicle type, Assembly line and assembly phase.

The shipment data contained all information about which items are needed to be picked as a batch order and from which area. Shipment data is for example: Shipment ID, Item ID, Quantity and Shelve ID. A shipment is unique for a certain phase for a specific vehicle and can therefore be linked to a production order.

Most important for the evaluation of the warehouse performance are the pick records. These records contain the time registrations of each scanned activity. Consider the activation of a shipment, the first pick of a shipment, the first pick at each area that is visited for the shipment but also the last pick of each area and the final exit scan.

Figure 17 shows an overview of the data structure of the historic data that was used for the evaluation of the pick performance of the Central Warehouse.

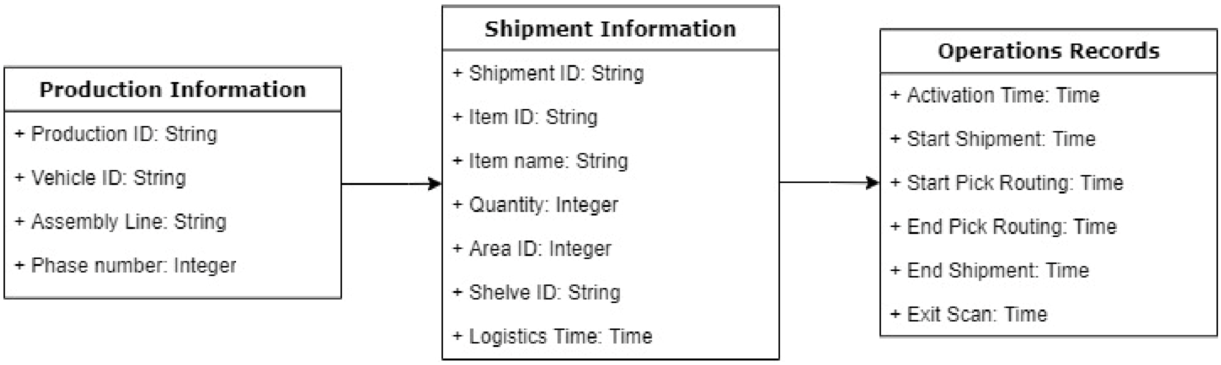


Figure 17: Data structure of historic pick data

Only for the pick activities within the pallet aisles data is available in the structure presented in Figure 10. For the OSR, the data availability is limited because the pick processes within the OSR are not managed by the WMS but by the software system of the supplier of the OSR. The difference is in the measurement of the pick activities. Where the WMS registers every individual pick of each picker in each aisle, the OSR returns one single time for each pick in a shipment. Therefore it is impossible to learn from the data how much time it cost the OSR to pick all items for a shipment.

2.3.2. On-Time Exit Scan

The On-Time Exit Scan score is the most important performance indicator that was used for the central warehouse. This measure shows the management whether the warehouse operations are able to deal with the workload or not. The On-Time score is measured as a Boolean measure, meaning that the outcome is positive or negative. A shipment is either on time or it is too late.

The On-Time score is measured by comparing the time of the Exit Scan of a shipment with the Logistics Time. The Exit Scan is the final scan of a shipment after consolidation that confirms the completion of the shipment and allows it to be taken to the assembly hall. The Logistics Time is already explained in Section 2.1.5.2 as the deadline for the pickers to finish the shipment. If the Exit Scan is before or equal to the Logistics Time, the shipment is On-time and otherwise it is too late. The number of On-Time shipments divided by the total number of shipments per time unit gives the On-Time ratio. Figure 18, that is a repetition of Figure 5 in Section 1.3.1.1., shows a report of the pick performance how it is prepared by the data science department.

This measure can easily be extended by quantifying the On-Time score by adding the minutes left or minutes too late per shipment.

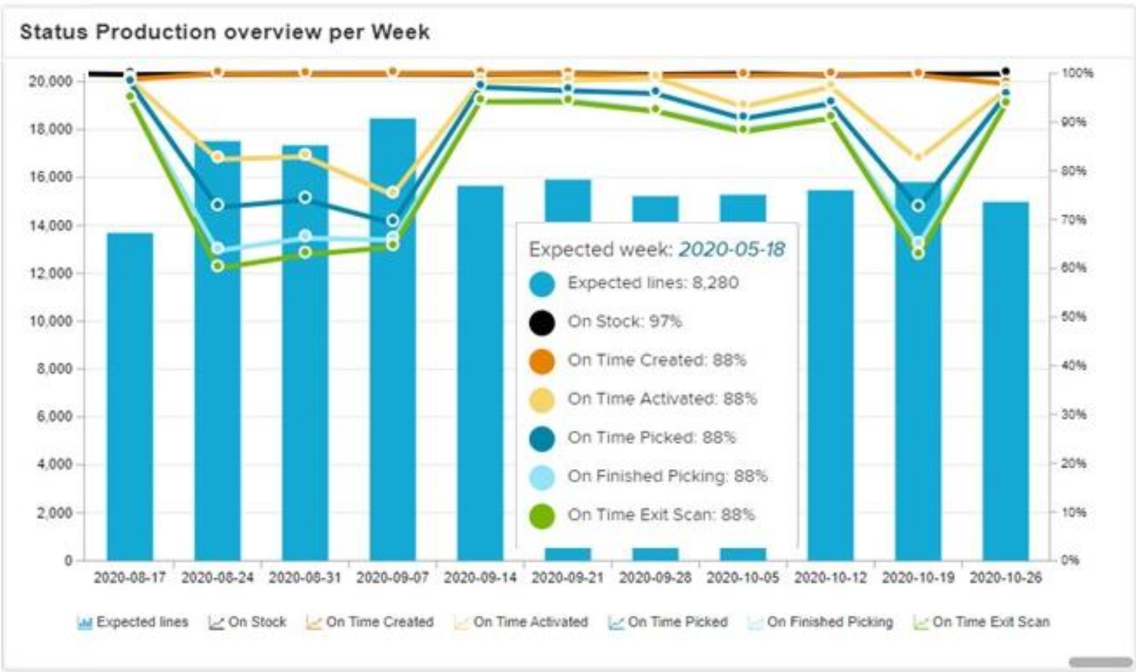


Figure 18: Celonis pick performance report

Figure 18 shows more performance measures than just the On-Time Exit Scan. The reason why the Exit Scan is more important than, for example, the On-Time Picked measure is that the Exit Scan is the final registration at the end of the complete pick process. The consolidation step, for example, is in between the completion of the pick routings and the final Exit Scan. In the next chapter, the influence of this consolidation process will be explored in detail. The On-Time Exit Scan measure shows whether the warehouse is able to complete the entire pick process in time.

2.4. Summary on Chapter 2

In this chapter the physical layout of the central warehouse and the assembly halls are presented. The central warehouse at Terberg Benschop is a multi-purpose warehouse. The Central warehouse stores both parts needed for the assembly of new vehicles as spare parts that are directly sold to existing customers for maintenance purposes. Pick assignments are therefore divided in different demand classifications. The production orders can be divided in Phase, VPL and 2Bin. The sales orders are divided in Spare parts and Malaysia orders.

The central warehouse is divided in two main storage sections with different characteristics. The first section contains a large AS/RS system, called the OSR, that involves picking by the goods to person principle. The OSR has two pick stations that both can be used in four different configuration: Production, Sales, Combined and 2Bin. The second section contains nine narrow pallet storage aisles. Within the pallet aisles, picking is done according to the person to goods principle. The picker uses an aisle master to travel both back and forth, and up and down the aisle. Pickers do not travel between aisles to complete a picking route. A picking route is dedicated for one aisle.

SKUs requested in an order can be spread over different pick areas, like each of the nine pallet aisles and the OSR. For each pick area a set of orderliness is generated and the combination of all orderliness for an order is called a shipment. When a shipment requires picks from different areas, the roll container carrying the goods are placed in one of the twelve consolidation areas where the shipment can be consolidated to the maximum number of carriers allowed to be taken to assembly.

The data science department has a lot of transactional data available of the different pick actions within the pallet aisles. Each SKU pick, the start of each picking route and the moment a shipment leaves the warehouse (Exit scan), are logged in the WMS system. The warehouse performance is measured with the On-Time score. This is determined by comparing the Exit Scan with the Logistics Time (pick deadline). The On-Time score is the percentage of the total orders per week that are completed in time.

3 | Operational Performance

The unequal division of workload is one of the core problems that was identified in Section 1.3. The workload can be measured in multiple ways. In this chapter the workload division over the pick and storage areas is explored in detail. In Section 3.1, the workload division in order lines and shipments over the storage areas is evaluated. In Section 3.2, the workload figures are transformed from picking routes into time measures. Section 3.3 reflects on the pick efficiency by defining a method to measure the degree in which the sperate areas are working on the same shipment in parallel.

3.1. Workload division in pick assignments

In Section 2.3.2, the performance indicator On-Time Exit Scan is introduced as the most important measure for the warehouse. Figure 18 in Section 2.3.2. showed that not each shipment is picked in time. This problem was briefly mentioned in Chapter 1 and the analysis of the problem led us to the core problem of the workload not being divided over the pick areas equally.

The workload of the central warehouse is currently measured in order lines. Figure 19 shows the division of order lines over the areas. The figure shows that the large majority of the order lines is picked at the OSR. At each area, except for aisle 31, the majority of the order lines are part of a Phase shipment.

The spare part items are deliberately placed as much as possible in aisle 31 so that pick activities for spare parts interfere as little as possible with the pick activities for production.

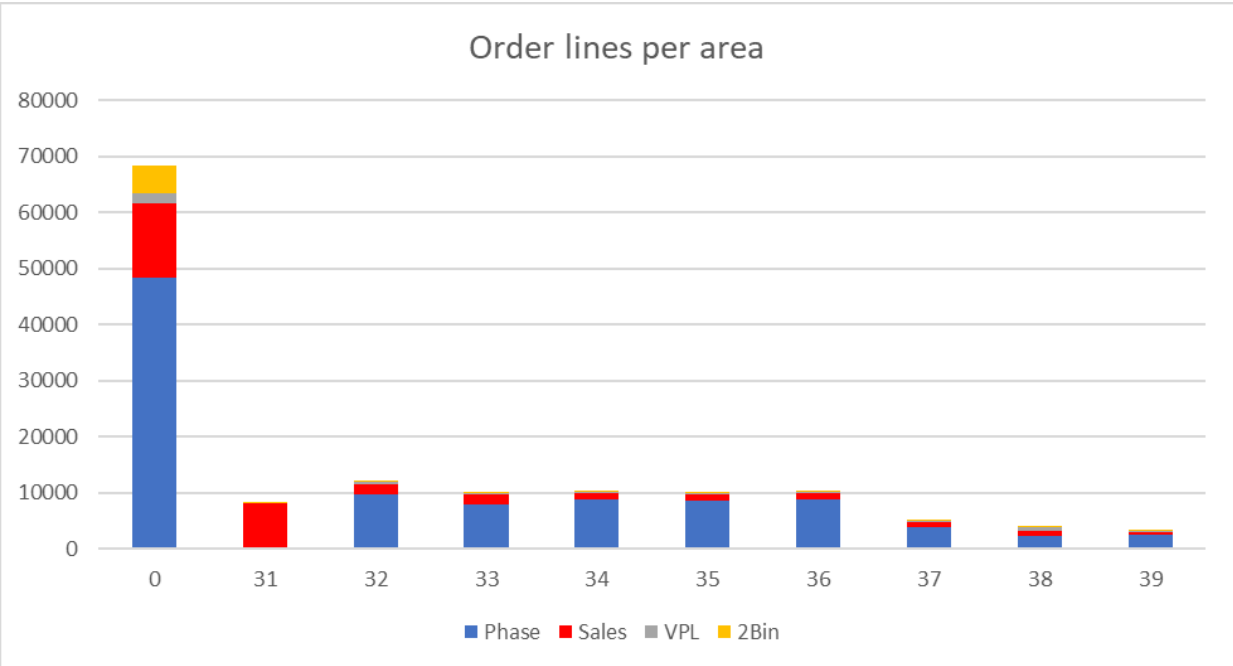


Figure 19: Order line division over pick areas

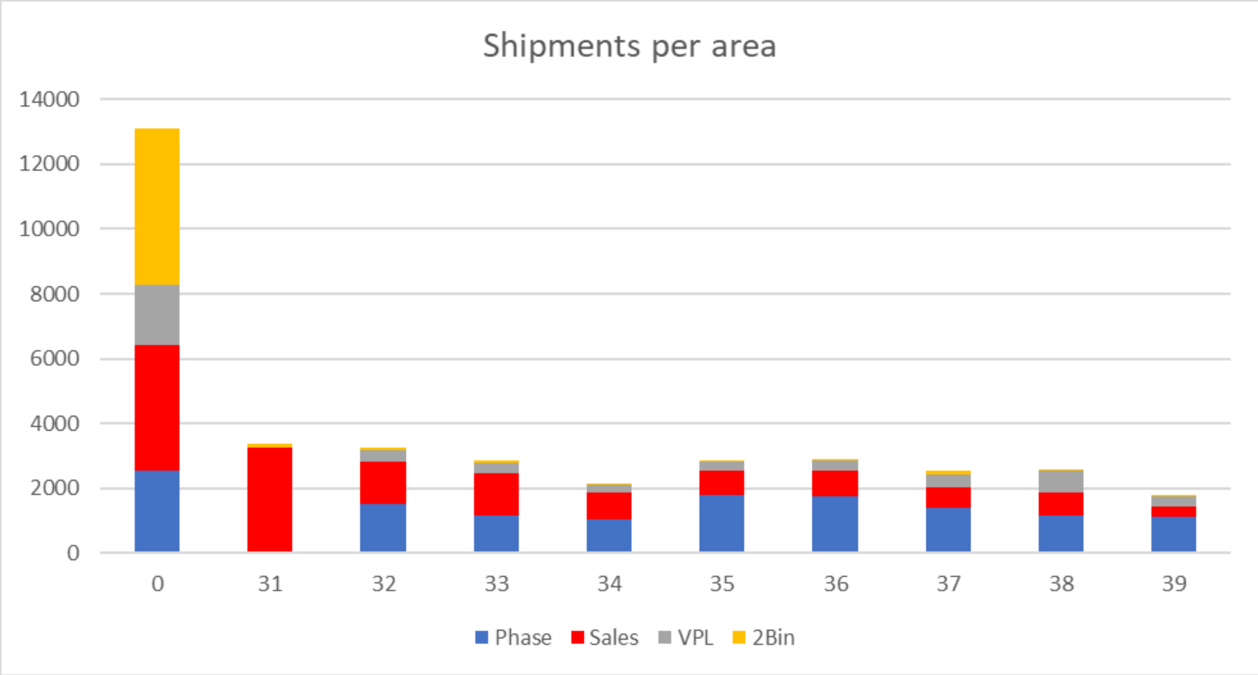


Figure 20: Shipment division over pick areas

Figure 20 shows the number of shipments per area. The relative share of Sales shipments is larger than the relative share of Sales order lines. The reason for this difference is the number of unique parts that are requested in each shipment type. Table 2 shows that for a Sales shipment the average order lines per shipment are lower than for Phase shipments.

Especially for the OSR, the difference between the order lines and the shipments per demand type is large. Figure 20 shows that the share of Two Bin and Sales shipments is larger than the share of Phase shipments.

Table 2: average order lines per shipment per aisle

	Average order lines per shipment									
	0	31	32	33	34	35	36	37	38	39
Production	18.97	1.13	6.42	6.78	8.51	4.90	4.98	2.83	2.08	2.38
Sales	3.41	2.52	1.48	1.41	1.35	1.33	1.42	1.31	1.27	1.17

It is relevant to look at the division of shipments over the pick areas rather than just analysing the order lines division. Order lines provide an indication of the number of pick actions that need to be completed but the shipments are the triggers for these pick actions per area, as is explained in Section 1.2.1.2 and Section 2.1.2. Shipments tell us more about how often a certain pick request occurs at a certain area.

Take the OSR for example. Figure 19 shows that a significant share of the total order lines are Phase order lines, but Figure 20 shows that the relative share of the shipments that form the basis for the order lines is not as significant. As explained in Section 2.1.5.2., Sales shipments have the highest priority. The higher share of Sales shipments for the OSR with a higher priority score, will delay the activation of Phase shipments. As explained in Section 2.1.5.3. the phase shipments are first awaiting completion of the order lines in each related area. The high workload in sales shipments for the OSR could therefore delay the exit scan for shipments that include parts that need to be picked at the OSR. The problem analysis in Section 1.3. and the problem cluster in Figure 4 already mentioned that the pickers have the feeling that they often need to wait for the OSR to deliver its share for a shipment.

Analysis of the pick data shows that the OSR is indeed most often the last area to finish the pick assignment for a shipment. Table 3 shows that the OSR is the last area to finish in 56,75% of all shipments. In a perfectly divided workload situation it would be expected that every area is last an equal number of times. In this situation, aisle 31 could be neglected since it is allocated for sales parts. With 9 areas left, that would mean that each area is last in 11% of the times. So, the results from Table 3 show that the OSR is last in a significant number of shipments.

Table 3: Results of last area to finish a shipment

	Count of times each area is the last to finish its share for a shipment									
	0	31	32	33	34	35	36	37	38	39
Shipment count	3560	28	314	529	504	401	318	191	222	206
Percentage of total	56.75%	0.45%	5.01%	8.43%	8.03%	6.39%	5.07%	3.04%	3.54%	3.28%

Aisle 33 is second in the score of last aisles to finish picking. For this aisle, the Sales shipment share is also the largest of the four shipment types (see Figure 20). So the priority on Sales shipments and the share of Sales shipments for an area can influence the pick performance of the Phase shipments for the total warehouse. Furthermore, aisle 33 till 36 share three Aisle Master for the four aisles, as explained in Section 2.1.5.3. This could be a reason for the scores of being the last for these aisles as well.

3.2. Utilization of operational capacity

The previous section showed how the order lines and shipments are divided over the different pick areas. This provides insight in the workload division over the different pick areas, but as mentioned before, not each order line or shipment is the same. A shipment can consist of a single order line or multiple, and each order line can consist of a single unit pick or multiple. Each part at its turn differs in size, weight and vulnerability which demands different ways of handling. Furthermore, the storage location and pick methods can differ. For aisle 38 and 39, for example, the number of order lines per shipment is low, because in these aisles the heavy parts are stored. These parts require extra handling support.

The picking principle of the OSR compared to the narrow aisles is completely different, as is explained in Section 2.1.5.3. The number of order lines at the OSR is more than five times larger than for the pallet aisles. The fact that the OSR has two pick stations is already considered in this analysis. The question is whether the difference in picking methods and order line characteristics makes it possible for the OSR to complete so much more order lines as the aisles. The numbers in the previous section cannot answer this question, because they do not provide information on speed and efficiency.

Therefore, the uncertainty in the order line and shipment analysis makes it interesting to analyse the workload in picking time. The picking time of a picking route is the time between the pick of the first SKU and the last SKU. Workload in time provides a better understanding of the actual capacity used. The working days are fixed from 7:30 till 16:30, with two breaks of 15 minutes and one lunch break of 30 minutes. The effective working time each day therefore is eight hours. The fixed working hours give a clear indication of capacity in time where it is harder to estimate the capacity in order lines, especially since the order lines are not all the same. Since we will compare the workload in time with the operational capacity in total working hours, we will refer to this indicator as the utilization of operation capacity, or short utilization.

Figure 21 shows the average utilization of resources per aisle per pick classification. The utilization of an aisle is calculated by dividing the sum of picktimes for all pick routings on a day by the total working hours of the day. Because the same resources, aisle cranes and pickers, are used for pick activities as well as storage activities in the pallet aisles, the time for inbound movements is added to the utilization analysis.

Striking about the figure is the missing bar for the OSR. As explained in Section 2.3.1, the picktimes at the OSR are not registered correctly, making it impossible to evaluate the utilization of the OSR based on pick times and compare the OSR to the other areas. This lack of information is one of the reasons why simulation is chosen as the research method for this thesis, since simulation might be able to provide the process data that is currently missing.

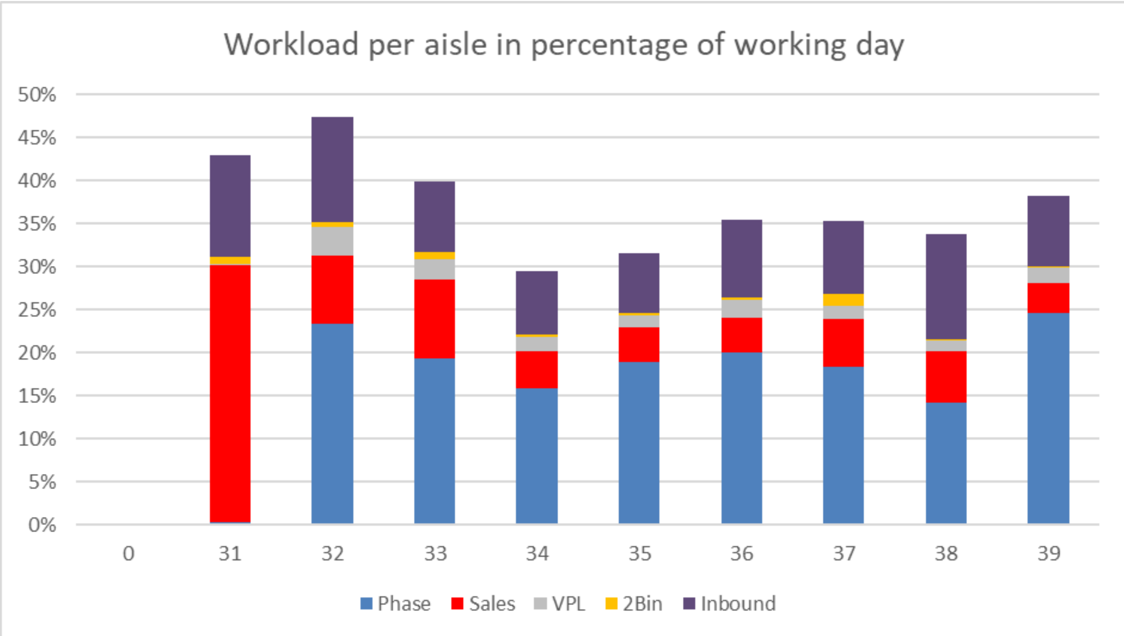


Figure 21: Average utilization of operational capacity per aisle per pick classification

Figure 21 also shows that aisle 39 needs the most time to complete the pick actions for Phase shipments while Figure 19 and 21 showed the least order lines and shipments for aisle 39. Pick activities in aisle 39 have longer pick times due to the use of a forklift instead of the aisle masters and the extra required lifting support for the heavy goods.

Aisle 38 has the relative largest inbound time. The reason for the almost equal share of Phase time versus Inbound time is the large number of palletized VPL items that are stored inside aisle 38. With many VPL items, aisle 38 has less pick actions from the same pallet as in other aisles, meaning that it requires a resupply sooner.

Although the total average utilization per aisle that is shown if Figure 21, might suspect room for an increase of workload for the aisles, it cannot be concluded from this data. Since the shipments are divided in pick assignment over the areas, the areas are connected for the completion of a shipment by consolidation as is explained in Section 2.1.5.3. Therefore, the areas are not independent. In the next section the effect of consolidation on the process performance is evaluated.

3.3. Waiting time

The items that are requested in Phase shipments are allocated to the pallet aisles per phase as much as possible. This is not the case for allocating items to the OSR since allocation decisions for the OSR are based on size characteristics of the items. The idea of storing items per phase is to minimise the areas visited per shipment. By minimizing the number of areas to visit for a shipment, the smaller the consolidation effort and the less dependent the areas are off each other.

In the current situation, the item allocation divides the Phase shipments on average over 2.7 areas, including the OSR. So although the items are allocated per phase, not each phase order is picked entirely from a single area. The main reason is that some items are requested in different phases for different vehicle types, making it difficult to link the item to a single phase.

When items from different areas need to be picked for a shipment, waiting time can be the result when the different pick assignments are not picked at the same time. If one area starts half an hour after another has already finished, the first part of the shipment is waiting in the consolidation area for the last part to be picked. This waiting time at first is not a problem only when it results in a late exit-scan. Another problem of the waiting time is the long occupation of a consolidation area. When all twelve areas are full, pick areas cannot start a new shipment and need to wait for a consolidation area to be released after a shipment is completed by another area. This can result in an actual stand still of a picker while there is still work in queue.

In the problem cluster in Section 1.4, the high occupation rate of the consolidation areas was mentioned as an inefficiency that limits the output of the warehouse. Unfortunately, the occupation levels of the consolidation areas are not registered let alone the actual stand still time of pickers. Simulation can help to fill this gap in information as will be explained in Section 6.1.1. In the rest of this section an attempt is made to show the effect of the interdependency of the areas by measuring the effect of non-parallel picking.

Parallel picking

Parallel picking is when different pickers in different aisles are all working on their share of the same shipment at the same time. When shipments are picked in parallel, the expected shipment time is equal to the longest pick time of all related pick routes. This expectation can be formulated in the following mathematical function:

$$PST_s = \max_{a \in A}\left(PT_{a,s}\right), \qquad \forall s \tag{1}$$

$PST_s = Parallel\ shipment\ time\ for\ shipment\ s$

$PT_{a,s} = Pick\ time\ for\ the\ share\ of\ shipment\ s\ that\ is\ picked\ in\ area\ a$

$A\ = set\ of\ pick\ areas\ \{0, 31, 32, 33, 34, 35, 36, 37, 38, 39\}$

Based on the problem identification, picking is not done in parallel regularly so the shipment times will often be larger than the parallel shipment time. Reformulating that observation in another mathematical function shows an option to measure the pick efficiency of the picking process:

$$ST_s > PST_s, \qquad \forall s \tag{2}$$

$$ST_s > max(PT_{a,s}), \qquad a \in A, \ \forall s \tag{3}$$

$$ST_s = max(PT_{a,s}) + WT_s, \qquad a \in A, \ \forall s \tag{4}$$

$$WT_s = ST_s - max(PT_{a,s}), \qquad a \in A, \ \forall s \tag{5}$$

$WT_s = Waiting\ time\ for\ shipment\ s$

With the available performance data it is possible to determine the shipment time of each shipment (ST_s) and the longest pick time for the areas visited for each shipment ($max(PT_{a,s})$). This means that the waiting time (WT_s) is the only unknown variable that can be solved with the two other variables being known. The variable waiting time can be used to measure the parallel picking performance of the warehouse. The lower the waiting time the quicker the warehouse is able to finish the shipments.

Figure 22 shows a histogram of the waiting time analysis on the historic data. The red bars show the waiting time based on the shipment time minus the longest pick time as formulated in function (5) above. The times on the x-axis are the upper bounds of the bins used for the histogram. The figure shows that just 1% of the shipments is completed within the time of the longest pick route, the single area shipments excluded, meaning that this 1% is picked in parallel. 61% of the shipments include waiting time over 21 minutes.

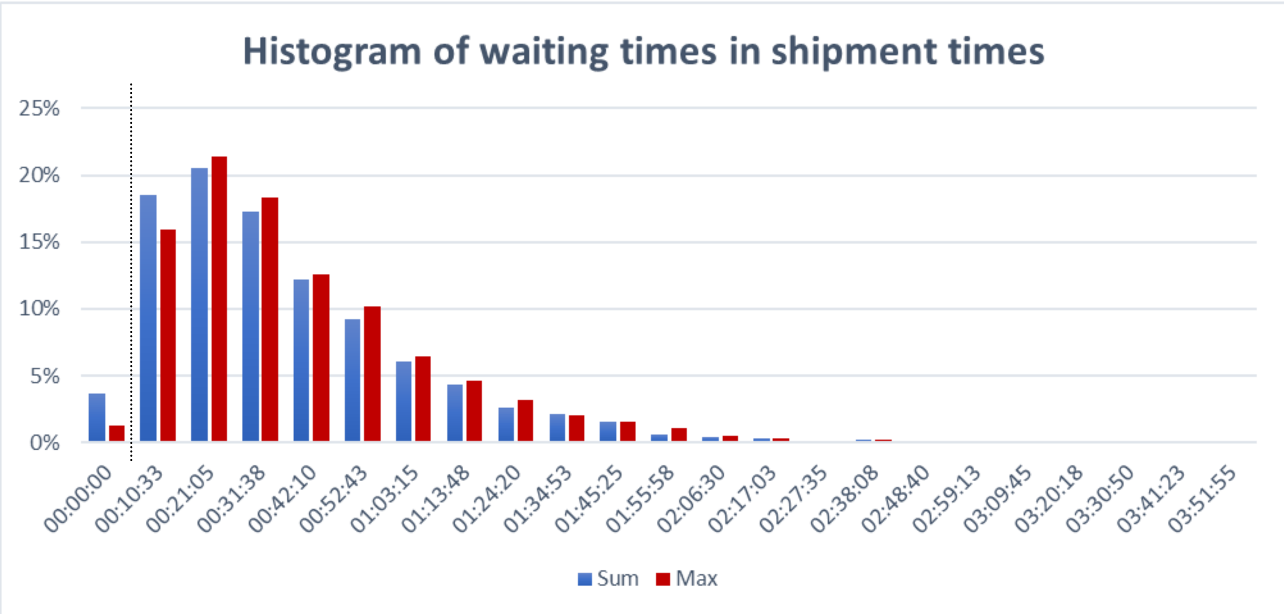


Figure 22: Distribution of waiting time in shipments

Since not each area has its own aisle master and picker, it is not always possible to pick a shipment completely in parallel. Furthermore, the histogram does not show whether 2 or 10 areas where visited for the shipment, which could make a difference in the evaluation of the waiting time. Therefore a second measure is suggested to evaluate the waiting time.

Instead of comparing the shipment time with the maximum pick time of one of the picking routes, the shipment time is compared to the sum of the pick times of each picking route that is part of the shipment. By taking the sum, the shipment time is compared to the pick times as if they were picked sequentially. The result is that the waiting time can be analysed as a share of the total pick time. The mathematical formulation would then be as follows:

$$WT_s = ST_s - \sum_{a \in A} PT_{a,s} , \qquad \forall\, s \tag{6}$$

The blue bars show that even when the shipment time is compared to the sum of pick times, the waiting time is still significant. The same bins are used to show that the share of pick time in the shipment time is marginal. Only 4% of the shipments have a waiting time lower or equal to 0 when measuring with the sum of pick times. This means that just 4% is fully or partially picked in parallel. The centre of gravity of the graph moved slightly to the left but still 57% of the shipments have a waiting time over 21 minutes.

Table 4 gives a short statistical summary of the differences in pick and shipment times. The average waiting time when considering the sum of picking routes is more than 32 minutes. The average sum of pick times in a shipment is 9 minutes. This shows that the larger share of the shipment time, 76,2%, is waiting on other areas to finish their part of the shipment.

Table 4: Statistical summary shipment waiting time

	Sum	Max
Average	00:32:20	00:34:52
Median	00:24:52	00:27:25
Min	(01:11:12)	00:00:00
Max	09:08:10	09:08:10

3.4. Summary on Chapter 3

In this chapter the workload division over the different pick areas was analysed. First the workload was analysed based on the total order lines and shipments per area, divided per demand classification. The number of order lines in a Sales shipment is a lot lower than for Phase shipments. The analysis of the order lines and shipments per area showed that the OSR has over four times more shipment requests than the pallet aisles.

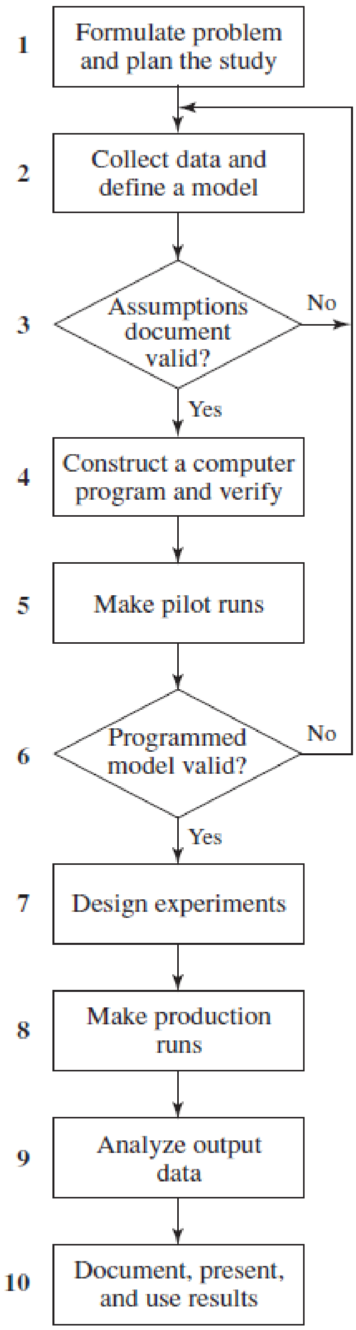
The picking method is entirely different at the OSR and the pallet aisles and not each pick line is the same. Therefore we have decided to not only evaluate workload in the number of pick lines, but transform the workload in pick time, utilization. Unfortunately, the data provided regarding pick actions at the OSR does not provide information on pick times at the OSR. The simulation should help us to get an understanding of the pick times at the OSR.

The interest of this research is the outbound efficiency of the entire warehouse, not the performance of each individual area. By comparing the pick times of the individual areas with the shipment times, we have found a way to measure the pick efficiency of the warehouse. For this performance measure we use the Waiting Time measure. The Waiting Time is defined in two ways, either as the shipment time minus the longest pick time of the related picking routes, or as the shipment time minus the sum of the related picking routes. The average waiting time is respectively 34 and 32 minutes.

4 | Simulation Model Design

In this chapter the design of the simulation model, that is used as the core problem solving method for this research, is presented. In Section 4.1, the design theory of our simulation study is described. Some theoretical background on Discrete-event simulation, which is the simulation method used, is provided in section 4.2. In Section 4.3. the conceptual model, showing the design principles and the simplifications needed to be able to model the system, is presented. In section 4.4. and 4.5 the input distributions for pick times at the pallet aisles and the OSR are explained. Section 4.4 reflects on the software used for the simulation model. The last section, Section 4.5, shows how we have validated the model.

4.1. Simulation study design



For the design of this simulation study the ten steps of a sound simulation presented by Law (2015) are used as the basis. Figure 23 shows the structure of the research and the ten steps.

Step 1
A sound simulations study starts with formulating a clear problem statement and research goal. In Section 1.2. the problem for this research is formulated. In this section the study design following these 10 steps of Law (2015) is presented.

Step 2
To be able to thoroughly understand the problem and make a model of the system, data should be collected and analysed. Chapter 2 elaborates on the current situation data collection and data analysis. The current situation processes are visualized in workflows and translated to workflows of the model.

Step 3
For modelling simplicity, simplifications and assumptions need to be made in the simulation. The assumptions as presented in Section 5.1.2 are discussed with the warehouse management and approved.

Step 4
With the understanding of the system and the accepted assumptions, a programmed computer model can be created as an imitation of the reality. For this research a simulation model is constructed using Siemens Tecnomatix Plant Simulation as explained in Section 1.4.2.1. The design of the model is presented in chapter 5.

Figure 23: Simulation study design

Step 5 & 6
Before the model can be used to support decision making, it should be validated. The outcomes of the first model pilot runs are compared with historical data to validate the model and adjust it where needed. The validation process and outcomes are explained in Section 5.4.

Step 7
Making a model that is able to reflect the current situation is one step, but the goal of the research is to find ways to increase the output levels. Therefore experiments are designed based on possible operational changes. These experiments are explained in Section 6.2.

Step 8 & 9
By making simulation runs with the different experiments designed, and comparing the output data to the current situation data, conclusions can be drawn on which operational changes could potentially increase the warehouse output. The analysis of the experiment runs are explained in detail per experiment in Section 6.2.

Step 10
This master's thesis is one important element of the documentation and presentation of the research results. It is further up to the warehouse management and board of directors of Terberg Benschop how to respond to the presented outcomes. To provide the board with a complete set of information and recommendations, a presentation was given to the full board of directors, in addition to handing over this thesis.

4.2. Discrete-event simulation

For this research, discrete-event simulation is selected as the modelling method to simulate the system. A discrete-event simulation concerns the system to evolve over time (Law. 2013). The change of the state of a discrete system is triggered by events at separate points in time, rather than continuously over time. The state of a system can be defined as the collection of variables necessary to describe the system at a particular time, relative to the objectives of a study (Law, 2013). The number of active pick areas or the number of shipments in the queue are examples of variables for the central warehouse. These variables change at events as for example the activation of shipments or the start of a pick routing.

Before experiments can be designed to find potential improvements of the warehouse operations, it is important to understand the characteristics of the system to determine how it is best modelled. System is the term used by Robinson (2014) to refer to the modelled representation of the processes that are being evaluated in the research. In our case the system is the combination of all operations within the central warehouse of Terberg Benschop.

The occurrence of the events is a stochastic process. The model is predicting future events based on probability distributions that are derived from historic data (Section 4.4). Therefore, the output that is generated by the model is itself random. The model provides an estimate or indication of the true characteristics of the system. Outcomes of the simulation study should not be treated as the actual truth. This is one of the main disadvantages of stochastic models. The validation of the simulation therefore, is one of the first steps in a sound simulation study that allows us to draw conclusion from the outcomes of the experiments.

4.3. Conceptual Model

As explained in Section 4.2 the simulation model is a discrete event simulation. In the simulation, the production phases of both the HVA and LVA and most importantly the pick processes in the central warehouse are modelled. The production phases are modelled to generate the phase shipments and therefore the production pick assignments for the central warehouse. The speed of the production as well as the schedule determine the workload for the warehouse. By including both production lines in the model, experiments can be done to explore the effect of changes in the production speed or schedule.

The goal of the simulation model is to evaluate the operational efficiency of the outbound process of the entire system. Therefore, the focus is on the movements and operating times of entire shipments and pick routings, rather than the details of each individual pick and the items requested in the order line.

4.3.1. Basic settings

Independent of the experiments the simulation model is based on a few basic settings listed below:

- Working hours at Terberg Benschop are Mon-Tue from 07:30 till 16:30 and Friday from 07:30 till 12:45. In the warehouse two employees stay during the Friday afternoon for the late sales orders; one at the pallet aisles and one at the OSR;
- Takt times in the HVA are anticipated to the completion of 26 vehicles per week. At the LVA 10-12 vehicles can be assembled per week;
- The standard configuration for pick station 1 at the OSR is Production, and for pick station 2 it is Combined. Both can switch to 2Bin and back;
- Aisle 31, 32, 37, and 38 have a designated aisle master. Aisles 33 – 36 share three aisle masters. Aisle 39 has a designated forklift. Each aisle master is daily operated by 1 FTE;
- The consolidation space contains 12 consolidation areas;
- Shipment activation is done automatically up to a maximum of 27 active shipments;
- The logistic time of phase shipments is two hours before needed at assembly;
- The maximum output of the OSR storage space is 10 bins per minute;
- Phase shipments are based on expected future production (Sections 4.3.3 & 4.3.4);
- Sales, 2Bin, VPL and inbound activities are based on historic workload (Section 4.3.6).

4.3.2. Assumptions and simplifications

For modelling purposes some assumptions and simplifications are made to be able to model the processes and do experiments with the simulation. Some general simplifications were already mentioned in Section 1.6 but below all assumptions and simplifications in relation to the simulation model are listed:

- It is assumed that stock levels of all items for the shipments are always sufficient, meaning that backorders do not occur. Therefore, there are no delays at the assembly halls due to backorders.
- The sequence of new vehicles to the assembly hall is random. The simulation does not consider batch production of multiple vehicles for the same customer.
- Technical malfunctions are not modelled in the simulation. Especially at the OSR malfunctions occur but there has been no data collection of the issues.
- For the picking times (Section 3.1.2) of the order pick routings in the aisle, picking time distributions are used based on historic data (Section 4.3.8). To be able to monitor the effect of SKU re-allocation the same pick time distribution is used for aisle 31-37. Picking times in aisle 38 and 39 are longer due to the heavy goods. Therefore aisle 38 and 39 have another distribution from the other aisles but the same for the two of them.
- Due to lack of picking time data at the OSR, the picking times are modelled as a fixed time. This time is based on estimation and a few time measurements (Section 4.3.9).
- The inbound process for the OSR is done at inbound stations and does not interfere with the capacity of the pick stations. Since stock levels are assumed to be infinite the inbound for the OSR is not included in the model.
- For the spare parts, multiple priority levels exist but in the simulation it is simplified to a single priority score for Sales.
- The pick deadline for sales orders is based on the activation time. Sales orders that activated before 15:00 need to be picked the same day, so before 17:30. All orders that are activated later receive a logistics time of 12:00 the next day.
- The production is not delayed by Phase shipments that do not meet the logistics time

4.3.3. HVA shipment generation

Shipments for the HVA are requested by the production manager on the advancement of the line as explained in Section 2.1.5.1. Figure 24 shows the logic flowchart of the generation of phase shipments from the HVA in the simulation.

The generation of shipments is triggered by the movement of the vehicle chassis to the next assembly phase. The production schedule for the simulation is based on the ordered vehicle configurations that are known for almost a year in advance. The sequence in which these vehicles enter the assembly hall is taken to be random in our simulation. Based on the sold vehicles a distribution is made to determine the chances of each vehicle type to enter the assembly hall. Table 7 shows the probability distribution for the different vehicle types produced in the HVA.

Table 5: Production probability distribution HVA vehicle types

Vehicle Type	Probability
dt183	0.1765
yt193	0.4465
yt203ev	0.0281
yt223	0.3489

After the selection of the vehicle type a configuration out of the list of future vehicles of the previously selected type is randomly selected and assigned to the vehicle. From the BOM of this configuration all the shipments for each production step are defined. By randomly selecting a vehicle type and configuration, the possibility of batch producing multiple vehicles for the same customer is neglected.

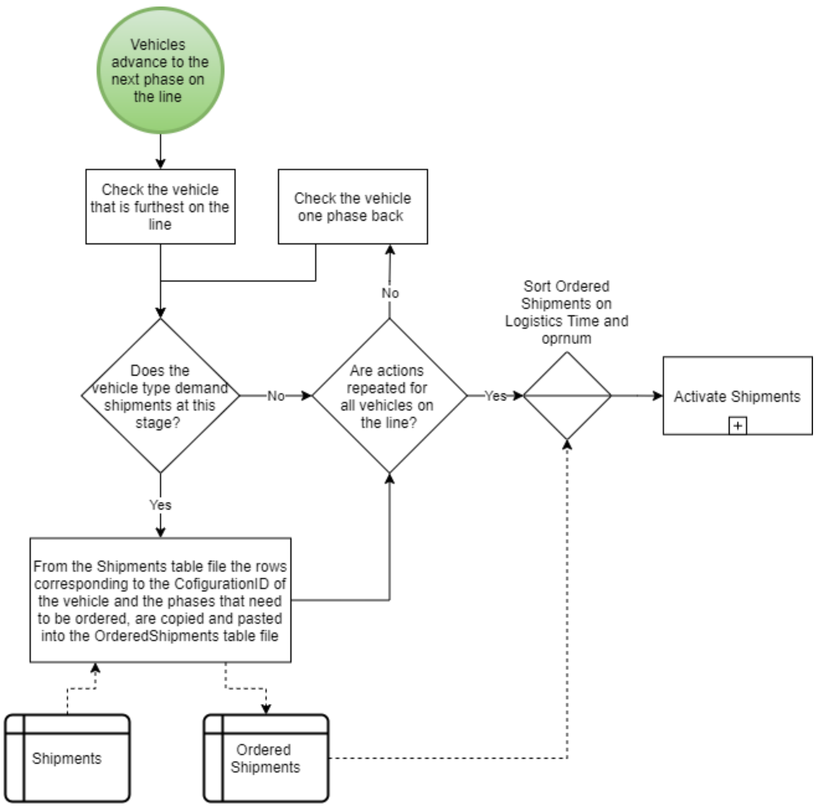


Figure 24: Logic flowchart HVA Phase shipment generation

4.3.4. LVA shipment generation

The shipment generation for the LVA is more complex than for the HVA since the vehicles do not all advance to the next phase at the same time and assembly times differ between vehicles. As explained in Section 2.1.5.1 the phase shipments for the LVA are requested at the beginning of the day based on the expected production schedule. So, to be able to request shipments based on the production schedule first a production schedule needs to be created. How this production schedule is generated in the simulation is explained in Section 4.3.4.1.

The phase shipments are requested at least eight working hours before they are needed at the assembly. Since production on Friday is just running for half a day, from 07:30 till 13:15, the shipments for the next Monday are already requested on Thursday. Figure 25 shows the logic flowchart of the generation of phase shipments from the LVA in the simulation.

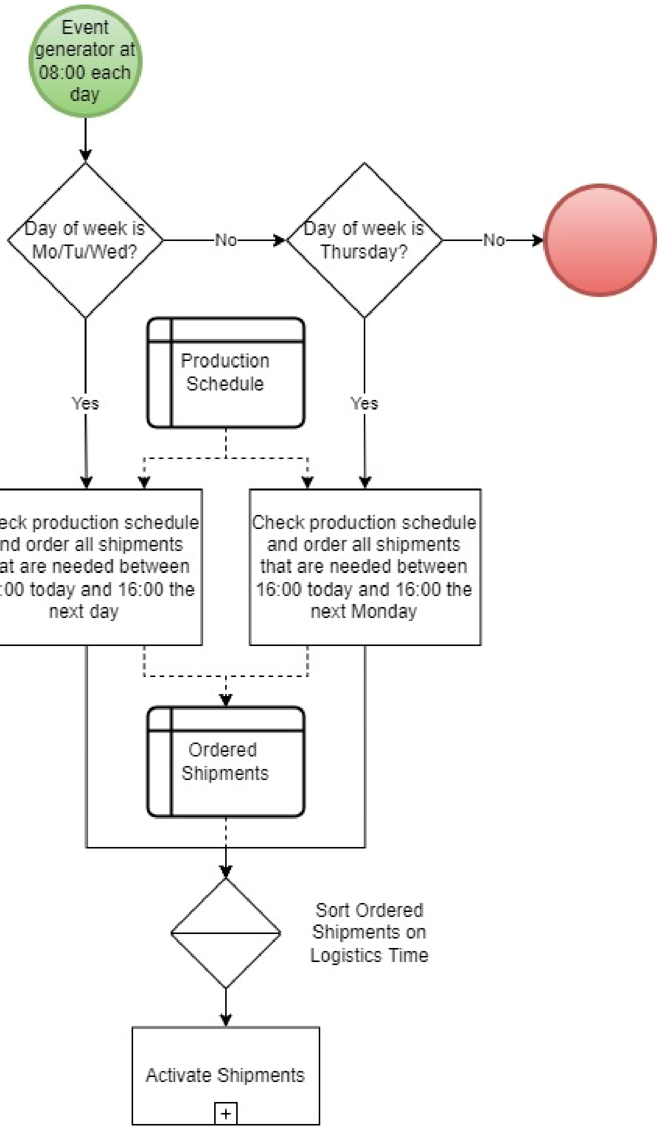


Figure 25: Logic flowchart LVA Phase shipment generation

Just as in the HVA the selection of new chassis entering the assembly hall is based on a random selection with a probability distribution over the different types produced at the LVA. Table 8 shows the probability distribution for the different vehicle types produced in the LVA.

Table 6: Production probability distribution LVA vehicle types

Vehicle Type	Probability
bc182	0.10112
bc183	0.23596
rt223	0.397004
rt283	0.17228
rt283cc	0.003745
rt403	0.0412
tt223	0.022472
tt223cc	0.003745
yt222cc	0.022472

LVA production schedule

Programming the expected journey of a vehicle through the assembly hall is difficult because of the three assembly positions at each phase, the different processing times at each phase for the different vehicles and the use of the two buffer zones. The production schedule is therefore created by logging the entrance of each vehicle at phase 55 (Figure 10 in Section 2.1.3). That will be the starting time of the assembly, and therefore the logistics time, of phase 55 for that vehicle. The starting times of phase 60 and 70 are estimated by adding the expected assembly times at the previous phase, respectively 55 and 55 plus 60, to the starting time of phase 55.

The start of the pre-assembly phases is defined by offsets from the starting time at phase 55. These offsets are determined by the expected assembly time of a pre-assembly stage and for which phase it is a pre-assembly of. In Table 8 in Section 4.4, an overview of all offsets is presented in a table. The starting time of phase 55 in the production schedule is equal to the simulation time at the moment of the vehicle entering the LVA at phase 55. Some of the pre-assembly phases have a starting time before phase 55. The phase shipments for these phases will not be generated when shipments are requested at the beginning of the day before the time registration are even added to the production schedule. For example, if a new vehicle enters the LVA at phase 55 at 10:00 a.m. a new line will be added to the production schedule with a start time of 10:00 a.m. for phase 55 for that vehicle. If for example phase 110 has a negative offset of three hours, the start time for phase 110 for that vehicle will be 16:00 p.m. the day before. Phase shipments for these specific phase vehicle combinations will never be requested because the next ordering moment is the next day at 08:00 and as explained in Section 2.1.5.1, only shipments over eight hours ahead will be requested.

To prevent that the early stage phases are never requested, the times of the production schedule generated in the simulation are all increased by fourteen days. So the LVA simulation generates a shifted schedule with a delay of fourteen days. Figure 26 shows a part of the production schedule that is generated by the simulation. Since assembly in the HVA and LVA are not interdependent in any way, the shift in time for the LVA does not influence the representation of the actual situation.

Vehicle	Configid	55	57	58	60	70	110
bc182	721423	2021/02/01 07:30:00.0000	2021/02/02 12:15:00.0000		2021/02/02 10:30:00.0000	2021/02/03 09:45:00.0000	2021/02/01 15:30:00.0000
rt403	721760	2021/02/01 09:45:00.0000			2021/02/02 13:45:00.0000	2021/02/04 08:45:00.0000	2021/02/01 16:00:00.0000
bc182	721206	2021/02/01 10:45:00.0000	2021/02/02 15:30:00.0000		2021/02/02 13:45:00.0000	2021/02/03 13:00:00.0000	2021/02/02 09:45:00.0000
bc183	721991	2021/02/02 11:45:00.0000			2021/02/03 14:45:00.0000	2021/02/04 14:00:00.0000	2021/02/03 10:45:00.0000
rt223	721474	2021/02/02 15:30:00.0000			2021/02/03 15:30:00.0000	2021/02/04 14:45:00.0000	2021/02/03 10:45:00.0000

Figure 26: Part of the production schedule for the LVA

4.3.5. Phase shipment activation

Figure 24 and 25 both show that after the generation of the shipments, the activation of shipments is triggered. In the current situation the phase shipments are activated manually by the pick coordinator. Since the behaviour and activation decision of this pick coordinator are unpredictable and therefore hard to model, the shipments in the simulation are automatically activated while the number of active shipments is lower than a predefined maximum active shipments. Figure 27 shows the logic flowchart of the shipment activation process in the simulation. The activated shipments are divided in separate pick routings for each area that holds one or more items that are requested for the shipment. When all the pick routings are added to the queues of the areas, they are sorted by priority and logistics time as explained in Section 2.1.5.2. New shipments are activated in three way: At the start of the day by a generator, After the shipments are requested by assembly as shown if Figure 25, or after an active shipment has received the exit scan by using a method control within the Exit scan object.

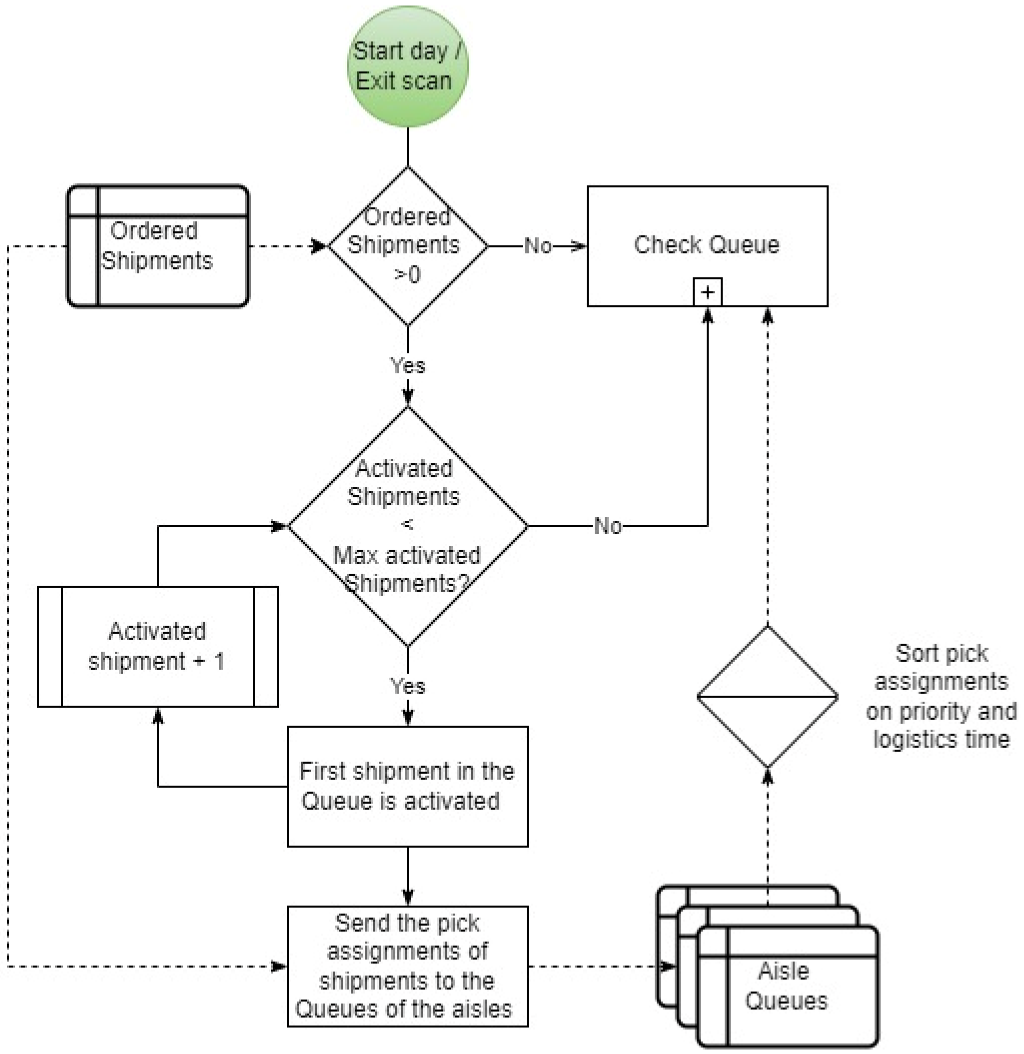


Figure 27: Logic flowchart of shipment activation

4.3.6. Generation and activation of VPL, 2Bin, Sales and Inbound

Different from the phase shipments, the VPL, 2Bin, Sales and inbound activities are not simulated based on expected future demand. Although the VPL and 2Bin orders are strongly correlated with the production schedule because of the BOM, we decided for modelling simplicity not to link 2Bin and VPL orders to the production. The reason is, as mentioned before, that the exact items that are subject of a pick activity are irrelevant. The frequency and duration of the shipments and the mixture of the whole determine the workload intensity that is subject of this research.

The VPL, 2Bin, Sales and Inbound shipments, or in short non-phase shipments, are generated by randomly drawing a sample set from the historic data. To make sure that the sample sets of historic data fit the future demand, a historic period is selected in which the number of vehicles produced per week at both assembly halls was equal to the basic settings presented in Section 4.3.1. A period of thirteen weeks was selected. Based on the date information, all the shipments were divided per unique day. This resulted in thirteen sample sets for every week day. The generation and activation of Sales, VPL and 2Bin orders are triggered by a generator that runs a method every 30 minutes.

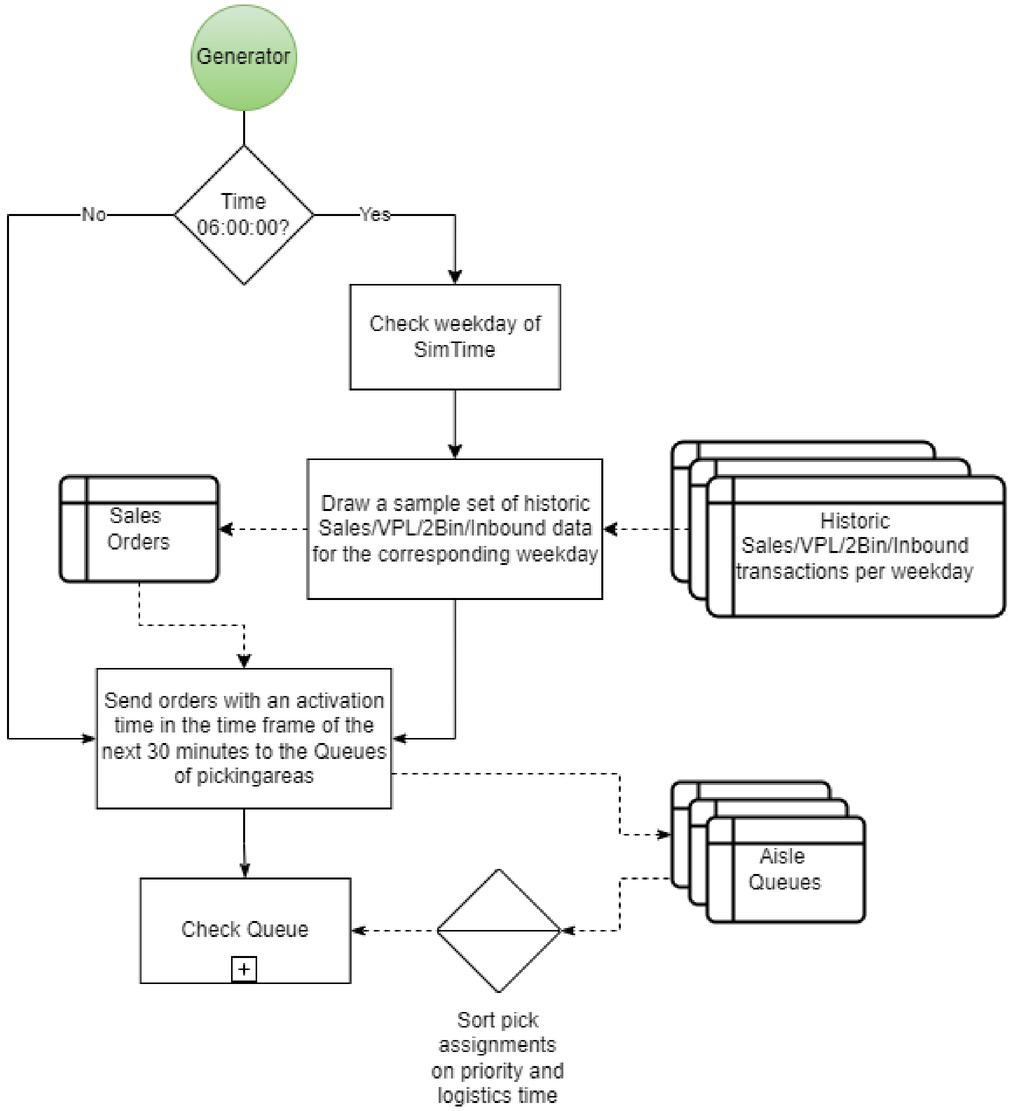


Figure 28: Generation and activation of Sales/VPL/2Bin and inbound orders

Figure 28 shows the logic flowchart of the Sales, VPL, 2Bin and inbound order generation and activation process in the simulation. Every simulated day at 06:00 a new sample set is drawn randomly from the thirteen available sets that correspond to the simulated day. After the start of the day, each half hour the orders that have an activation time in the next half hour are activated. To realise the activation of the non-phase shipments, a generator is modelled that starts the process, which is visualised in Figure 28, every half hour. After the activation of the non-phase shipments the queues of each pick area are sorted again on priority and shipment time.

4.3.7. Start picking routes

Figure 27 and 28 show the next step after shipment generation and activation: the check for work in the queue and start a picking route. In the current situation the queue with work for the pallet aisles is presented to the pickers visually on big screens. If work is in the queue, the picker can use the hand-held scanner to start a pick activity and receive the routing information. In the simulation it is assumed that a picker will directly start a pick activity at activation or after finishing the previous route when the queue still contains work. Figure 29 on the next page shows the logic flowchart of the check queue process for the pallet aisles.

The start of picking routes is programmed in a method. As shown in figure 27 and 28, the is method is called after every shipment activation. This method is also called after an aisle has complete a picking route to immediately start a new pick activity.

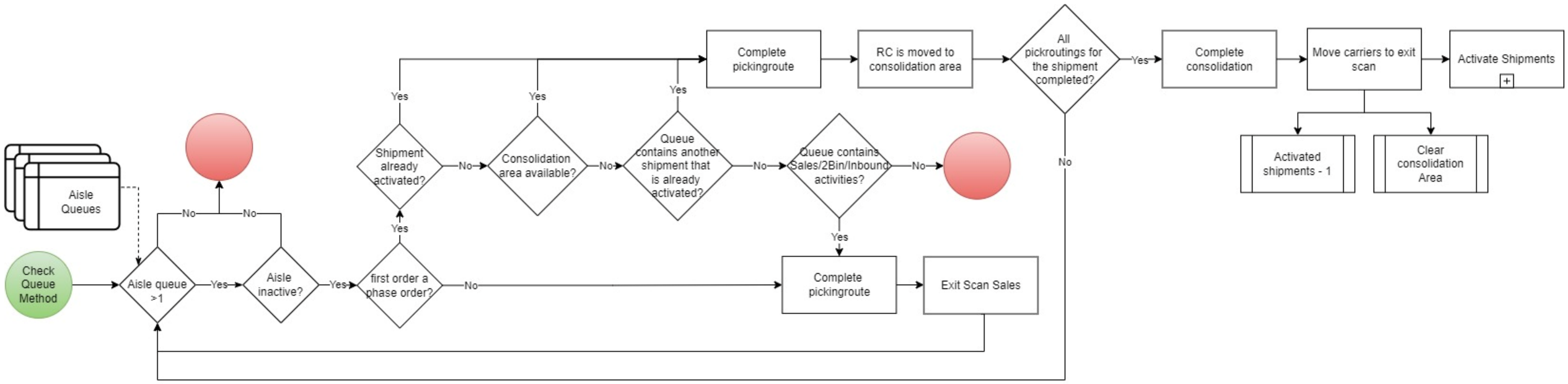


Figure 29: Start pick routings for pallet aisles

In the process of starting a picking route, the effect of consolidation is included. The process shows that the first picking route in queue is started when the phase order is part of a shipment that is already active, or when at least one of the consolidation areas is still free, or when it is a non-phase shipment order. When the first order in queue is a shipment phase order that cannot be picked, the queue is searched for another phase order of which the shipment is already active. When an alternative phase shipment order is not found, the queue is searched for a non-phase shipment order. When no order in the queue can be started the activities within the area stop.

Figure 29 also shows that there is a loop over the activation of shipments and the completion of phase shipment pick routings. After a phase shipment picking route is completed, it is checked to be the last routing to complete a phase shipment. If the shipment is completed, the consolidation is completed, the number of active shipments is decreased by 1 and a new shipment can be activated if one is still in queue. At the end of the shipment activation, the process of checking the queues is activated again. This loop is repeated until the last activated phase shipment is completed.

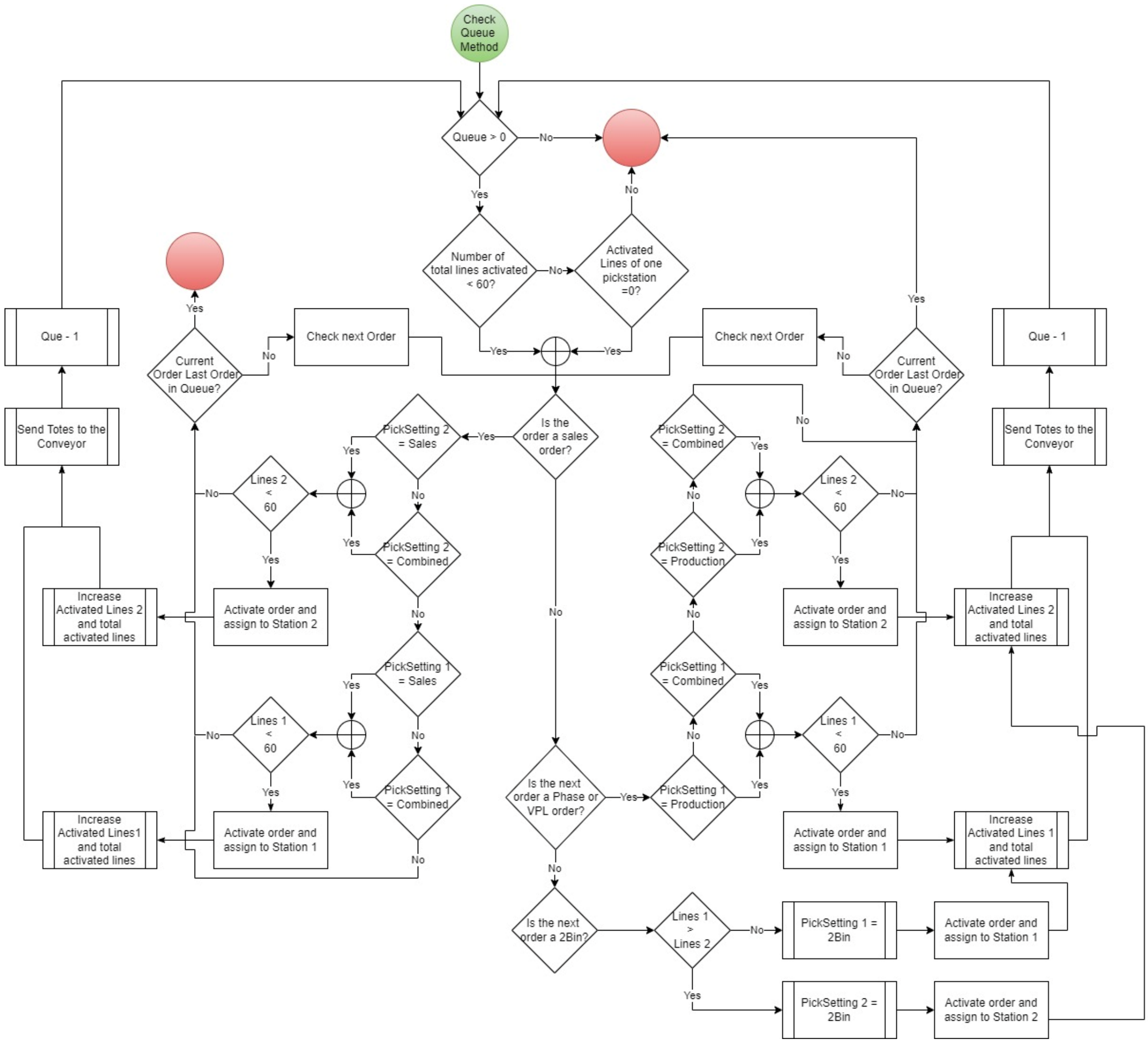


Figure 30: Pick activation at the OSR

Figure 30 shows the logic flowchart of the process of starting pick activities at the OSR. Comparing Figure 30 with Figure 29 shows that the start of the pick activities at the OSR differs a lot form starting pick routings in the pallet aisles. The main reason is the difference in pick strategy for the areas as explained in Section 2.1.5.3. In the pallet aisles, the picker takes the initiative to start a pick, at the OSR the system determines when it sends a tote from its storage position to the pick station. Besides that, the OSR is considered as one area with pick stations operating in parallel. The configuration of each pick station (Phase, Sales or combined) determines which type of orders are send to each station. Furthermore the OSR is not hindered by the occupation of the consolidation areas. As long as there is work in the queue for the OSR, the system will continue to send out totes to the pick stations.

The start of activity at the OSR is triggered by the same shipment activation and check queue method as explained at the start of this section.

4.3.8. Picking time distributions pallet aisles

When a picking route is started at the pallet aisles, a picking time is assigned to the routing. This picking time is dependent on the number of SKUs that need to be picked. As explained in Section 2.1.2, each picking route contains a different number of SKUs to be picked from an area. Let us explore whether linear regression can be used to evaluate the relation between the number of SKUs to pick and the total picking time per routing. Figure 31 shows a scatterplot of the picking times versus the SKUs per pick routing.

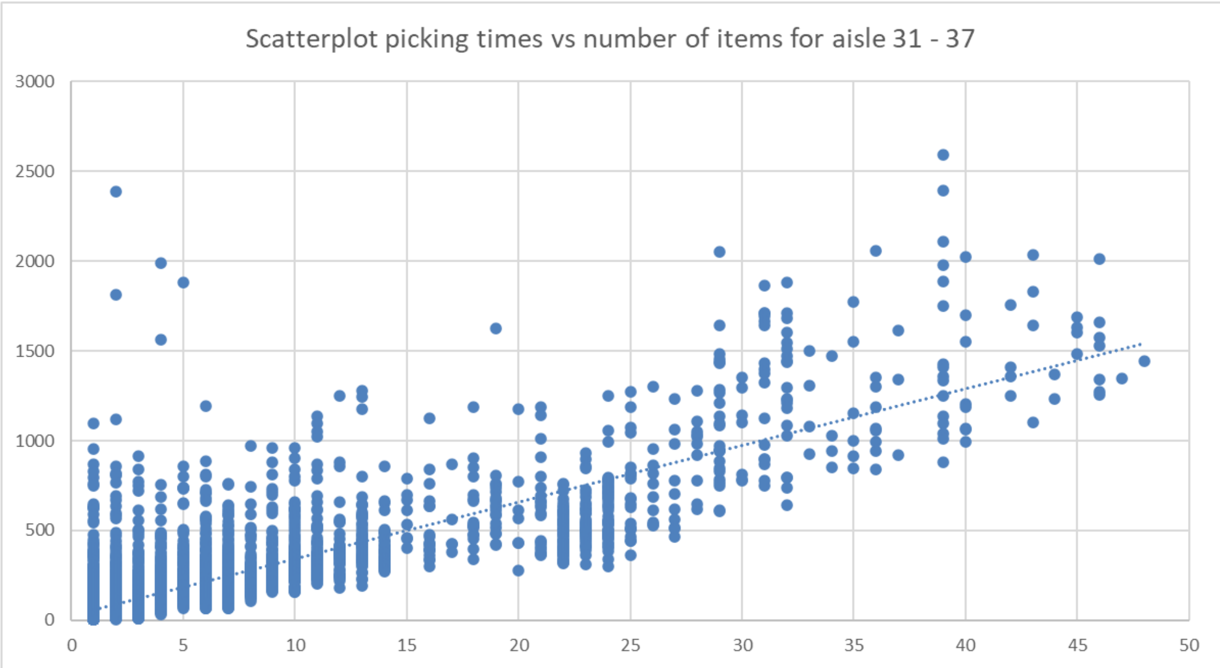


Figure 31: Scatterplot picking times versus number of items picked

The scatter plot in Figure 31 shows a positive relation between the number of SKUs to pick and the picking time. The correlation coefficient that was the result of the regression analysis is 0.84, confirming a strong positive relation. However, the scatter plot still shows large dispersion of the picking times around the trend line. The longest picking time for a certain number of SKUs can be over twice as long as the shortest picking time. More SKUs in a routing can be picked in less time than little SKU routings. Therefore, we conclude that the picking times cannot be simply modelled by a simple linear function.

The longer picking times for small picking routes compared to short picking times for larger routings can be explained by the location of SKUs within an area. A picking route for 3 SKUs dispersed over the entire aisle can require more picking time than 8 SKUs that are all stored at the front bottom of the aisle. Even SKU characteristics like size can affect the picking time or the regularity in which the SKUs are requested that determines how well the picker knows the location by heart.

So, the linear regression analysis showed that the expected picking time of a routing cannot be determined solely on the number of SKUs to be picked. Therefore, the picking time data and SKUs per routing data are translated to pick time per SKU data. The goal of this data transformation is to find a distribution for the expected pick time per SKU for each pick routing..

Figure 32 shows a histogram of the historic spread of pick times per SKU for aisle 32. For the analysis, eight weeks of historic pick data from 25-01-2021 until 17-03-2021 is used. The x-axis shows the upper bound of the pick times in seconds bins. The blue bars present the percentage of times the average pick time per SKU for a routing was within the respective bin. The red line is the plotted gamma distribution that was found by using the solver in Excel. For aisle 32 the parameters of the gamma distribution are: alpha = 1.97 and Beta = 17.12.

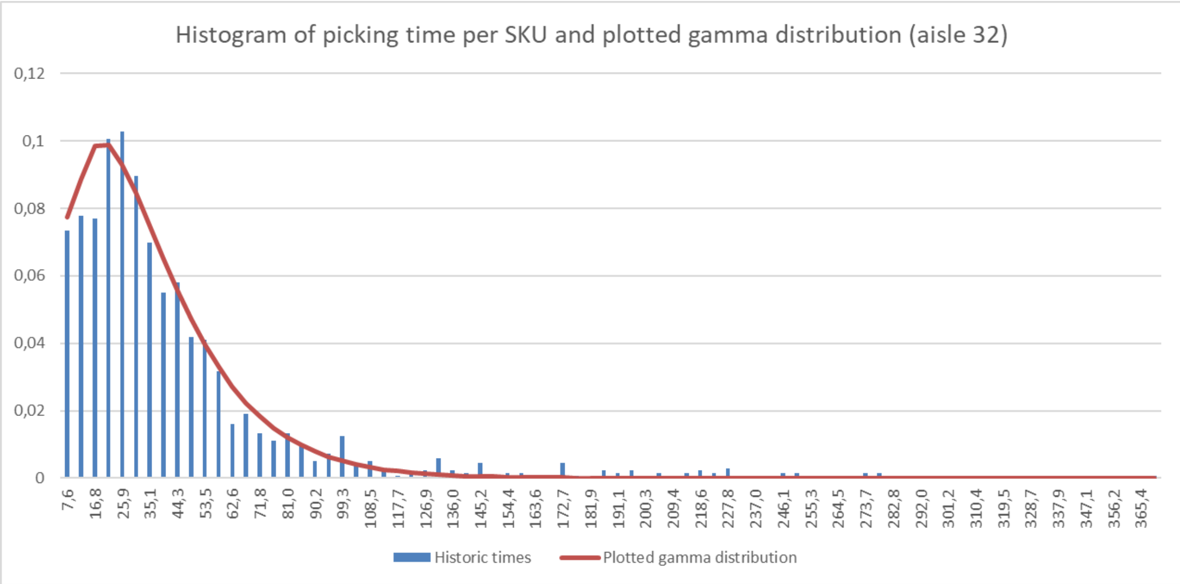


Figure 32: Plotted distribution of pick times per SKU for aisle 32.

This exercise of finding the pick time per SKU distribution was repeated for every aisle but as explained in Section 4.3.2. it is assumed for the simulation that the distribution of pick times per SKU is the same for aisle 31-36 and aisle 38-39. So to find these distributions the same method is used, only the data points for the aisles are combined in one data set. The results of both distributions are presented in Figure 33 and 34.

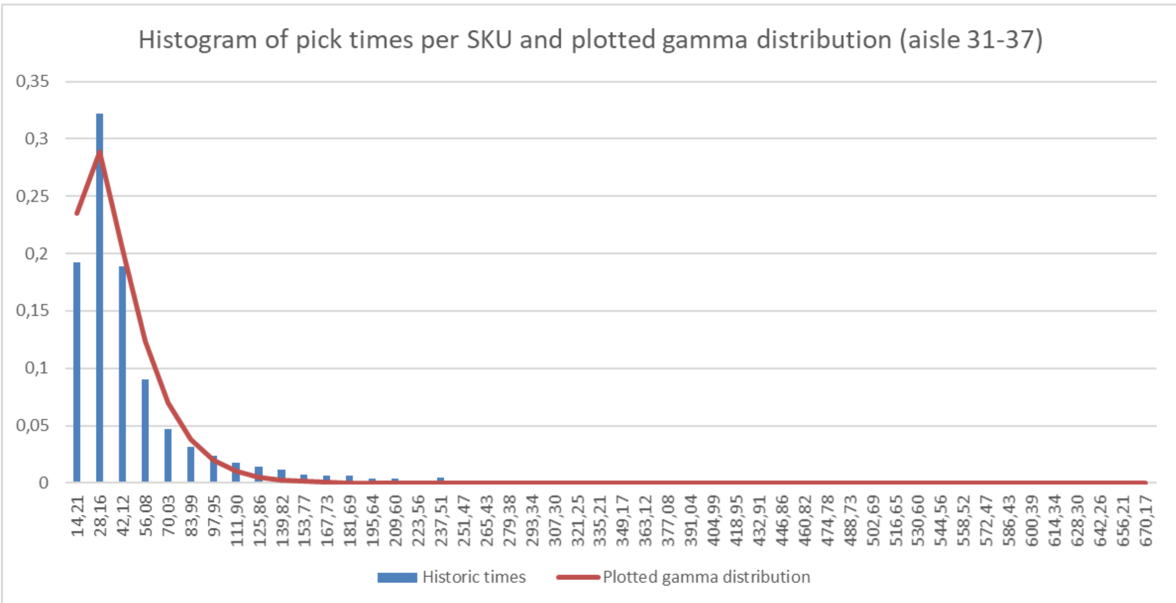


Figure 33: Plotted distribution of pick times per SKU for aisles 31-37

Figure 33 shows the distribution of the pick times for aisle 31-37. The parameters of the plotted gamma distribution are: alpha = 1.82 and Beta = 17.87. The parameters of the plotted gamma distribution for aisle 37 and 38, shown in Figure 34, are: alpha = 1.82 and Beta = 17.87.

Both graphs show a large tail to the right. The majority of the picks can be completed in relatively short time, but sometimes pickers have trouble to find the correct items straight away. For the flow of the entire system it is good to include the probability of the longer pick times. When a shipment is divided over multiple areas, the longer pick time in one of the aisles can have a negative impact on the shipment pick time efficiency as explained in Section 3.1.3.

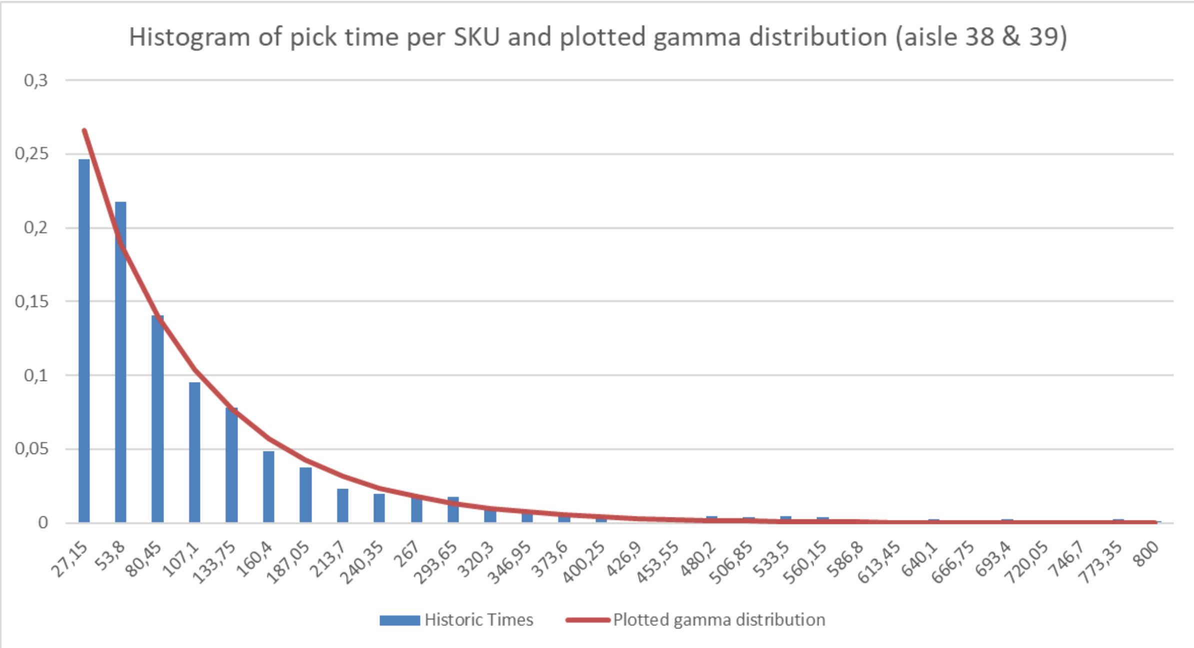


Figure 34: Plotted distribution of pick times per SKU for aisle 38 & 39

The pick times of the routings at the aisles are based on the times between each pick scan in the aisle. However, the actual pick of the SKUs are not the only activities in a pick routing. It starts with preparing a product carrier like the RC at the start of the routing and it ends by placing the filled RC at the front of the aisle after completing the pick. Time records of these actions are not included in the available data. Measurements were done to determine the average time needed to prepare and complete a pick routing. For aisle 31 to 37, the average time needed is 51 seconds. For aisle 38 and 39, this time is longer due to the heavy goods. The average time needed in aisle 38 and 39 is 1 minute and 32 seconds.

For the pallet aisles, the expected pick time for a picking route is built up from the expected pick time per SKU, based on the gamma distribution, multiplied by the number of SKUs and added by the average time needed to prepare and complete the routing.

4.3.9. Pick times at the OSR

Pick times at the OSR are not based on distributions as for the pallet aisles. As mentioned in Sections 2.3.1 and 3.1.2, the individual picks at the OSR are not registered in the available data, making it impossible to evaluate historic picking times and create a distribution for expected picking times. Therefore, the picking times at the OSR are based on estimates. The pick of an SKU at the OSR is a matter of seconds and sometimes the picker picks the SKUs from two totes simultaneously before turning around and dropping them in the RC. This makes it difficult to time the pick times from each tote.

The pick time for phase shipments is estimated at five seconds per pick. For sales orders the pick time is eleven seconds per pick since the average units to pick per SKU is larger and a small packing step of placing the items in a plastic bag is included in the pick step.

Just as with the pallet aisles the pick assignments are prepared by preparing an RC for the phase shipments. After completing a pick, the picker leaves the station and pushes the filled RC to a buffer zone ready for consolidation with the items from the pallet aisles. The picker takes back an empty RC and starts a new pick assignment. The time needed to move the RCs is 55 seconds for the picker at station 1 and one minute 15 seconds for the picker at station 2. The travel distance is larger for pick station 2. For sales orders the picked items are placed in a new tote that is transported on the roller conveyor to the packing area. Therefore, preparing and completing sales picks at the OSR does not require the preparation and replacement of an RC.

4.4. Siemens Tecnomatix Plant Simulation©

For constructing the simulation in this research, Siemens Tecnomatix Plant Simulation© software was selected. Plant Simulation is highly suitable for the evaluation of logistics systems and processes with focus on, for example, material flows or resource utilization (Siemens 2022). These systems are modelled as discrete systems. The modelling technique used is called discrete-event Simulation, which was explained in detail in Section 4.2.

Plant Simulation uses pre-programmed objects that can easily be implemented and connected to configure the desired system. The behaviour of the objects can be manipulated by the user by selecting the input parameter values and distributions. The behaviour of the system can also be manipulated or guided by inserting methods with code, using programming language SimTalk. The use of pre-defined objects makes it easier to quickly construct larger and more complex systems.

Furthermore, it is relatively easy to visualise the systems operations within Plant Simulation, which supports the validation step but also helps in presenting the system and outcomes to the ones that are unfamiliar with simulation studies and statistics. Figure 35 till 38 show multiple screenshots of how we have modelled the Central warehouse an assembly lines of Terberg Benschop in Plant Simulation.

Figure 35 shows the main frame of the model. The main frame contains the event controller and the model parameters that are used to define and control each simulation run. Furthermore, the main methods, that are programmed to control the events in the simulation, are presented on the main frame. The right side of the main frame contains multiple table files that store input data, like vehicle configurations and shipment data, and outbound performance data, like shipment times and On-Time performance data. Therefore, the main frame is used to set up each simulation and can be used to live track the system performance.

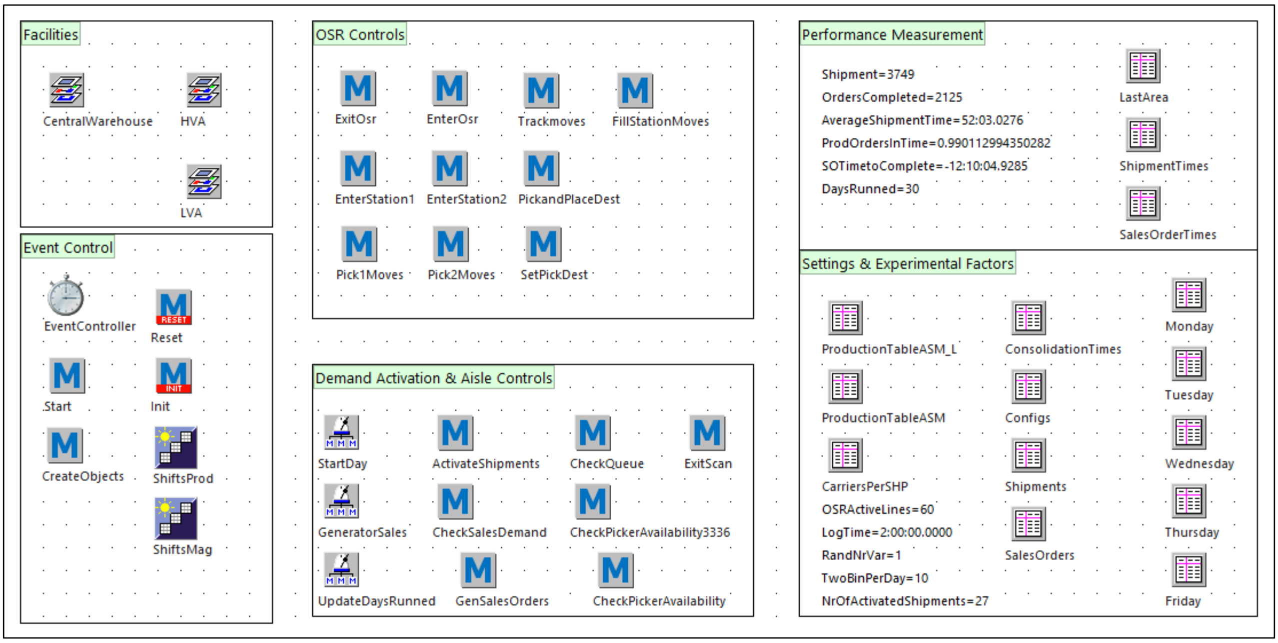


Figure 35: Main frame of simulation model in Plant Simulation (Screenshot)

The Central warehouse is modelled on a separate frame in the simulation model. Figure 36 shows how the Central warehouse is modelled in Plant simulation. We have decided to model the conveyor of the OSR and the movement of the totes over the conveyor in detail, since the capacity of the conveyor is a potential limiting factor in the throughput at the OSR and the travelling times of the totes are an important element in the total pick time. Since the movement within the pallet aisles is a relatively simple up and down movement of a single aisle master, we have decided not to model the movements within the aisles but model the pallet aisles as individual SingleProcs (Mes. 2017). How the operations times at the pallet aisles are determined was explained in Section 4.3.8. Modelling the consolidation areas in the simulation model allows us to generate data on the occupation of the consolidation areas which was not yet available in the current data.

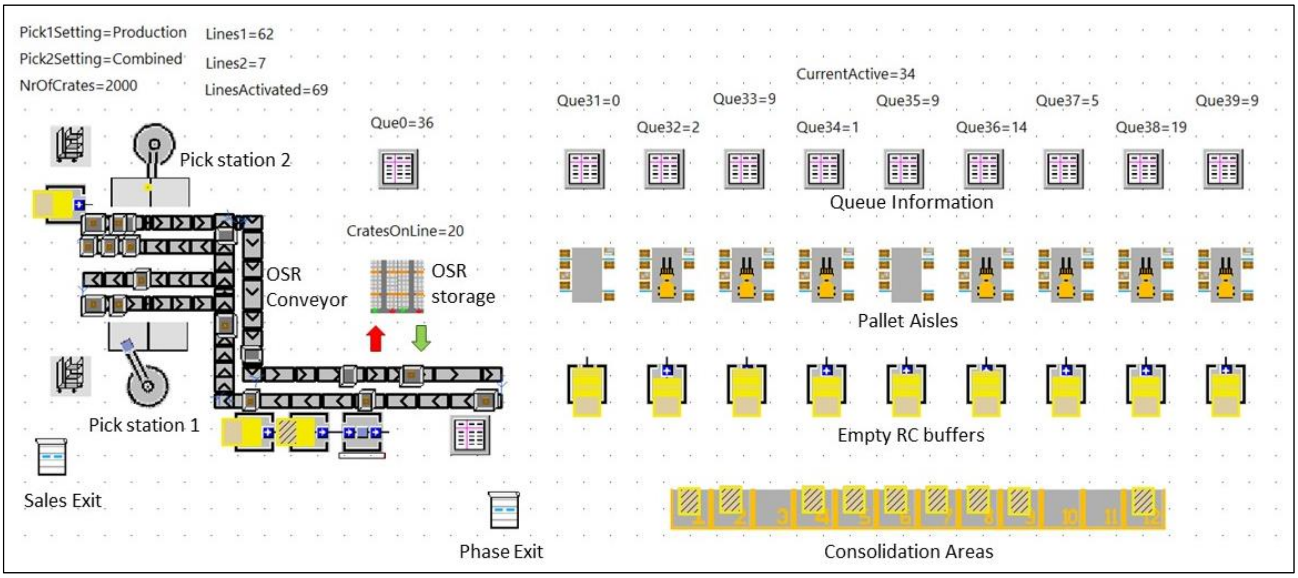


Figure 36: Central warehouse modelled in Plant Simulation (Screenshot)

Figure 37 shows how we have modelled the HVA in Plant Simulation. The figure clearly shows that the HVA is modelled as a production line. Each production phase is connected with a connector line, meaning that the Vehicles can only flow through the model in a phase by phase sequential manner. Besides the six main production phases we have modelled eight phases in advance of Phase 52. The reason for these stages before production is the order process at the HVA as explained in Section 2.1.5.1. Each shipment required for a certain main production phase or one of the pre-phases is ordered three takt times in advance of when the items are needed. We have decided to convert these order times to the takt time relative to the vehicle entering the Assembly hall at phase 52.

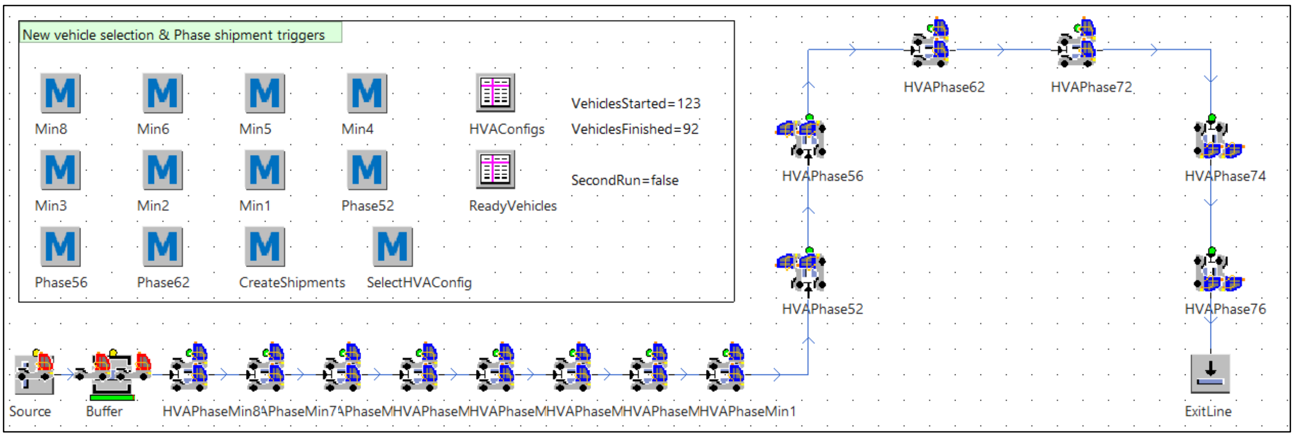


Figure 37: HVA modelled in Plant Simulation (Screenshot)

Table 7 shows the order moments for each main and pre-phase at the HVA (Figure 9) relative to the moment the chassis enters the assembly hall at phase 52. As Table 7 shows, phase 52 itself is requested three takt times in advance of the start of phase 52. For the electric version of Terberg's YT, the YT203ev, the first (pre-)phases are requested eight takt times ahead. That is the reason why the HVA frame in the simulation model contains up to eight phases in advance of the main assembly phases. The table shows at what stage in the simulation which phases orders are requested at the warehouse. This shows that after the vehicle has entered Phase 62, all shipments should be requested at the warehouse for that specific vehicle and are being processed.

Table 7: Shipment order times of each phase and vehicle combination relative to Phase 52

Vehicle / Relative Phase	DT223	DT193	YT193/223	YT203ev
-8				107, 120
-7				
-6	105, 106 130	105, 106 130	120, 142, 145, 156	142, 145, 156
-5	107, 108	107, 108	102	102
-4	140	140	130, 140	130, 140
-3	52, 110, 115, 135	52, 110, 115, 135	52, 110, 115, 135	52, 110, 115, 135
-2	56, 147	56, 147	56, 147, 151, 153	56, 147, 151, 153
-1	62	62	62	62
0 (Basis 52)	72	72	72	72
1	74	74	74	74
2	76	76	76	76

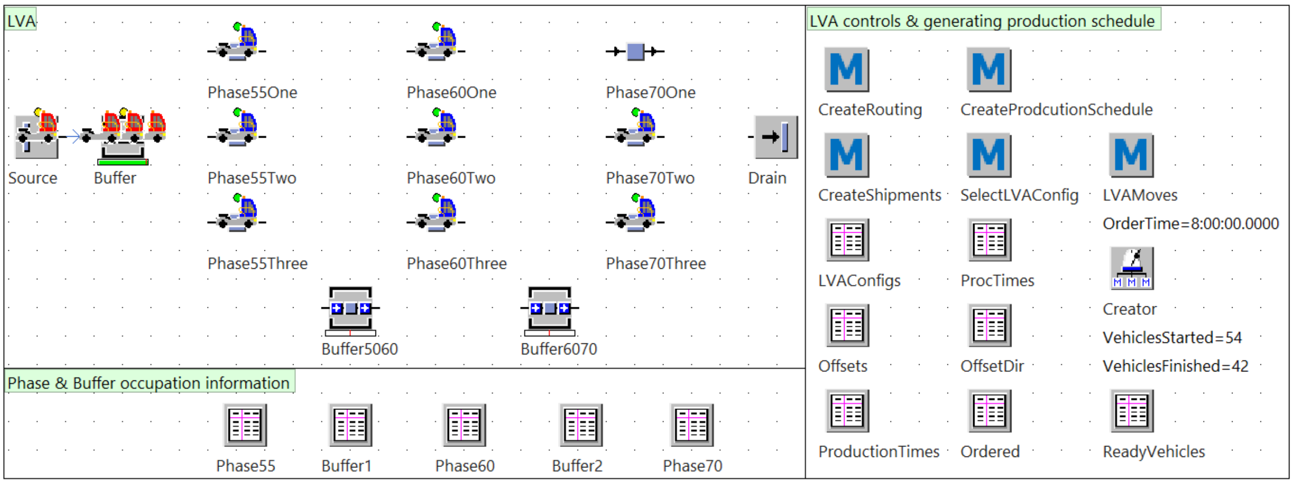


Figure 38: LVA modelled in Plant Simulation (Screenshot)

Figure 38 shows how we have modelled the LVA in Plant Simulation. A clear difference with the HVA in Figure 37, is that the main assembly phases are not directly connected with a connector line. The main reason is that the LVA is not a production line, since the different vehicle types can require different assembly times at the same phase.

Each main phase has space for three different chassis. If one of the vehicles is ready to advance to the next phases, it can move if there is a spot available at the next phase. If not, the vehicle is moved to the buffer zone. When there is no spot available in the next phase or the buffer zone, the chassis has to wait on its current position. Potentially blocking other chassis behind. All of these movements within the LVA are programmed as a pull system in one of the Methods. When a vehicle is ready and able to move forward, the method checks whether there is a chassis in the buffer behind or waiting to enter the LVA, that can be moved forward. This check is repeated until all positions at the LVA are occupied and operational or there are no vehicles left waiting.

Table 8: Offsets and offset direction of LVA (pre-)phases relative to Phase 55

	Offsets in time relative to starting phase 55												
Vehicle / Phase	**57**	**58**	**60**	**70**	**110**	**115**	**120**	**125**	**130**	**135**	**140**	**145**	**160**
bc182	13:45:00		12:00:00	20:15:00	08:00:00	08:00:00	04:30:00		04:30:00	05:00:00	09:00:00	10:45:00	
bc183	13:45:00		12:00:00	20:15:00	08:00:00	08:00:00	04:30:00		04:30:00	05:00:00	09:00:00	10:45:00	
rt323			09:00:00	17:15:00	04:15:00	04:15:00	09:30:00	03:30:00	13:10:00	00:00:00	02:30:00	07:40:00	06:15:00
rt223			09:00:00	17:15:00	04:15:00	04:15:00	09:30:00	03:30:00	13:10:00	00:00:00	02:30:00	07:40:00	06:15:00
rt283			09:00:00	18:00:00	20:15:00	20:15:00	18:00:00	12:40:00	1:12:30:00	21:45:00	01:30:00	14:00:00	08:15:00
rt283cc			14:00:00	23:00:00	15:15:00	15:15:00	13:00:00	07:40:00	1:07:30:00	16:45:00	03:30:00	14:00:00	13:15:00
rt403		23:00:00	13:00:00	1:02:00:00	06:15:00	06:15:00	07:00:00	03:30:00	12:00:00	00:00:00	06:15:00	15:15:00	20:30:00
tt223			08:15:00	16:30:00	18:00:00	17:30:00	18:00:00	12:00:00	1:00:00:00	19:15:00	08:30:00	12:00:00	05:45:00
tt223cc			14:00:00	22:15:00	12:15:00	11:45:00	12:15:00	06:15:00	18:15:00	13:30:00	02:15:00	12:00:00	11:30:00
yt222cc			14:00:00	18:00:00	18:00:00	19:00:00	1:05:00:00		1:16:00:00	21:00:00	19:15:00	14:00:00	
	Offset directions relative to starting phase 55												
Vehicle / Phase	**57**	**58**	**60**	**70**	**110**	**115**	**120**	**125**	**130**	**135**	**140**	**145**	**160**
bc182	1		1	1	1	1	-1		-1	-1	1	-1	
bc183	1		1	1	1	1	-1		-1	-1	1	-1	
rt323			1	1	1	1	-1	-1	-1	1	-1	-1	1
rt223			1	1	1	1	-1	-1	-1	1	-1	-1	1
rt283			1	1	-1	-1	-1	-1	-1	-1	-1	-1	1
rt283cc			1	1	-1	-1	-1	-1	-1	-1	1	-1	1
rt403		1	1	1	1	1	-1	1	-1	1	1	-1	1
tt223			1	1	-1	-1	-1	-1	-1	-1	-1	-1	1
tt223cc			1	1	-1	-1	-1	-1	-1	-1	-1	-1	1
yt222cc			1	1	-1	-1	-1		-1	-1	-1	-1	

As explained in Section 4.3.4, the movements of vehicles through the simulated LVA is used to generate a future production schedule that is based on the vehicles entering the LVA at Phase 55 and the expected time offsets of the other main and pre-phases. Table 8 shows all offsets in time and all offset directions. The offset times represent working hours, meaning that an offset of 24 hours is not just a single day offset but three days, based on an eight hours working day. An offset direction of -1 means that for that vehicle type and pre-phase combination, assembly activities are expected to start before the chassis enters the assembly hall at Phase 52. So, at each time a new chassis enters the LVA at one of the three spots of Phase 52, a new line is added to the production schedule with expected starting times for each of the (pre-)phases, based on the current simulation time added with the offset times the offset direction. To prevent that the simulation creates a production schedule that is partly in the past, due to the negative offsets, all starting times of the newly added line are increased by fourteen days, as explained in section 4.3.4. Therefore, the calculation of the starting times for each vehicle at each phase at the LVA is defined by the following equation:

$$(Current\ SimTime + Offset * Offset\ direction + 14:00:00:00\ (dd:uu:mm:ss))$$

4.5. Simulation model validation

The simulation model as explained in the previous sections needs to be validated before conclusions can be drawn from any experiment. The validation is done by running the simulation with a historic production schedule. After running the simulation with a historic production schedule, the simulation is validated by comparing the number of phase picking routes requested per production hall, the shipment times, and the utilization of operational capacity of the simulation output with the historic data.

4.5.1. Picking route validation

Table 9 shows the picking route data of the historic phase shipments compared to the picking routes of the phase shipments generated in the simulation. The table shows that the simulation data is based on 57 simulated days and the historic data in based on 65 historic days. The lowest row shows the comparison between each data measure for the simulation and the historic data. From the lowest row we can tell that the simulation generated an equal amount of picking routes per day for the LVA but a slightly higher demand for the HVA.

The reason for this higher workload for the HVA is that in the simulation, 26 vehicles per week are assembled at the HVA as explained in Section 4.3.1, but the historic data showed that on average 23.3 vehicles were assembled each week on the HVA. 26 is 112% of 23.3, so the higher number of picking routes is a result of more vehicles being assembled per week.

The number of areas over which the shipments are divided is shown in Table 9 in the last column. the average number of areas is a little lower in the simulation. Reason for the difference is the higher number of HVA vehicles assembled. The average number of areas visited for HVA shipments is a little lower than for LVA shipments.

Based on the figures in Table 9 and de additional analysis of the number of vehicles assembled, we conclude that the simulation is well able to translate the production schedule into phase pick assignments for the warehouse.

Table 9: Comparison number of picking routes Simulation vs. History (percentages indicate Simulation divided by History)

	#Days	#Routes LVA	#Routes HVA	#Total Routes	Avg. LVA vehicles per day	Avg. HVA vehicles per day	Avg. Carriers per SHP
History	65	4502	11553	16055	69.26	177.74	2.71
Simulation	57	3924	11565	15489	68.84	202.89	2.66
Sim vs. Hist	88%	87%	100%	96%	99%	114%	98%

The same analysis for VPL, 2Bin, and Sales picking routes is of no value since these orders are generated based on historic sample sets as explained in Section 4.3.6.

4.5.2. Shipment times validation

As explained in Section 3.1.3 the length of the shipment times is a good indicator for the pick efficiency within the warehouse. The shorter the shipment times for multi-area shipments, the better these shipments are picked in parallel. The shipment times will be used as a performance indicator in the evaluation of experiment results in chapter 6. Therefore, the shipment times are validated in this section.

Figure 39 shows the distribution of the shipment times in the historic data set and the distribution of shipment times in the simulation. The figure shows that the distribution of shipment times in the simulation is a near approximation of the distribution of the historic shipment times.

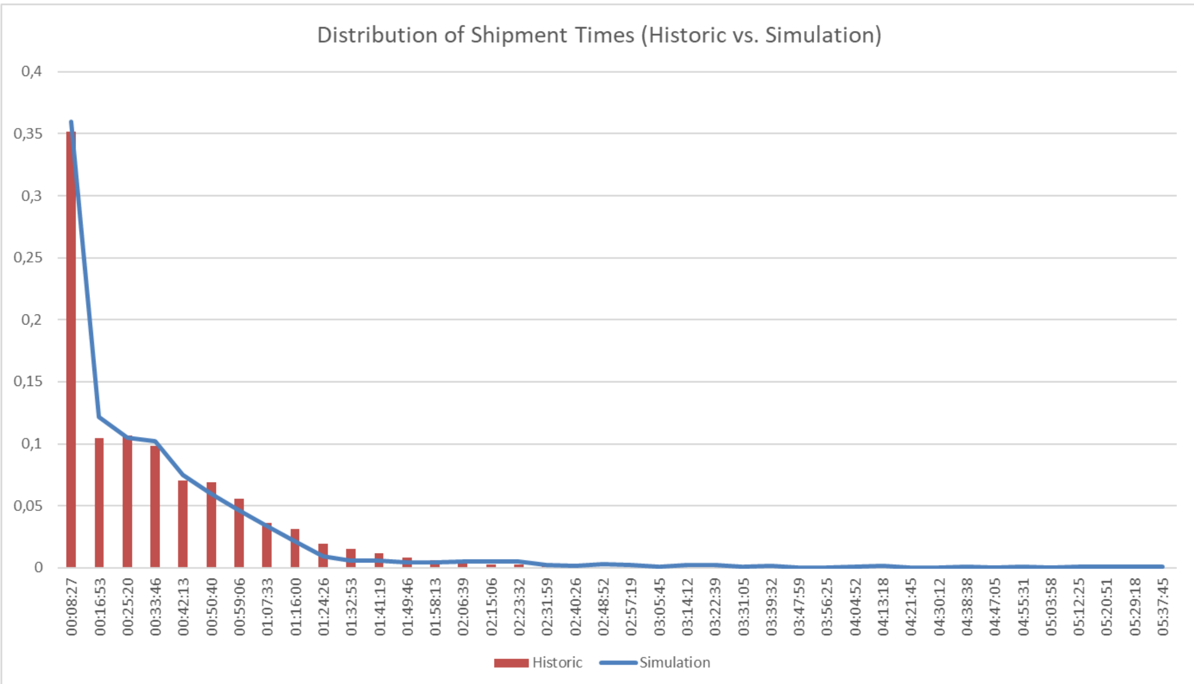


Figure 39: Distribution of shipment times in historic data set versus simulation output.

4.5.3. Workload division validation

Chapter 3 explained that it is best not to solely evaluate the performance of the system based on order lines and shipments but also consider the workload measured in time, utilization. Therefore, the utilization in the simulation is compared to the historic utilization as part of the validation. Figure 40 shows the average utilization (as defined in Section 3.1.2) per day and per area for the historic data set and the simulation output. The figure shows a similar pattern per area for both data sets. The division per day is not exactly the same for each area for both data sets but that can be explained by the difference in shipment activation, automatic versus manual, as explained in Section 4.3.5. The utilization per area is on average 5% higher in the simulation than it was in history with the same production schedule. This is the result of the higher production rate at the HVA in the simulation as shown in Table 9.

Figure 40 shows that the workload generated for the warehouse in the simulation model is similar and we might say equal to the historic workload based on the same production schedule. Therefore, the utilization analysis supports the same conclusion as the picking route analysis that the simulation is strong representation of the real system and able to generate the correct workload relative to the operations in both assembly halls.

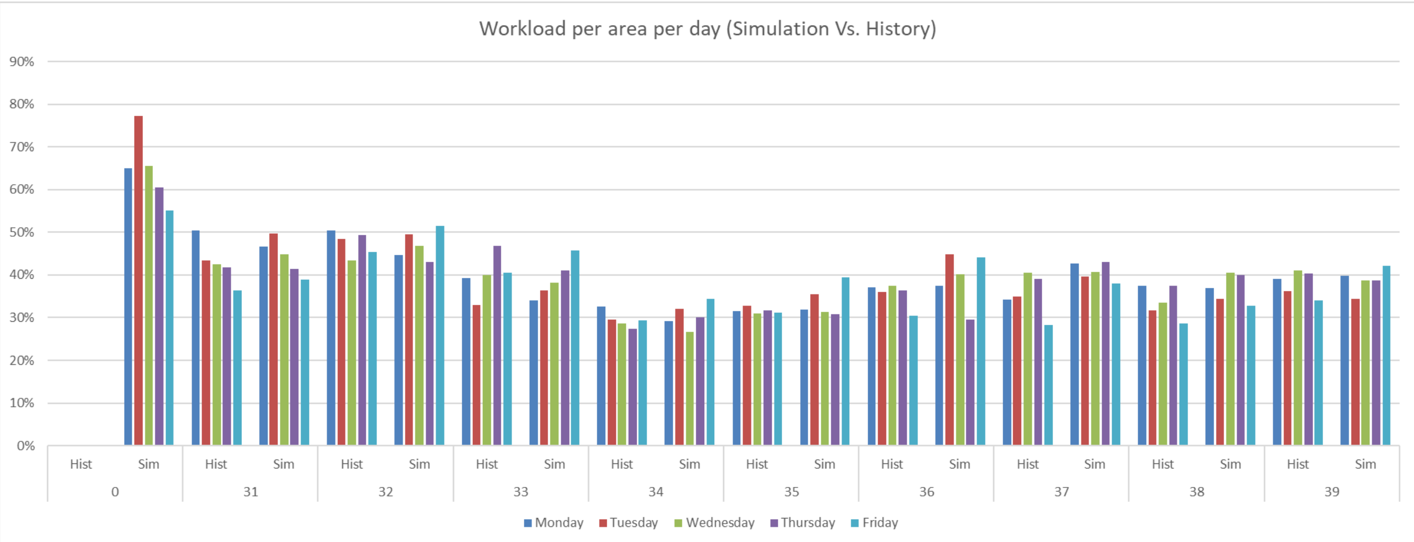


Figure 40: Comparison of average utilization per aisle per day of historic data and simulation output

The operations at the OSR within the simulation model is harder to validate because of the lack of data available. An effort is made by analysing the number of picks per hour at the OSR in historic and simulated data. A distinction is made between sales and phase order picks because of the difference in pick times as explained in Section 4.3.9. Table 10 shows that the pick speed at the OSR in the simulation is close to the historic performance. The historic data shows that at a specific hour the historic performance at the OSR was better than the most productive hour in the simulation but the simulation is a good approximation of the real system.

Table 10: Pick lines per hour analysis History vs. Simulation

	Max total	Max phase	Max sales	MinSecsPhase	MinSecsSales
History	504	450	215	4.82	16.74
Simulation	464	464	210	4.22	17.14

Unfortunately the validation of the utilization is not possible for the OSR because of the lack of historic data. However, the movements of the totes over the conveyors and into both pick stations is visualised in the simulation model. Therefore, we were able to evaluate the system visually as an addition to the data analysis. The speed of the conveyor and the output speed of the shuttles are based on the system setting data supplied by KNAPP, the manufacturer of the OSR system at Terberg Benschop. Figure 41 shows how the OSR is visualised.

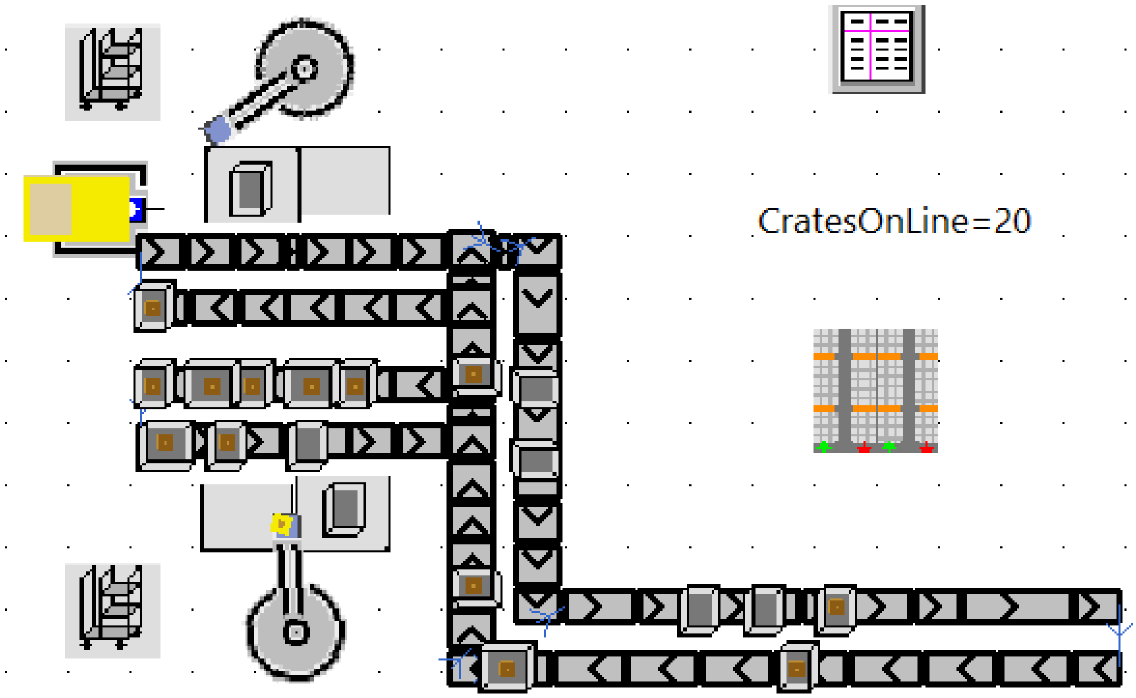


Figure 41: Screenshot of OSR visualisation in the simulation model

4.6. Summary on chapter 4

In this chapter the design of the simulation model, including the assumptions and simplifications, is presented. We have shown by validating the outcome data of the model, that we are able to provide a strong representation of the current situation in the central warehouse using Tecnomatix Plant Simulation.

For the input of pick times at the pallet aisles we used pick time distributions based on historic data per pick area. The Phase shipments are generated based on the vehicles entering the simulated assembly halls. The Sales, VPL and 2Bin orders are generated by drawing sample sets from the historic data.

Validation showed that the model is able to generate the correct number of shipments and orderliness in relation to the production schedule. The distribution of the shipment times for these shipments does correspond with the shipment time distribution from the historical data set as well. The result is that the utilization in the simulation model is equal to the utilization of the historic data.

Because of the lack of pick time data for the OSR, it was not possible to determine a distribution for pick times at the OSR. Therefore we used an average pick time per tote based on self-timed pick times. By comparing the number of pick lines per hour in the simulation with the historic data, we were able to validate the operation as good as possible.

5 | Item allocation methods

In chapter 4 the design of the simulation model for this research is explained. This simulation will be used to evaluate the current performance of the central warehouse and test potential improvements by running multiple experiments. One of the potential improvements will be the re-allocation of SKUs over the storage areas. Chapter 3 explained the effects of non-optimal division of the workload over the aisles. The phase orders account for the highest workload in the pallet aisles and for the high occupation of the consolidation areas. Storing the items in the same area as much as possible is expected to decrease the waiting time in shipments. Grouping items that are often ordered together is called Slotting. In this section the concept and application of Slotting is explored in literature. Two methods are selected from literature and presented in the context of this thesis, of which one will be tested by experiments in the simulation model as explained in Section 6.2.

5.1. Literature on Slotting

Extensive research has been conducted on the advantages of slotting within a storage zone with the purpose of minimizing the travel distance of pickers. Depending on the difficulty of the problem and availability of information, different approaches are selected to come to solve the optimization problem. In some cases exact mathematical programming like MILP (Kim and Smith (2011), Boysen et al. (2018)) are proposed to find the optimal solution. Both Kim and Boysen showed that slotting problems become NP-hard quickly when the solution space increases. For these complex problems, where exact methods require too much computation time, meta-heuristics like Cube per Order Index (Malmborg and Bhaskaran (1990)), Simulated Annealing (Yingde and Smith (2008)) and Order Oriented Slotting (Mantel and Schuur (2007)) are used that may provide a sufficiently good solution. The systems in many of the studies are based on pick systems in which the picker or the item carrier is allowed to move through different areas. Slotting is then used to minimize the travel distance of each pick route. Little to no literature can be found on how items are best allocated over the storage areas, for a system in which pickers are assigned to a single area, to minimize the consolidation effort.

Boysen et all. (2018), explored a sequencing problem for an AS/RS system with a putt wall as an intermediate storage system for consolidation. The purpose of the paper is to reduce the idle time of both the picker as the packer. The goal in this paper is somewhat similar to the intended operations improvement at the warehouse of Terberg Benschop, but the system differs. The paper describes a single conveyor, sequentially bringing bins with items of multiple orders to the picker. The picker has to place these items in a putt wall that acts as an intermediate storage location. Each shelve in the putt wall is reserved for a single order so the picker has to sort the items from the bins. When all items of an order are placed in the putt wall, the packer can empty the shelve and start packing. The sequence in which the bins arrive and from which order they carry items influence the speed in which an order is completely consolidated and ready to be packed. This problem is referred to in the paper as the batched order bin sequencing problem.

Different form the batched order bin sequencing problem, the system at the warehouse of Terberg Benschop involves a multiple input flow from the ten different areas that each bring their part of the order to the consolidation area. Since pickers only pick goods of one shipment at a time, the RCs containing the goods of a certain shipment do not need to be sorted by the picker and can directly be placed in the designated consolidation area. Pick activities within an area are picked sequentially because an aisle can only be occupied by one picker at a time, but the sperate pick activities for a shipment in each area can be picked in parallel as explained in Section 3.1.3.

Parts of shipments are brought to the consolidation area at different times depending on the areas they are divided over, the workload in each of these areas and the pick sequence in each of these areas. The allocation of the items over the areas to optimize the pick output therefore is a difficult problem that is not solved easily. Therefore, two of the approaches that are explored in the literature for solving the allocation problem are selected for this research. The first approach is the mathematical programming method Mixed-integer Linear Programming (MILP), which will be discussed in Section 5.2. The other approach is the local search heuristic Simulated Annealing, which is explained in Section 5.3. One assumption that counts for both allocation optimization methods is that each item requires the same storage space and each aisle can store each item, meaning that all items are freely moved between aisles.

5.2. Mixed-Integer Linear Programming

Mixed-Integer Linear Programming (MILP) is a mathematical programming method in which some variables are restricted to be integers and others are continuous. Mathematical programs are formulated with a maximization or minimization objective function which should result in the global optimum.

Integer or Mixed-Integer Linear Programming always starts with making a qualitative model formulation including a problem formulation, the objective function, parameters, constraints and decision variables. The full formulation of our designed MILP is presented in appendix 3.

Design of our MILP model

For this thesis the objective of the MILP used for improving the item to storage area allocation, is to equally divide the phase shipments workload and numbers of unique SKUs over each storage area. Because of the restrictions that all the small parts are stored inside the OSR, and aisle 31 is a dedicated spare parts aisle and the heavy goods are stored in aisle 38 and 39, only the allocation of items in aisle 32 to 37 is considered in the MILP.

In the MILP, the individual items are allocated to a storage area. Key information is the information for which phase shipments each SKU is required. The production schedule at Terberg Benschop was already determined for almost a year in advance during the time of this research. For 1015 vehicles the exact configuration was known, providing data of future phase shipments. Based on the configurations of these vehicles, each item was first assigned to a phase (Figure 9 and 10) and vehicle type (Figure 1) combination. As explained in Section 2.1.1.1, a phase order is constructed by the items needed for a vehicle at a certain production phase.

To equally divide the items and the workload over the storage areas, the objective function is formulated as a minimization of the sum of deviations between the workload and items in each area compared to the average workload and items over all areas. The objective function is complete by adding the total number of picking routes (total times an aisle is visited for all shipments) that is influenced by the SKU to aisle allocation decision.

Qualitative models like a MILP can be solved using modelling software. For this thesis AIMMS © was selected as the solver for the MILP. However, the model turned out to be computationally heavy resulting in a very long computation time. After running the model for more than 48 hours it still did not generate a solution. In the paper of Boysen at all. (2018) the researchers tried to solve slotting problem, which is comparable to ours, using MILP and concluded that the problem is NP-hard. Given the similarities of the two problems, we assume that our problem is NP-hard and therefore not solvable using MILP. That is why we continued using the local search heurist Simulated Annealing.

MILP test and comparison with heuristic

To show that the MILP model we have formulated does work and to compare it with the Simulated annealing heuristic, we have tested both with a smaller problem. To test both models we formulated a problem including three pallet aisles, 190 SKUs in eleven different shipments.

The formulation of the MILP remains the same as presented in Appendix 3, only the size of the sets is adjusted. The heuristic we have tested the MILP against is the simulated annealing model, presented in section 5.3.

Table 11: Comparison results of MILP and Simulated Annealing

	MILP				Simulated Annealing			
	32	33	34	Total	32	33	34	Total
Items	63	63	64	190	64	63	63	190
Shipments	4	4	4	12	7	7	8	22
ItemsError	0.33	0.33	0.67	1.33	0.67	0.33	0.33	1.33
SHPError	0	0	0	0	0.33	0.33	0.67	1.33
			Solution	**13.33**			**Solution**	**24.67**

Table 11 shows the outcome solution of both the small MILP and Simulated Annealing. The outcome of the objective function for the MILP is 13.33 and for the Simulated Annealing 24.67. Since the objective function is a minimization problem, this comparison shows that the MILP is able to generate a much better solution. The largest difference is in the shipment division over the aisles. The MILP is better in understanding which items are related to which shipment, so that when optimally dividing the items, the total number of shipments per aisle is also optimized.

However, looking at the Simulated Annealing we see a strong result in item division over the aisles. The starting solution of the Simulated Annealing had a solution value of 42. This shows that the Simulated Annealing is indeed able to significantly improve the solution.

This small problem test shows that the MILP is able to find the global optimal solution, where the simulated Annealing ends in a local optimum. Both methods found a solution which is significantly better than the starting situation. Unfortunately, enlarging the problem by adding shipments and aisle towards the real size problem, quickly resulted in the MILP not finding a solution within acceptable time. This small comparison showed that the MILP is able to provide the stronger solution, but given the issues with larger problems Simulated Annealing is a suitable alternative.

5.3. Simulated Annealing

Instead of a mathematic model that strives to find the global optimum, a heuristic approach could be used to find a suitable solution. As an alternative for the MILP the local search heuristic Simulated Annealing is selected to solve the storage allocation problem. The knowledge on Simulated Annealing used for this section is based mainly on Kirkpatrick et al. (1983).

A local search heuristic explores solutions by making little changes to the starting situation, for example by moving one item from aisle 32 to 33. The new configuration that occurs from this change is called a neighbour solution. The outcome of this neighbour is determined and based on certain criteria the neighbour solution is accepted or not. If a neighbour solution is accepted, this is the new starting situation to which a change is made to find a new neighbour. Greedy heuristics only accept neighbours that have a better result than the current situation, with the risk of getting stuck in a local optimum. Explorative heuristics also accept worse solutions to avoid getting stuck in a local optimum, but with the risk of moving away from a local optimum. The focus on better solutions is called intensification and exploring the solution set is called diversification.

Simulated Annealing is a local search heuristic that uses both diversification and intensification. At first the heuristic acts like a random search heuristic accepting almost every outcome, while at the end only improvements are accepted. Just as with every heuristic it starts with an initial solution. A small change to the current situation is made and the outcome calculated. If the outcome (B) is better than the current situation (A) the solution is accepted, if the outcome is worse than the current situation the solution is accepted with chance P and denied with chance 1-P. P is large at the beginning but decreases over the iterations. This can be presented mathematically by the following expression:

$$P_{AB}(c) = \begin{Bmatrix} 1 & if\ B \leq A \\ e^{\frac{A-B}{c}} & else \end{Bmatrix} \tag{1}$$

The probability of accepting a worse outcome is determined by the variable c, which is called the cooling parameter or temperature. The cooling parameter changes after M iterations. M is a pre-defined and fixed number of iterations called the Markov chain length. Updating the cooling parameter can be done in many ways. Two commonly used examples are presented as mathematical expressions below:

$$C_{k+1} = \alpha C_k \tag{2}$$

$$C_{k+1} = \frac{C_k}{1+\beta C_k} \tag{3}$$

To reach a final solution a stopping criterium needs to be defined, otherwise the heuristic will continue infinitely. Stopping criteria can be a maximum number of iterations, no improvement after x iterations or the temperature to reach a predefined minimum value.

The heuristic approach like Simulated Annealing results in a local optimum. The solution could be the global optimum, because at least one of the local optima is the global optimum, but that is never certain. The quality of the final outcome of the Simulated Annealing heuristic relies heavily on the parameters chosen and the initial situation. Often the Simulated Annealing gives a better final outcome when started with a randomly generated starting situation rather than a partly optimized starting situation.

5.3.1. Design explanation of our Simulated Annealing model

Different from the MILP method, the simulated annealing model for this thesis considers the allocation of individual items rather than a set of items. The goal of the simulated annealing model is to minimize the number of areas visited per shipment and equally divide the items and workload over each area. For the MILP the minimization of the number of areas visited per shipment was sought by creating the sets of items based on the vehicle shipment combinations as a preparation for the models input. In the simulated annealing the optimization of storing items together in the same area is part of the result of the model rather than the input.

The starting solution is a random distribution of all items over the areas. A neighbour solution is the selection of a single item and moving that item to a neighbouring aisle. The solution is evaluated by adding the sum of the shipments per aisle (4) to the item deviation (5) and the shipment deviation (6).

$$TotalPickRoutings = \sum_a SHP_a \tag{4}$$

$$ItemDev = \sum_a \frac{|Items_a - AvgItemsPerAisle|}{AvgItemsPerAisle} \tag{5}$$

$$SHPDev = \sum_a \frac{|SHP_a - AvgSHPPerAisle|}{AvgSHPPerAisle} \tag{6}$$

The explanation of the simulated annealing solution calculation results in the following goal function:

$$\textbf{Minimize } TotalPickRoutings + ItemDev + SHPDev \tag{7}$$

The item to an aisle and the shipment to an aisle relation are both Boolean variables. The item to aisle relation is obvious but for the shipment to aisle a small matrix transition needs to be done. A shipment is present in an aisle if at least one of the items that occurs in the shipment is allocated to that aisle. To determine the shipment to aisle relation first an item to shipment matrix (I x S) is created. By multiplying the transposed items to aisle matrix (A x I) with the item to shipment matrix (I x S) the aisle to shipment matrix (A x S) is created.

$$(A \text{ x } I) * (I \text{ x } S) = (A \text{ x } S) \tag{8}$$

However, the resulting (A x S) matrix is not a Boolean matrix since the aisle to shipment relation is increased by one for every item in the shipment that is located in the aisle. Therefore the (A x S) matrix needs to be transformed to a Boolean matrix to evaluate the number of aisles per shipment without the multiplication factor of the number of items that need to be picked in each aisle. When programming the model this transformation can be accomplished with loops and if statements. With both the (A x I) Boolean matrix and the (A x S) Boolean matrix it is possible to calculate the outcome of the objective function (7).

The full code of the Simulated Annealing model is presented in appendix 4.

5.3.2. Outcome and starting solution

For the starting solution of the simulated annealing, the current item locations are used as the starting solution. Table 12 shows the starting solution of the simulated annealing.

Table 12: Starting solution Simulated Annealing

	32	33	34	35	36	37	Total
Items	357	242	197	262	240	157	1,455
Shipments	4236	3393	1937	4832	4359	3445	22,202
ItemsError	114.5	0.5	45.5	19.5	2.5	85.5	268
SHPerror	204.4	72.29	1864.19	1986.16	1357.07	995.4	6,479.51
							25,709.755

As could be expected from the results from chapter 3, especially the shipment error is large. Table 12 shows the results from the simulation run with the following settings:

- Markov chain length = 600
- Alpha = 0.98
- Temperature updating method is: $C_{k+1} = \alpha C_k$
- Stopping criteria is when de Temperature c is lower than 0.20

Table 13: Solution Simulated Annealing

	32	33	34	35	36	37	Total
Items	243	244	242	242	242	242	1,455
Shipments	3954	2968	2994	3195	2976	3789	19,876
ItemsError	0.5	1.5	0.5	0.5	0.5	0.5	4
SHPerror	21.2	27.76	6.82	274.15	17.12	186.2	533.25
							20,146.625

Table 13 shows that the simulated annealing model is very well able to equally divide the items over the different areas. Because of the one to many relation between items and shipments an equal division of the items does not directly lead to an equal division of the shipments, but the shipment division improved significantly.

Since both the item division and the shipment division improved, the simulated annealing run resulted in a good overall improvement. The total number of pick routes has decreased by 10.5% from 22202 to 19876. Furthermore, the average areas per shipment score, for the six areas considered, improved as well. The average number of areas per shipment was 1.77 and improved to 1.61. How these results will affect the operations efficiency of the warehouse will be tested by one of the experiments with the simulation model. The results of this experiment are presented in Section 6.5.3.

6 | Experimental setup

To find alternative operational solutions that could potentially increase the output of the central warehouse, experiments are designed and executed in the simulation model. The design principles of a variety of experiments and the combination of experiments are explained in this chapter. Section 6.1 presents the base model that is used to set the benchmark performance. Section 6.2 shows how the results of the simulation model will be presented. Section 6.3 reflects on the warm-up period. In Section 6.4 multiple interventions that are an adjustment to the base model are explained, and the philosophy and results of each experiment are explained in detail in Section 6.5.

6.1. Base model

The design of the base model is equal to the extensive explanation of the model design presented in chapter 4. As the name predicts, this model forms the basis for the experiments. Slight changes are made to the base model to create the models for the experiments as will be explained in Section 6.4. The outcomes of the experiment runs are compared to the outcomes of this base model. Therefore, it was important to validate the base model as is explained in Section 4.5.

6.2. Output of the models

As explained in Section 2.3.2 and Section 3.1.2, the operational performance of the central warehouse is measured by the On-Time Exit Scan (in short: On-Time) score and the shipment times. These are the main measures of the simulation output that are evaluated to determine the performance of each experiment run. Table 14 and 15 show how this data will be presented for each experiment. Table 14 shows the Phase shipment performance of the base model simulation. Table 15 shows the pick performance for sales orders.

Table 14: Phase shipment performance of the base model simulation run (brackets indicate negative values)

OnTime	AvgShipmentTimes	AvgTimeLeft
99,798%	00:46:16	06:10:37
Min	00:00:00	(08:05:28)
Max	10:49:06	14:27:54

Table 15: Sales shipment performance of the base model simulation run (brackets indicate negative values)

OnTime	AvgTimeLeft
99,613%	05:17:35
Min	(06:48:43)
Max	08:59:08

The difference between Table 14 and 15 is the second column from Table 14. For the sales shipments it is irrelevant to evaluate the shipment times because the large majority of sales orders are single SKU orders or entirely picked from the same area. Therefore, the pick performance in shipment time for sales orders is not influenced by the workload division over the areas. However, the On-Time score and Average Time Left are also relevant for the smaller sales shipments because these measures are the result of the efficiency of the total system.

The average time left measure is an additional measure to quantify the On-Time score of the system. On-Time only tells us the percentage of shipments that received the exit scan on time, but it does not tell the time left or how many minutes or even hours a shipment is late. The average time left is measured by subtracting the exit time from the logistics time. For shipments that are finished in time, the outcome of the time left is positive, for the late shipments the outcome is negative, which is indicated with time between brackets. The largest negative number can be referred to as the maximum lateness score. Table 14 shows that for the base model the maximum lateness for Phase shipments is eight hours and 5 minutes. Table 15 shows that for the sales shipments in the base model the maximum lateness is six hours and 48 minutes.

Next to shipment times and On-Time scores, the average utilization per day per aisle is used to evaluate the workload division over the areas. As explained in Section 3.1.2, the utilization is defined by dividing the sum of the pick times per day by the total working hours in a day. Table 16 shows the utilization performance of the base model. By comparing Table 16 with Figure 21 in Section 3.1.2 we can see that the simulation provides the missing utilization information for the OSR. Furthermore, we see that the percentages are a little higher in Table 16 compared to Figure 21. Figure 21 is based on the historic data set that only contained the pick time of each individual pick. In the simulation model we added the preparation time for pick routes at the pallet aisles and the RC preparation at the OSR.

Table 16: average utilization per area per day base simulation

	0	31	32	33	34	35	36	37	38	39
Monday	91%	62%	78%	59%	44%	57%	56%	49%	73%	67%
Tuesday	91%	58%	73%	49%	43%	58%	61%	48%	66%	66%
Wednesday	88%	59%	67%	57%	42%	58%	59%	46%	66%	62%
Thursday	88%	53%	79%	69%	39%	53%	63%	57%	76%	69%
Friday	83%	64%	64%	37%	34%	40%	40%	38%	46%	41%

Table 16 shows the high utilization rate of the OSR based on the output of the simulation model. This outcome of the base simulation shows a possible explanation why the OSR is often the last to finish its part of a shipment, as was presented in Table 3 of Section 3.1.1. Another effect of the high workload at the OSR is measured in the performance of 2Bin picking.

2Bin orders at the OSR receive lowest priority due to the way 2Bin pick activities are started at the OSR. As explained in Section 2.1.5.1, the 2Bin orders are started based on the initiative of the picker at the station. In the simulation this is modelled by only allowing the pick station to start with 2Bin when there are no other pick assignments left in the queue. Table 17 shows that due to the high workload at the OSR, the 2Bin orders are postponed and not picked in time.

Table 17: 2Bin pick performance at the OSR

	2Bin Orders OSR
Picked	1091
Still in Queue	115
Percentage not Picked	9,54%
Percentage Same Day	2,66%

The incoming empty bins should be filled before the end of the same day to be considered on-time. Table 17 shows that just 2.66% of all 2Bin picks is completed the same day. The table also shows that the longer the simulation runs, the lower this on-time score gets. The table shows that at the end of the simulation run, still 115 2Bin assignments are in the queue. Around ten 2Bin assignments are created per day, meaning that the system is running over eleven days late. So the system is overflowing and not able to handle the current workload at the OSR.

Besides the pick time, shipments and utilization data, the simulation allows us to track other performance data that is not available in the historic data. For example, the occupation rate of the consolidation areas. In Section 1.3.1.1, a statement is made that aisle pickers experience waiting time due to a fully occupied consolidation zone. The historic data cannot back this statement. However, the occupation of the consolidation is tracked in the simulation.

The occupation of consolidation areas is presented in two ways. Table 18 shows the frequency and duration data on the number of consolidation areas occupied by a shipment.

Table 18: Data on number of consolidation areas occupied

# Areas occupied	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	227	0.84	50.35	-
1	481	1.79	3.85	8%
2	512	1.9	3.39	7%
3	528	1.96	2.29	5%
4	574	2.13	1.04	2%
5	640	2.38	1.95	4%
6	766	2.85	1.7	3%
7	1042	3.87	1.5	3%
8	1799	6.69	2.67	5%
9	3465	12.88	3.18	6%
10	6101	22.67	6.64	13%
11	7298	27.12	8.42	17%
12	3476	12.92	13.04	26%

The duration of 0 occupied areas is the largest because the system continues to count overnight. At the end of the day no new shipments are activated resulting in empty or nearly empty consolidation areas at the end of the day. The last column is created to show the duration distribution of the states in which at least one area is occupied. This column shows that in the current situation, when at least one of the areas is occupied, 26% of the time twelve consolidation areas are occupied by shipments.

When all twelve areas are full, it does not directly cause waiting time at the pallet areas. Only when an area wants to start a 13th shipment, the area needs to wait for one of the twelve areas to be emptied. The second presentation of occupation data is used to analyse the occurrence of waiting time. The simulation was modelled to count the duration in which a pallet aisle needs to wait for a consolidation area to be emptied. Table 19 shows that almost 20% of the time, at least one area is waiting due to fully occupied consolidation areas.

Table 19: Duration data of fully occupied consolidation areas causing waiting time.

Fully Occupied	Duration [%]
false	80.66
true	19.34

So, the system performance of the experiments can be evaluated by On-Time scores, shipment times, utilization and occupation of consolidation areas. In the rest of this chapter the same tables and visualisations are used to present the performance of the experiments and compare it with the base model.

6.3. Warm-up Period

For the experiment runs, a warm-up period needs to be considered before the simulation generates useable output. The reason for the warm-up is that the simulation starts with an empty system. The warm-up length is determined by evaluating the shipment times using the graphical method, the Welch approach. Figure 42 shows the visualisation of the Welch approach to determine the warm-up length. The warm-up length in the Welch approach is based on five independent replication runs of 200 days and a moving average window of 450 shipments.

By using this visual method we found a warm-up length of 2000 shipments. This can be converted to a warm-up of 30 days. Considering the design of the simulation the warm-up period should be at least longer than 14 days because of the shifted production calendar for the LVA as explained in Section 4.3.4. Therefore, the warm-up of 30 days was accepted and used in the data evaluation of the experiment runs.

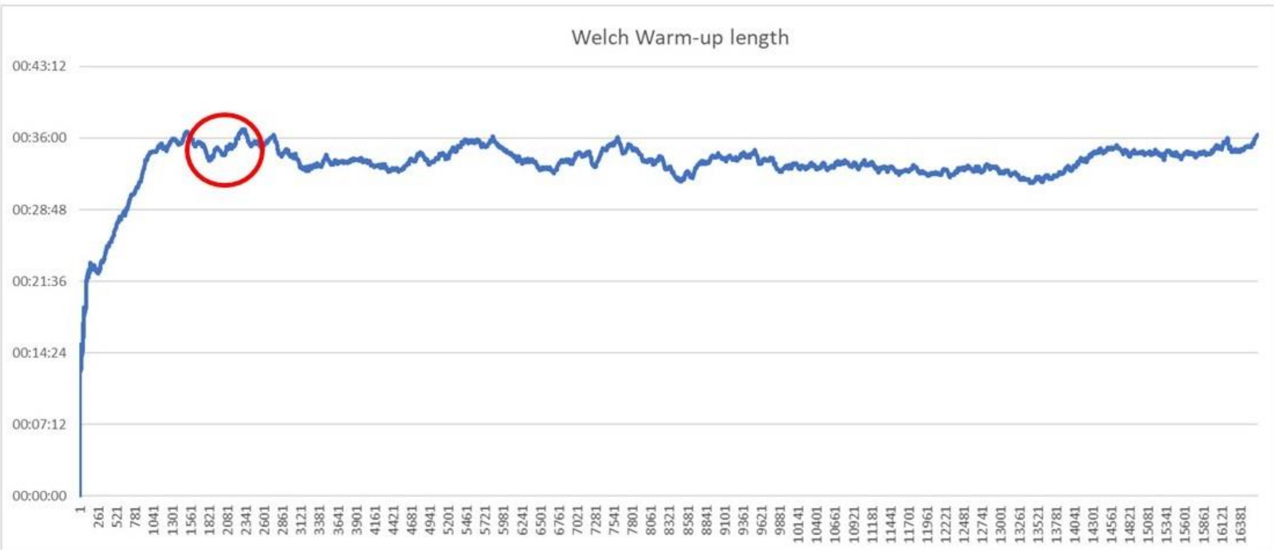


Figure 42: Welch approach to determine warm-up period

6.4. Interventions

The experiments are designed by making some adjustments to the base simulation, by changing the input data or some of the systems parameters. Experiments are done to find possible solutions to improve the systems outbound efficiency. The experiments are created based on several possible operational changes in the warehouse. We refer to these operational changes as interventions. The list of interventions are the result of ideas that we decided to be relevant during the course of this research, and ideas that were (partly) suggested by the logistics management of Terberg Benschop.

1. **Variable end of working day**
   Instead of ending all operations at exactly 16:30, each area continues pick activities until all shipments with a logistics time of the active day are completed.

2. **Switching the priority rules on sales orders and the logistics time**
   As explained in Section 2.1.5.2, the priority rules are based on two elements, the order type and the logistics time. In the current situation, Sales orders receive higher priority than other orders independent of the logistics time. In this experiment the priority rules are switched meaning that the logistics time is valued over the order type.

3. **Relocating the SKUs over the pick areas based on the outcome of simulated annealing**
   In Section 5.3.2. a suggestion for relocating the SKUs over aisle 32 till 37 is made, based on a simulated annealing heuristic. In experiment 3 (Section 6.5.3.) the effect of this relocation is tested in the simulation.

4. **Outsource the supply of 2Bin materials**
   The logistics management of Terberg Benschop is exploring options for outsourcing the supply of 2Bin SKUs at the assembly halls. Furthermore, this intervention is tested in the experiments to decrease the workload at the OSR as a reaction to the outcomes of the current situation analysis.

5. **Malaysia orders picked only on Friday afternoons when the activities at the assembly halls are stopped**
   Malaysia orders are export orders for an international production partner of Terberg in Malaysia as explained in Section 2.1.1.5. These orders are not bonded to the assembly schedule in Benschop and because of the overseas shipment, the deadline for picking these orders are not strictly linked to a day but more so to a week. Therefore, the suggestion was made to pick these Malaysia orders on Friday afternoons when work at the warehouse is less loaded with Phase orders for the Assembly at Benschop.

6. **Splitting the outbound flow of the OSR and the pallet aisles, making the consolidation independent of the part of the shipments picked at the OSR**
   The problem analysis showed that the OSR is 56.75% of the time the last to complete a shipment. The base model showed that this results in high occupation levels of the consolidation areas. The pick process at the OSR differs from the pick process at the pallet aisles. Therefore, we experiment with the system by separating the outbound processes of the OSR and the pallet aisles, making both sections independent of each other. How this is implemented in the simulation model is explained in Section 6.5.6.

7. **Increasing the assembly speed at the HVA**
   The growth perspective of Terberg Benschop is to increase the production numbers at the HVA from 26 to 40 vehicles per week. Therefore, the intervention is created to see the effect of this production increase on the operation at the central warehouse. Furthermore, this intervention is designed to use in combination with above mentioned interventions to test the durability of these interventions with larger production numbers.

8. **Extend the working day of the OSR with 1.5 hour**
   This last intervention is the result of the outcomes of experiments with other interventions. Different from intervention 1 the working day is only extended for the OSR and with a fixed time of 1.5 hour. The idea behind this experiment is explained in more detail in Section 6.10.1.

Simulations were run with just a single intervention or a combination of the above-mentioned interventions. Table 20 shows an overview of which intervention is included in each experiment. In the remainder of this chapter more detailed explanations on the experiment designs and the different interventions are provided.

Table 20: Overview of the interventions in each experiment

Experiment Nr.	Interventions
1	1
2	1, 2
3	3
4	4
5	4, 5
6	4, 6
7	4, 7
8	4, 6, 7
9	4, 6, 7, 8
10	3, 4, 5, 6, 7, 8

6.5. Experiments results

In Section 6.1 till 6.4, the experimental setup is explained including the performance visualisation and the performance of the base model that sets the benchmark for the experiments. In this section, the setup of the individual experiments are explained and the outcomes of the simulation runs are presented.

6.5.1. Experiment 1: Variable end of working day

In the first experiment, the effect of a variable end time of a production day is explored. Instead of ending all activities in the warehouse at 16:30, the end time of the production day depends on the work left in the queue. Each area has to start and complete all assignments with a logistics time of the active day that are still in the queue after 16:30. Furthermore all shipments that are assigned to a consolidation area, because they were started by an area before 16:30, need to be completed by the rest of the areas that have picking routes in the queue for this shipment. Other assignments in the queue are skipped and saved for the next day.

Shipment pick performance

Table 21 shows the pick performance of the phase shipments in a system with a variable end of the working day. We can compare the performance of the experiment run with the base model to see whether the intervention has a positive effect on the operational performance. Table 22 shows the Phase shipment performance of the base model.

Table 21: Phase shipment performance experiment 1

OnTime	AvgShipmentTimes	AvgTimeLeft
99,977%	00:44:48	06:18:37
Min	00:00:00	(01:19:04)
Max	14:57:40	15:49:40

Table 22: Phase shipment performance of base model

OnTime	AvgShipmentTimes	AvgTimeLeft
99,798%	00:46:16	06:10:37
Min	00:00:00	(08:05:28)
Max	10:49:06	14:27:54

The evaluation of Table 21 and 22 tells us that the On-Time score, the average shipment time and the maximum lateness score improve when the end of the day is variable. Especially the maximum lateness, negative score of minimum time left, decreases significantly from little over eight hours to one hour and nineteen minutes. The most important reason for this improvement is the less work taken to the next day, resulting in less large peak load during the day.

Table 23: 2Bin pick performance at the OSR for experiment 1

	2Bin Orders OSR
Picked	1205
Still in Queue	0
Percentage not Picked	0,00%
Percentage Same Day	100,00%

Table 23 shows the 2Bin performance with a variable end time. Table 17 in Section 6.2.1. told us that in the base simulation the system was overflowing. The result of the variable end time is that every 2Bin assignment is completed at the end of the day. Therefore 100% of the 2Bin assignments is picked at the same day the empty bins are brought to the warehouse.

End times per area

Obviously, it is interesting to evaluate the extra time needed at each area to realise the completion of the assignments for each day that resulted in the improvement in pick performance scores. The end of the day for an area is determined by the completion time of the last picking route. Table 24 shows the average end of the day for each aisle on each day based on the output of experiment 1. The table shows that except for aisle 39, each area has at least one day for which the average end of the day is later than 16:30. However. An average below 16:30 for the other days does not mean that the area did not complete a pick routing after 16:30 at all on that day. Evaluating averages could be misleading. Therefore, we decided to create box-plots of the measured end times per day per area.

Table 24: Average end times per area per day (hh:mm:ss) (Experiment 1)

	0	31	32	33	34	35	36	37	38	39
Max	**18:45:02**	**17:14:53**	**17:47:50**	**17:20:00**	**17:25:00**	**17:15:00**	**17:15:00**	**17:20:00**	**17:05:07**	**17:13:41**
Avg Mon	17:11:20	16:44:31	16:50:15	16:51:30	16:33:59	16:31:14	16:27:43	16:23:32	16:40:24	16:12:25
Avg Tue	17:01:38	16:29:20	16:52:51	16:35:29	16:33:26	16:28:04	16:32:15	16:45:39	16:25:04	16:18:49
Avg Wed	16:57:41	16:35:42	16:40:32	16:41:09	16:18:22	16:37:00	16:36:51	16:22:56	16:32:39	16:11:04
Avg Thu	17:45:56	16:20:15	16:35:17	16:20:02	16:32:10	16:16:58	16:20:35	16:13:38	16:22:16	16:17:25
Avg Fri	16:01:07	15:48:32	15:21:09	15:44:16	15:31:44	15:05:56	14:31:26	15:05:06	14:51:19	14:14:16

Figure 43 shows the box-plot of the measured end times in experiment 1 per area. The box plot shows that for every aisle, except for aisle 39, over 50% of the days the last pick is completed after 16:30. This is a surprise since the utilization figures for the pallet aisles are not that high but the explanation has to do with the workload at the OSR. As the box-plot shows, the OSR is over 75% of the time finishing the last job of the day after 16:30 and 50% even after 17:00. When the consolidation areas are full, the pallet aisles are waiting for the OSR to complete a shipment to empty a consolidation area so that the pallet can start a new shipment.

The late end times for the OSR are no surprise based on the high utilization that was presented in Table 16 in Section 6.2.1. One of the main reasons why the OSR is so much later than the pallet aisles, are the 2Bin orders that are pushed to the end of the day.

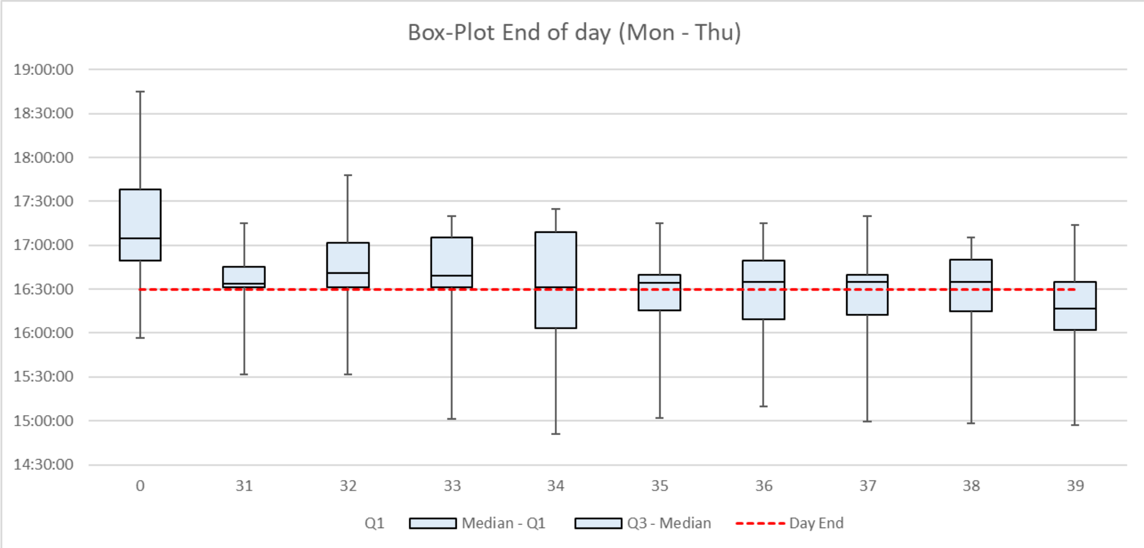


Figure 43: Box-plot of end of day pick completion times per area on Mondays to Thursdays (Experiment 1)

The Fridays behave slightly different. As mentioned in Section 4.3.4, work at the assembly halls stops at 13:15. This means that there are also less phase shipments with a logistics time on Friday to be picked in the warehouse. Therefore, the operations at the warehouse on Friday are slightly different. Until 12:45 the warehouse operates with 1FTE at each pallet aisle and 2FTE at the OSR. After 12:45 there is one picker left at the OSR and one to continue picking for all pallet aisles. Figure 44 shows the Box-plot for the end times on Friday for each area.

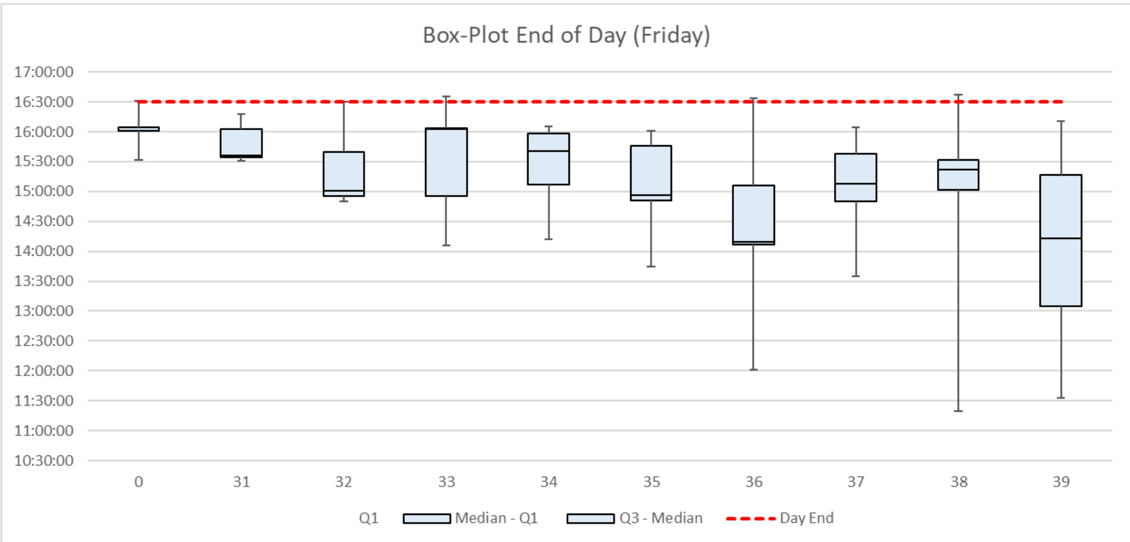


Figure 44: Box-plot of last pick per day for each area on Fridays (Experiment 1)

Figure 44 shows that each area in the warehouse is able to complete its work on Friday before the end of the day at 16:30. The high density around 16:00 for the OSR is the result of the large number of sales orders that continue to be placed on Friday afternoons. The same holds for aisle 31 that is mainly filled with spare part SKUs.

So, we have seen – for Monday to Thursday - that using a variable end of the day results in all areas to continue working after 16:30 while the utilization for the pallet aisle is not considered high. Therefore, we also took a look at the average starting time of the day for each aisle. This is determined by the start of the first picking route within each area. Table 25 shows the average start time per area. The table shows that only the OSR and aisle 31 consistently start their operation at the beginning of the day at 07:30. The other areas start on average on some days around ten minutes later. The reason is that they did not take work from the previous day to the next and the generation of new phase shipments is not necessarily at the beginning of the day. The OSR and aisle 31 have a higher rate of sales shipments that are activated at the start of the day and therefore these aisles can start picking straight away. This analysis shows us that with the variable end time the work day is shifted for some of the aisles.

Table 25: average start of the day per area (hh:mm:ss) (Experiment 1)

	0	31	32	33	34	35	36	37	38	39
Avg Mon	07:31:48	07:31:31	07:31:51	07:31:51	07:35:04	07:30:56	07:35:15	07:37:34	07:33:22	07:33:07
Avg Tue	07:30:56	07:30:21	07:32:17	07:39:09	07:38:09	07:32:32	07:37:58	07:41:05	07:35:22	07:43:32
Avg Wed	07:30:54	07:30:00	07:40:26	07:40:25	07:39:27	07:35:14	07:36:30	07:43:17	07:36:02	07:43:17
Avg Thu	07:30:53	07:30:00	07:31:10	07:31:10	07:34:57	07:31:31	07:31:52	07:35:04	07:36:08	07:37:11
Avg Fri	07:30:56	07:30:05	07:31:03	07:31:03	07:32:38	07:29:59	07:30:06	07:30:02	07:30:08	07:36:17

Workload performance

Because of the variable end of day, the utilization cannot be calculated based on a fixed eight hours working day. The utilization of the areas with variable end times per day is therefore defined by the summation of picking times, divided by the average operational hours in each working day. These hours are determined by using the average end times per area per day of Table 24 and the average starting times in Table 25. This definition for utilization measurement resulted in the figures as presented in Table 26.

Table 26: Average utilization per aisle per day (Experiment 1)

	0	31	32	33	34	35	36	37	38	39
Monday	89%	60%	77%	55%	44%	55%	56%	51%	75%	68%
Tuesday	89%	57%	72%	47%	43%	54%	62%	49%	67%	67%
Wednesday	90%	55%	63%	56%	44%	53%	59%	52%	66%	68%
Thursday	93%	52%	82%	67%	44%	53%	66%	58%	76%	68%
Friday	67%	59%	55%	35%	36%	36%	35%	31%	40%	42%

Table 27: Average utilization per aisle per day (Base Model)

	0	31	32	33	34	35	36	37	38	39
Monday	91%	62%	78%	59%	44%	57%	56%	49%	73%	67%
Tuesday	91%	58%	73%	49%	43%	58%	61%	48%	66%	66%
Wednesday	88%	59%	67%	57%	42%	58%	59%	46%	66%	62%
Thursday	88%	53%	79%	69%	39%	53%	63%	57%	76%	69%
Friday	83%	64%	64%	37%	34%	40%	40%	38%	46%	41%

The utilization figures for the system do not change much compared to the results of the base model, which are presented in Table 27. The reason is that still the same work needs to be done and for the pallet aisles the average total operational time per day does not change much, yet only shifts back a few minutes. The biggest change is on the Friday for the OSR. Because the working days at the OSR are extended on Monday to Thursday to complete all the 2Bin orders and shipments for the active day, as shown in Table 24 and Figure 43, the system does not pile up work to take to the next day. The Friday used to be the day on which the OSR, unsuccessfully, tried to complete all the built-up work from the rest of the week. By extending the workdays at the OSR, the Friday becomes less busy for the OSR, thus improving the 2Bin pick performance as presented in Table 23.

Conclusion on Experiment 1

Although the evaluation of the pick performance for the system with variable end times showed a slight improvement in the On-Time score, shipment times and maximum lateness, the solution does not seem to be a durable one. It does not improve the efficiency of the outbound process, it just reduces the workload at a certain day by reducing the work shifted to the next day. This requires flexibility from the employees that some days need to work after 16:30 and no longer have the certainty of fixed working hours. The solution also seems to be effective mainly for the OSR and the 2Bin performance. By allowing longer working days, the OSR gets the chance to catch up with the rest of the system every day.

In short, this solution only solves the problems partly by working longer, not by working more efficient.

6.5.2. Experiment 2: Switching the priority rules

In experiment 2 we stick to the test with the variable end times but combine it with a change in the priority rules. As explained in Section 2.1.5.2, the sales orders always receive the highest priority independent of their logistics time. After the sales priority, the priorities of phase shipments are determined by their logistics time.

For this experiment the priority is changed. The logistics time is the first qualifier on which the pick sequence is determined. Only for shipments with an equal logistics time the priority score is evaluated. In that case Sales goes before Phase shipments followed by VPL and last 2Bin. The reason for this intervention is to observe whether this change in sequencing results in fewer days that an area is finished after 16:30.

Figure 45 shows the box-plot of the last pick completion times per area over all Mondays to Thursdays for experiment 2. Although the figure differs from Figure 43, for all areas at least 50% of the last picks are competed after 16:30. This shows that switching the priority does not result in less days with a finish time after 16:30.

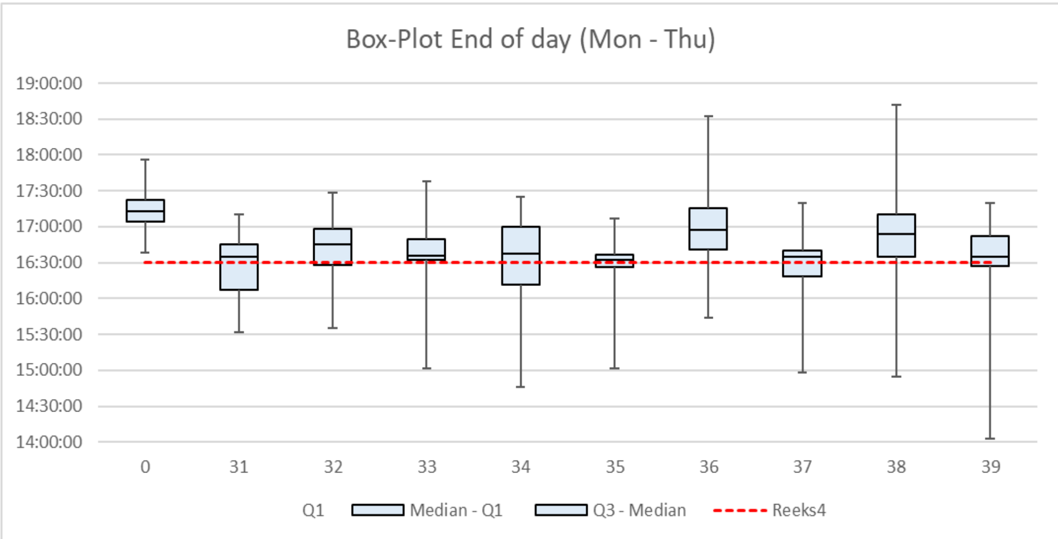


Figure 45: Box-plot of end of day pick completion times per area on Mondays to Thursdays (Experiment 2)

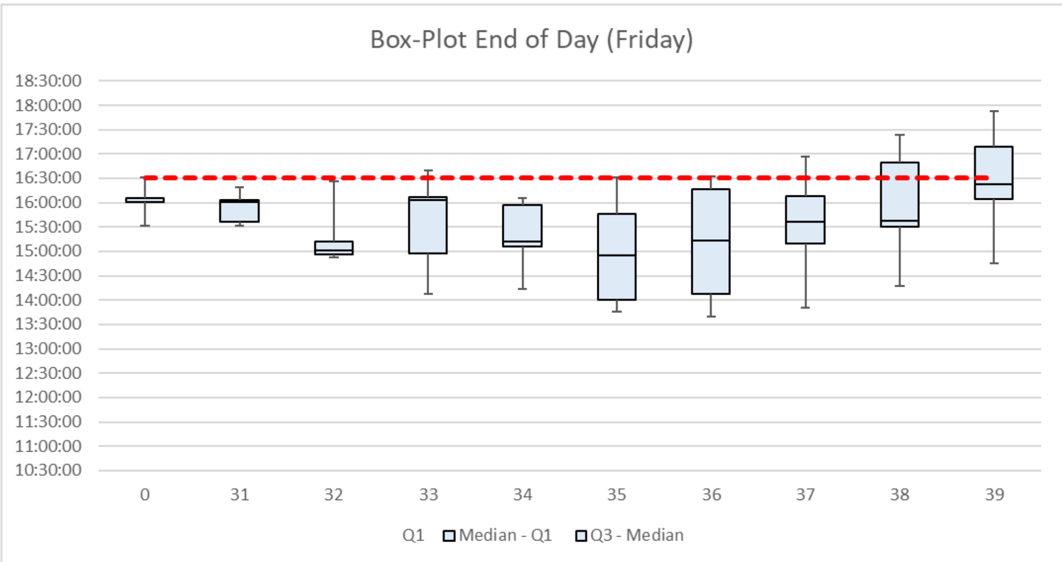


Figure 46: Box-plot of end of day pick completion timer per area on Fridays (Experiment 2)

Figure 46 shows that even on Fridays, area 37, 38 and 39 at some days did not finish their last job before 16:30 when the priority is switched. The reason for this result is the effect of 2Bin picking. The 2Bins have the lowest priority, or no priority score, but they do receive a logistics time that is equal to the end of the active day. As explained in Section 6.1.1, the results of the base model, the 2Bin orders are pushed ahead with the regular priority rules. In experiment 1 we already saw that all 2Bin orders were picked on-time due to the variable end of the day. This was because all 2Bin assignments were completed at the end of the day. However, in the case with the switched priority, the 2Bin orders are picked before Sales and Phase shipments with a logistics time on the next day or later, where this is the other way around with the current priority rules. The result is that these Sales and Phase shipments are now pushed to the next day. On Friday afternoon just a single FTE is left to complete the work in the pallet aisles. Because of the single picker, the picking routes for shipments are not picked in parallel but sequential, with the result that the single FTE is not able to complete all picking routes before 16:30 on Fridays.

Shipment pick performance

We already saw the effect of 2Bin orders receiving a higher priority on the Box-plot of the end of day analysis. A higher priority on the 2Bin also influences the pick performance for Phase and Sales shipments. Table 28 shows the phase shipment performance of the system with switched sorting and a variable end of day. Comparing the results in Table 28 with the results of experiment 1 in Table 29, shows that switched sorting worsens the results on every performance measure for the phase shipments. Especially the significant decrease in the On-Time score is a surprising result considering the higher priority on the logistics times.

Table 28:Phase shipment performance Experiment 2

OnTime	AvgShipmentTimes	AvgTimeLeft
92,735%	01:02:21	02:06:32
Min	00:00:00	(03:27:34)
Max	14:58:56	14:59:47

Table 29: Phase shipment performance experiment 1

OnTime	AvgShipmentTimes	AvgTimeLeft
99,977%	00:44:48	06:18:37
Min	00:00:00	(01:19:04)
Max	14:57:40	15:49:40

Table 30 shows the performance of the Sales shipments for experiment 2. Just as for the Phase shipments, the On-Time score of the Sales shipments decreased significantly compared to the results of the Base model (repeated in Table 31). For the Sales orders this could have been expected because of the changed priority rules, but surprisingly the performance decrease of the Sales shipments is less than for the Phase shipments.

Table 30: Sales shipment performance (Experiment 2)

OnTime	AvgTimeLeft
96,346%	04:05:45
Min	(04:42:39)
Max	05:59:08

Table 31: Sales shipment performance (Base model)

OnTime	AvgTimeLeft
99,613%	05:17:35
Min	(06:48:43)
Max	08:59:08

The base model showed that the OSR is not able to complete the entire workload within the fixed working hours. The result was the push back of 2Bin orders. With the changed priority rules, the settings of the pick stations at the OSR are changed to 2Bin during the day more often. Especially pick station 2 switches to 2Bin from Sales more often. The duration of completing 2Bin picks to fill a 2Bin rack is 24 minutes. The earlier demand on the OSR for 2Bin orders and the relative long duration to complete 2Bin orders, now pushes back the start of Phase and Sales picks, which results in the performance decrease as presented in Table 28 and 30. Table 32 shows that the system is now able to complete all 2Bin orders before the end of the day just as we saw in the first experiment due to the variable end of the working day.

Table 32: 2Bin pick performance at OSR (Experiment 2)

	2Bin Orders OSR
Picked	1205
Still in Queue	0
Percentage not Picked	0,00%
Percentage Same Day	100,00%

Conclusion on Experiment 2

There is no need to look into more performance details of the system in experiment 2. The goal was to shorten the days with variable end times, by switching the priority rules. The analysis shows that this goal is not reached and the switched priority intervention even caused a significant performance decrease in the efficiency of Phase and Sales shipment picking. Therefore, we can conclude that the intervention of switching priorities is not effective.

The conclusion is similar to the conclusion we have already drawn after experiment one. The only difference is that the problem is replaced to the phase and sales shipments, but the experiment shows that the system is still not able to deal with the workload and complete all outbound assignments in time. Switching priorities is not improving the systems performance. Working longer is not a durable solution.

6.5.3. Experiment 3: Relocating the SKUs

For the third experiment the outcome of the Simulated Annealing heuristic presented in Section 5.3.2. is used to relocate the SKUs over pallet aisle 32 till 37. The goal of the relocation of SKUs is to minimise the number of areas visited for a shipment and with that decrease shipment times and increase the On-Time scores.

Shipment pick performance

Table 33 shows the Phase shipment performance of experiment 3. For the evaluation of this experiment we have added the Carriers per Shipment measure (CPS) that shows the average number of aisles over which the SKUs for a shipment are divided. Comparing Table 33 with Table 34 (Phase shipment performance of the Base model) shows us that relocating the SKUs as suggested by the outcome of the Simulated Annealing heuristic, results in a 6% lower CPS. This lower CPS seems to have a positive effect on the On-Time scores. The On-Time score increased from 99,798% to 99,899%. The largest improvement is in the maximum lateness. Table 33 shows that the maximum lateness after relocation is decreased to 02:42:46 (hh:mm:ss). The average shipment time however increased a little bit. A reason for this increase could be less shipments with little SKUs from one single aisle that occurred for the more exceptional vehicle configurations.

Table 33: Phase shipment performance (Experiment 3)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
99,899%	00:48:12	06:09:49	2,761
Min	00:00:00	(02:42:46)	
Max	09:26:03	14:53:04	

Table 34: Phase shipment performance (Base model)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
99,798%	00:46:16	06:10:37	2,926
Min	00:00:00	(08:05:28)	
Max	10:49:06	14:27:54	

Workload performance

For the evaluation of the workload performance we focus mainly on the utilization of aisle 32 till 37. Table 35 shows the average utilization per day per aisle for the system with relocated SKUs over aisle 32 till 37. Table 33 shows, by the figures but also by the conditional format, that the workload is spread more evenly over area 34 till 37. The workload for 32 is decreased a bit and for aisle 33 the workload is barely changed. A reason for these results for aisle 32 and 33 is the relatively large share of sales workload, as presented is Figure 21 in Section 3.1.2, which is not changed when relocating the Phase SKUs.

Table 35: Average utilization per area per day (Experiment 3)

	0	31	32	33	34	35	36	37	38	39
Monday	94%	66%	76%	61%	48%	53%	50%	52%	74%	68%
Tuesday	95%	56%	69%	49%	50%	48%	54%	48%	64%	60%
Wednesday	91%	63%	65%	58%	50%	51%	53%	57%	65%	66%
Thursday	96%	52%	70%	68%	48%	44%	58%	54%	70%	65%
Friday	82%	69%	62%	37%	38%	40%	34%	41%	47%	44%

Table 36: Average utilization per area per day (Base model)

	0	31	32	33	34	35	36	37	38	39
Monday	91%	62%	78%	59%	44%	57%	56%	49%	73%	67%
Tuesday	91%	58%	73%	49%	43%	58%	61%	48%	66%	66%
Wednesday	88%	59%	67%	57%	42%	58%	59%	46%	66%	62%
Thursday	88%	53%	79%	69%	39%	53%	63%	57%	76%	69%
Friday	83%	64%	64%	37%	34%	40%	40%	38%	46%	41%

Relocating the SKUs over aisle 32 till 37 based on the simulated annealing heuristic resulted in a better workload division over these areas but the effect is limited since the utilization at the OSR did not decrease as presented in Table 35.

The system is still not able to complete all the work within the given time. Table 37 shows that in experiment 3, the 2Bin orders are again postponed. Due to a better workload division in the aisles and less areas visited per shipment, areas can start new shipments sooner, causing even less space for 2Bin orders to come in to play. A comparison between Table 37 and 38 (2Bin pick performance at the OSR of the base model) shows that even less 2Bin assignments are completed during the experiment run.

Table 37: 2Bin performance at OSR (Experiment 3)

	2Bin Orders OSR
Picked	1045
Still in Queue	165
Percentage not Picked	13,64%
Percentage Same Day	0,00%

Table 38: 2Bin pick performance at OSR (Base model)

	2Bin Orders OSR
Picked	1091
Still in Queue	115
Percentage not Picked	9,54%
Percentage Same Day	2,66%

Conclusion on Experiment 3

The system with relocated SKUs over aisle 32 till 37 is still not able to complete all work within the given time. The reason for the limited effect of the intervention is that the operations efficiency at the aisles is not the bottleneck of the current situation. Furthermore the relocations based on the Simulated Annealing heuristic requires the move of 531 different SKUs, which is 36,5% of the SKUs in the respective aisles. With the introduction of new vehicles and new SKUs the locations should be re-evaluated.

However, the experiment has proven that the relocation of SKUs based on simulated annealing does improve the workload division over the aisles and at the same time decreases the total utilization for these aisles. A lower CPS does seem to have a positive effect on the On-Time score, though due to the high performance of the base situation this effect seems limited. The maximum lateness score did increase significantly, showing that the relocations resulted in an improvement of operational efficiency during the day.

In later experiments we will see if relocating SKUs can have a more positive effect in combination with other interventions.

6.5.4. Experiment 4: Outsourcing 2Bin

The logistic management of Terberg Benschop is evaluating the different flows of goods through the Central warehouse and exploring options with just in time (JIT) delivery of goods from suppliers directly at the assembly line. The first category of SKUs for which this option seems possible without increasing the risk of stock outs to much are the 2Bin SKUs. At the same time the current situation analysis and the base model showed that 2Bin accounts for a large share of the workload at the OSR. Therefore, outsourcing of the 2Bin SKUs could potentially decrease the utilization of the OSR significantly.

Analysis conducted by the data analytics department showed that the ten largest suppliers of 2Bin items are responsible for the delivery of 80% of all the items. For this experiment we assume that the delivery of 80% of the 2Bin items is outsourced to a third party that delivers these items in pre-prepared bins directly at the assembly line. We assume that this process does not cause any delays and requires no interference of the Central warehouse.

The outsourcing of 2Bin SKUs is integrated in the simulation by reducing the 2Bin pick assignments at the OSR with 80%. 2Bin orders are picked per rack with around forty empty bins on both sides. In the current situation the OSR needs to fill five of these racks per day. With the 2Bin outsourced intervention the OSR is requested to fill only one rack per day. The few 2Bin requests at the pallet aisles remain unchanged, since we assume that these are most likely not part of the 80% most requested 2Bin SKUs.

Shipment pick performance

By outsourcing the 2Bin, the workload at the OSR is reduced (Table 45) resulting in an improvement of the shipment pick performance. Table 39 shows that the On-Time score improves, but more striking is the large decrease of the average shipment time. This shows that as a result of the workload reduction at the OSR, the OSR is able to complete its part of a shipment sooner and the system has to wait less on the OSR to finish consolidation. The maximum lateness is decreased by almost 50% from over eight hours to little over 4.5 hours.

Table 39: Phase shipment performance (Experiment 4)

OnTime	AvgShipmentTimes	AvgTimeLeft
99,946%	00:41:28	06:26:07
Min	00:00:00	(04:30:54)
Max	08:03:21	14:50:06

Table 40: Phase shipment performance (Base model)

OnTime	AvgShipmentTimes	AvgTimeLeft
99,798%	00:46:16	06:10:37
Min	00:00:00	(08:05:28)
Max	10:49:06	14:27:54

The sales performance of the system did improve as well as can be concluded by comparing Table 41 with 42. The On-Time score increased and, although less strongly than for the phase shipments, the maximum lateness of the sales shipment decreased. The sales orders are often single SKU orders and therefore rely less on the workload division over the different areas. Due to the priority rules the Sales performance was already strong in the base model. However, the reason why the performance did increase, is that pick station 2 is less often switched from the Sales to 2Bin configuration due to less 2Bin orders.

Table 41: Sales performance (Experiment 4)

OnTime	AvgTimeLeft
99,982%	05:23:07
Min	(04:01:04)
Max	08:59:09

Table 42: Sales performance (Base model)

OnTime	AvgTimeLeft
99,613%	05:17:35
Min	(06:48:43)
Max	08:59:08

By outsourcing the 2Bin orders, the 2Bin workload is reduced at the OSR but not eliminated. Therefore, we still have a look at the 2Bin pick performance at the OSR. Table 43 shows that with the reduced number of orders all the requested orders are picked within the simulation run time and 96.4% is picked on the same day as requested. This shows that even with a 80% reduction of 2Bin orders at the OSR, not all the 2Bin orders are completed before the end of the day.

Table 43: 2Bin performance at OSR (Experiment 4)

	2Bin Orders OSR
Picked	221
Still in Queue	0
Percentage not Picked	0,00%
Percentage Same Day	96,380%

Table 44: 2Bin performance at OSR (Base model)

	2Bin Orders OSR
Picked	1091
Still in Queue	115
Percentage not Picked	9,54%
Percentage Same Day	2,66%

Workload performance

As expected by outsourcing a demand category that forms a large share of the shipments at the OSR, the utilization of the OSR is decreased significantly. Table 45 shows that the average utilization for the OSR is decreased from a percentage around 90% to 80% for Monday to Wednesday. Especially the difference on the Fridays is large. This shows that the system is not overflowing anymore and the OSR does not have to catch up on the work still in queue on Friday. Table 45 also shows that Thursdays are busy days, which is the result of the early activation of shipments for the LVA for the next Monday as explained in Section 2.1.5.1.

Table 45: Average utilization per area per day (Experiment 4)

	0	31	32	33	34	35	36	37	38	39
Monday	82%	68%	85%	67%	49%	62%	60%	54%	77%	69%
Tuesday	80%	57%	70%	45%	41%	54%	61%	48%	62%	60%
Wednesday	76%	63%	66%	54%	43%	60%	53%	51%	64%	65%
Thurday	92%	58%	87%	73%	44%	55%	70%	57%	82%	70%
Friday	41%	66%	57%	37%	33%	40%	36%	37%	45%	40%

Table 46: Average utilization per area per day (Base model)

	0	31	32	33	34	35	36	37	38	39
Monday	91%	62%	78%	59%	44%	57%	56%	49%	73%	67%
Tuesday	91%	58%	73%	49%	43%	58%	61%	48%	66%	66%
Wednesday	88%	59%	67%	57%	42%	58%	59%	46%	66%	62%
Thursday	88%	53%	79%	69%	39%	53%	63%	57%	76%	69%
Friday	83%	64%	64%	37%	34%	40%	40%	38%	46%	41%

Consolidation Occupation performance

The workload reduction at the OSR that resulted in less waiting on the OSR to complete Phase shipments also has a positive effect on the occupation of the consolidation areas. Table 47 shows that the duration in which all twelve of the consolidation areas are occupied is reduced from 26% (Table 48: Consolidation area occupation of Base model) to 13%, of the total time that at least one of the areas is occupied. Also the higher duration, 63.5% versus 50.35%, of a fully empty consolidation area shows that at the end of the day more often all work is completed, causing less occupied areas overnight.

Table 47: Consolidation area occupation of Experiment 4

# Areas Occupied	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	263	0.97	63.50	0%
1	537	1.99	5.27	14%
2	562	2.08	2.24	6%
3	610	2.26	1.71	5%
4	692	2.56	1.07	3%
5	795	2.94	1.11	3%
6	940	3.48	2.07	6%
7	1273	4.72	1.27	3%
8	1995	7.39	1.18	3%
9	3553	13.16	3.82	10%
10	5951	22.04	4.9	13%
11	6730	24.93	7.22	20%
12	3096	11.47	4.64	13%

Table 48: Consolidation area occupation of Base model

# Areas occupied	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	227	0.84	50.35	-
1	481	1.79	3.85	8%
2	512	1.9	3.39	7%
3	528	1.96	2.29	5%
4	574	2.13	1.04	2%
5	640	2.38	1.95	4%
6	766	2.85	1.7	3%
7	1042	3.87	1.5	3%
8	1799	6.69	2.67	5%
9	3465	12.88	3.18	6%
10	6101	22.67	6.64	13%
11	7298	27.12	8.42	17%
12	3476	12.92	13.04	26%

The less pressure on the consolidation areas has a direct positive effect on the waiting time for the aisles caused by fully occupied consolidation areas. By comparing Table 49 with Table 50 we see that the percentage of time that a fully occupied consolidation are causes waiting time is reduced from 19.34% to 10.44%.

Table 49: Duration of fully occupied consolidation areas causing waiting time (Experiment 4)

Fully Occupied	Duration [%]
false	89.56
true	10.44

Table 50: Duration of fully occupied consolidation areas causing waiting time (Base model)

Fully Occupied	Duration [%]
false	80.66
true	19.34

Conclusion on Experiment 4

The outsourcing of 2Bin orders is the first intervention in the experiments that is focussed on reducing the workload rather than changing the operation to deal with the workload. The OSR seemed to be the bottleneck of the system that was often the last to finish its part of a shipment. Reducing the workload at this area has an overall positive effect on the outbound performance of the central warehouse. At each performance measure the system improved, however the pick performance scores still not indicate 100% On-Time.

By outsourcing a part of the process, the system becomes dependent on an external party. For this experiment we neglected the potential new challenges that arise from this dependability. However it should be taken into consideration by the logistic management of Terberg Benschop when further evaluating the possibilities of outsourcing.

6.5.5. Experiment 5: 2Bin outsourced and Malaysia orders to Friday afternoon

The utilization analysis of the base model and the previous experiments show that the workload on the Friday afternoons is lower than for the rest of the week due to the early stop at the assembly halls at 13:15. Therefore the idea came to postpone Malaysia order picking to the Friday afternoons to make them interfere as little as possible with production orders. Malaysia orders are activated to the warehouse as a category of Sales orders, meaning that they have a higher priority than the Phase orders. Different from standard SKU sales orders, Malaysia orders are larger batch orders for the production location in Malaysia. However, the Malaysia orders do not have the critical day deadline and can be planned for export. Therefore, it could be possible to make it standard procedure to pick Malaysia orders on Friday afternoon and make them ready for shipment the next week.

To implement this intervention in the simulation model, the historic data that forms the input for Sales orders is modified. The generation time of Malaysia orders are all set to 13:15 on the Friday of the week they were originally activated.

Picking the Malaysia orders on Fridays is combined with the intervention of outsourcing 2Bin. The base model showed that the system overflows in the current situation. By postponing Malaysia orders to Friday afternoons only the order in which the work is done is adjusted but that does not reduce the workload. Furthermore, the utilization analysis of experiment 4 showed that by outsourcing the 2Bin, capacity at the OSR has been freed on Friday afternoons, which was a trigger for this experiment.

Shipment pick performance

Table 51 shows that by picking the Malaysia orders on Friday afternoon the phase pick performance improves. The On-Time score improves slightly and the average shipment time decreases by more than one minute. The largest improvement is in the decrease on maximum lateness. The maximum lateness is reduced significantly to little over an hour. The logistics time is two hours ahead of the time the shipment is needed at assembly. So with one hour and 18 minutes delay the shipment is late, but when this can be identified quickly, the milk run could still be able to bring the filled RC to the corresponding assembly phase in time.

Table 51: Phase pick performance (Experiment 5)

OnTime	AvgShipmentTimes	AvgTimeLeft
99,977%	00:40:01	06:31:15
Min	00:00:00	(01:18:40)
Max	08:07:35	15:15:33

Table 52: Phase pick performance (Experiment 4)

OnTime	AvgShipmentTimes	AvgTimeLeft
99,946%	00:41:28	06:26:07
Min	00:00:00	(04:30:54)
Max	08:03:21	14:50:06

Table 53: Sales pick performance (Experiment 5)

OnTime	AvgTimeLeft
99,927%	05:22:33
Min	(04:04:07)
Max	08:59:08

Table 54: Sales pick performance (Experiment 4)

OnTime	AvgTimeLeft
99,982%	05:23:07
Min	(04:01:04)
Max	08:59:09

The Sales pick performance worsens slightly. The On-Time score decreased with 0.055% and the maximum lateness score increased with three minutes. These numbers are marginal. The reason for the Sales performance decrease is the On-Time score of the Malaysia orders. Table 55 shows that all Malaysia orders were picked in time when they were picked during the week. Table 55 shows that the system is not able to complete al Malaysia orders in time when they are only activated on Friday afternoons. Because the Malaysia orders are a category of sales orders, the Malaysia order performance reflects on the Sales order performance.

Table 55: Malaysia On-Time score (Experiment 5)

OnTime Malaysia
99,831%

Table 56: Malaysia On-Time score (Experiment 4)

OnTime Malaysia
100,000%

Workload performance

In experiment 4 we saw that by outsourcing the 2Bin orders, the average utilization was reduced on Friday afternoons, especially at the OSR and aisle 32. Therefore it is interesting to analyse the effect on the utilization of picking all Malaysia orders on Friday afternoons. Comparing Table 57 with Table 58 shows that for almost each area, except aisle 37, the utilization on Friday afternoon increases with a few percentages. The growth is largest for aisle 32, which tells us that a large share of the Malaysia SKUs are allocated to aisle 32.

Table 57: Average utilization per area per day (Experiment 5)

	0	31	32	33	34	35	36	37	38	39
Monday	83%	71%	85%	72%	51%	60%	60%	54%	81%	69%
Tuesday	79%	58%	71%	50%	39%	55%	56%	48%	67%	60%
Wednesday	75%	58%	66%	51%	42%	55%	56%	49%	66%	65%
Thursday	91%	53%	78%	66%	40%	52%	70%	61%	76%	72%
Friday	44%	69%	75%	49%	38%	45%	42%	37%	47%	47%

Table 58: Average utilization per area per day (Experiment 4)

	0	31	32	33	34	35	36	37	38	39
Monday	82%	68%	85%	67%	49%	62%	60%	54%	77%	69%
Tuesday	80%	57%	70%	45%	41%	54%	61%	48%	62%	60%
Wednesday	76%	63%	66%	54%	43%	60%	53%	51%	64%	65%
Thurday	92%	58%	87%	73%	44%	55%	70%	57%	82%	70%
Friday	41%	66%	57%	37%	33%	40%	36%	37%	45%	40%

Besides the change in the utilization on Fridays, some areas do show an increased utilization on Mondays. The reason for this increase of workload on Monday is that not all work is completed on Friday afternoons. Although by looking at the utilization figures we might expect that the system has enough capacity left, there is one important operational difference on Friday afternoon to take in consideration. On Friday afternoon just a single picker is present to fulfil all pick assignments for each aisle, meaning that the pick routings are not completed in parallel but sequential. This single picker is not able to complete all tasks on the Friday afternoon, which is the reason for the non 100% score on Malaysia orders and the slight decrease in Sales pick performance

Conclusion on Experiment 5

The analysis of the simulation outcomes of experiment 5 showed that postponing the completion of Malaysia order picks to Friday afternoons could potentially improve the output of Phase orders during the rest of the week. However, the workload on Friday afternoons increases while the number of pickers in the pallet aisles remains limited to a single picker. The figures showed that this single picker is not able to complete all picking routes over the aisles in time on his own.

Picking Malaysia orders on Friday afternoons is a good and relatively easy implementable intervention to improve the operational efficiency of the system during the rest of the week, but to make sure that the performance on Friday does not suffer from it, additional workforce should be used on Friday afternoons to deal with the added workload.

6.5.6. Experiment 6: Separate OSR from consolidation and 2Bin outsourced

Performance and utilization analysis of the current situation in Section 3.1.1 showed that there is a large difference in workload in number of shipments and pick lines between the OSR and the pallet aisles. Table 3 showed that this difference in workload resulted in the OSR often being the last to complete its part of the shipment. Section 3.1.3 and the simulation of the current situation showed that this resulted in longer shipment times and high occupation of the consolidation areas.

In experiment 4 and 5, attempts are made to reduce waiting on the OSR for phase shipments by reducing the workload at the OSR. This has shown to be effective, although the On-Time score is still not 100% and we could argue whether the decrease in shipment time from 46 minutes to 40 minutes is enough. The average sum of individual pick times is 9 minutes, as explained in Section 3.1.3, which means that on average the shipment times still contain 31 minutes of waiting time after the interventions of outsourcing 2Bin and picking Malaysia orders on Friday afternoons. Therefore, we have searched for other interventions in addition to decreasing the workload at the OSR to limit the negative effect of the system waiting for the OSR.

For this experiment, the OSR is separated from the pallet aisles for the consolidation effort for phase shipments. Only the filled Roll Containers (RCs) that come from the pallet aisles run through the consolidation areas. The SKUs that are picked at the OSR are taken to the assembly halls directly without the need to combine them with the SKUs from the pallet aisles. The activation of shipments is still done simultaneously for the respective areas. The completion of the consolidation of the parts of the shipment that are picked in the pallet aisles determine when a shipment is completed, the consolidation area is released and a new shipment can be activated. Even if the OSR is not finished picking its share of the shipment, the pallet aisles send their part of the shipment to the exit scan, triggering the activation of the next shipment. This process remains the same as presented in Figure 29 of Section 4.3.7.

By separating the OSR from the pallet aisles in the outbound flow of phase shipments, we expect to limit the waiting times in Phase shipments and with that, speed up the outbound performance. This intervention is combined with the reduction of workload at the OSR. Without the outsourcing of the 2Bin orders the system is overflowing which makes it less relevant to evaluate the intervention.

Shipment pick performance

Because of the separated outbound flow for phase shipments in the pallet aisles and the OSR, we do evaluate both areas separately for these phase shipments as well. Table 59 shows the Phase pick performance for the pallet aisles in this experiment. The table shows that for the first time a 100% On-Time score is achieved for Phase shipments. The average shipment time decreased dramatically as well. From 41 minutes with the 2Bin outsourced intervention only (Table 60), to just 20 minutes when adding the intervention of separating the OSR from consolidation. This is the most dramatic improvement of phase pick performance we have seen so far. The CPS score decreases because the RCs from the OSR are not included in the count anymore. Table 59 shows that for each phase shipment completed at the pallet aisles, at least 38 minutes are left before the logistics time.

Table 59: Phase pick performance pallet aisles (Experiment 6)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
100,000%	00:20:00	07:12:53	2,30
Min	00:00:52	00:38:13	
Max	03:53:44	18:11:56	

Table 60: Phase pick performance (Experiment 4)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
99,946%	00:41:28	06:26:07	2,93
Min	00:00:00	(04:30:54)	
Max	08:03:21	14:50:06	

By separating the outbound flow of the OSR and the pallet aisles we had anticipated that the performance for the pallet aisles would improve due to eliminating the wait on the OSR. What we did not expect was an improvement at the OSR, which did occur as is presented in Table 61. All Phase shipments are not only picked in time at the pallet aisle, but the OSR is also able to complete all Phase shipments before their logistics times, with a minimum of 33 minutes left. This is an impressive and surprising result. We will come back to the explanation of this result after evaluating the occupation of the consolidation areas.

Table 61: Phase pick performance at the OSR (Experiment 6)

OnTime	AvgTimeLeft
100,000%	06:45:18
Min	00:33:07
Max	14:50:28

Besides the improvement for Phase shipments the Sales shipments slightly improve as well. The On-Time score improved marginally. Just one single sales shipment extra is picked in time. However, the maximum lateness decreased significantly from 4 hours to little over 3 minutes. With this maximum of 3 minutes late, we can hardly speak off lateness.

The improvement of both the phase and the sales performance are not at the expense of the 2Bin orders. For the 2Bin orders at the OSR, the On-Time score improved from 96.380% to 97,738%

Table 62: Sales pick performance (Experiment 6)

OnTime	AvgTimeLeft
99,988%	05:34:57
Min	(00:03:19)
Max	05:59:02

Table 63: Sales pick performance (Experiment 4)

OnTime	AvgTimeLeft
99,982%	05:23:07
Min	(04:01:04)
Max	08:59:09

Consolidation occupation

Table 59 showed that the CPS has decreased to an average of 2.3 areas visited per shipment. Table 64 shows that the reduction of CPS has a large positive influence on the occupation of the consolidation areas. In 46% of the occupied time, 10 to 12 areas where filled (Table 65) for the system with only 2Bin outsourced. When the OSR is separated from consolidation, in addition to the outsourcing of 2Bin, the percentage of occupied time in which 10 to 12 areas are occupied is reduced to 19%. For the full occupation of all twelve areas specifically, the percentage has decreased from 13% to 4%. This shows that the pressure on the consolidation area can be significantly reduced by separating the outbound flow of the OSR and the pallet aisles.

Table 64: Consolidation area occupation (Experiment 6)

Value	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	436	1.62	76.34	0%
1	891	3.31	4.37	18%
2	948	3.52	3.14	13%
3	1026	3.81	1.15	5%
4	1176	4.37	1.77	7%
5	1513	5.62	2.55	11%
6	2059	7.65	1.59	7%
7	2786	10.36	1.45	6%
8	3678	13.67	1.48	6%
9	4355	16.19	1.62	7%
10	4154	15.44	1.84	8%
11	2879	10.7	1.72	7%
12	1000	3.72	0.97	4%

Table 65: Consolidation area occupation (Base model)

# Areas Occupied	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	263	0.97	63.50	0%
1	537	1.99	5.27	14%
2	562	2.08	2.24	6%
3	610	2.26	1.71	5%
4	692	2.56	1.07	3%
5	795	2.94	1.11	3%
6	940	3.48	2.07	6%
7	1273	4.72	1.27	3%
8	1995	7.39	1.18	3%
9	3553	13.16	3.82	10%
10	5951	22.04	4.9	13%
11	6730	24.93	7.22	20%
12	3096	11.47	4.64	13%

The reduction in the occupation of consolidation areas also has a positive effect on the percentage of waiting due to the fully occupied consolidation area. Comparing Table 66 with 67 shows us that by separating the OSR from the consolidation, the percentage of waiting on a fully occupied consolidation area is reduced with little over 8%, from 10.44% to just 2.31%.

Table 66: Duration of fully occupied consolidation areas causing waiting time (Experiment 6)

Fully Occupied	Duration [%]
false	97.69
true	2.31

Table 67: Duration of fully occupied consolidation areas causing waiting time (Experiment 4)

Fully Occupied	Duration [%]
false	89.56
true	10.44

Because of the low occupation of the consolidation area that results in very little actual waiting, a more continuous flow of phase shipment activation is realised. This is the reason why performance at the OSR increased as well, which we will explain next.

The activation of shipments is limited to a predefined maximum. For this simulation the maximum number of activated shipments is 27. When a maximum of 27 shipments is reached and all consolidation areas are full, only a new shipment can be activated when one of the twelve shipments that are assigned to a consolidation area is completed. So a high occupation of consolidation areas slows down the activation process of new shipments. This can result in situations in which all active phase lines for the OSR are assigned to one of the pick stations and the other is waiting on new shipment to be activated. If the OSR still has 2Bin orders in the queue, this will be assigned to the waiting pick station. The 2Bin picks cost 24 minutes to complete. So, when new shipments are activated in the meantime, the OSR first needs to complete the 2Bin before the configuration is returned to Phase picking. Switching between configurations at the OSR does cost time for the system to adjust to this switch as well. The stream of totes to the pick station is interrupted, meaning that the first 2Bin tote can be send earliest to the system after the last phase or sales pick is completed and the configuration is switched. The picker than needs to wait for the next tote to travel the entire distance on the roll conveyor. The travel time is at least 45 seconds. When there are other Totes in the queue for the other pick station or the Tote has to wait due to a full conveyor, the wait at the pick station will be extended. This shows the importance of a continuous stream of Totes that can be realised by a continuous activation of new shipments.

Conclusion on Experiment 6

Separating the OSR from consolidation is shown to be a very effective operational change. With this intervention, combined with the outsourcing of 2Bin, a 100% On-Time score is reached for phase orders. For the Sales orders, the On-Time score is nearly 100% and the maximum lateness is reduced to a marginal number of 3 minutes. This is the most effective intervention we have seen so far.

The separation of the OSR from consolidation is an internal operational change that does not require investment in additional resources or the extension of working hours. Therefore, it is not only effective but potentially cost efficient as well.

However, the separation of the OSR from consolidation requires an adjustment of the IT structure. The activation of the separate parts of the shipments for each area still happens simultaneously but the outbound registration needs to be separated.

Furthermore, the separate outbound stream of SKUs from the OSR and the pallet aisles that are not consolidated will result in a higher pressure on the milk run. The capacity of the milk run was out of scope for this research, but it is important to take this extra stream of product carriers from the OSR in consideration when evaluating the effect of this intervention.

6.5.7. Experiment 7: 2Bin outsourced and HVA production increased

In the previous experiments, interventions were tested to see if the outbound performance of the system with the current production numbers could be improved. In the following experiments, combinations of these interventions are tested together with larger production numbers at the HVA.

The ambition of Terberg Benschop is to produce 40 vehicles at the HVA per week instead of the current 26. The assembly has already proven to be able to do so in historic production weeks, but the central warehouse turned out to be the bottleneck.

In this experiment, the larger production numbers at the HVA are combined with the intervention of outsourcing 2Bin orders. The simulation model can be adjusted to generate larger production numbers, by decreasing the assembly takt times at the HVA from 2 hour and 51 minutes to 1 hour and 51 minutes. The Assembly team has proven to be able to complete 40 vehicles per week in previous tests. To give the Central warehouse enough time to complete all the work, Phase shipments for the HVA are requested four takt times in advance instead of three.

Shipment pick performance

The On-Time score of the system producing 40 vehicles per week at the HVA is 98.3%. This is a large decrease compared with the 99.9% score of the system with just the 2Bin outsourced (Table 69). The maximum lateness almost doubled as well, showing that the number of times the system is late does not only increase but also the length of the delay increases. However, the On-Time score above 98% is still a high performance for a significant increase in workload, showing potential for the system to handle the increased production.

Table 68: Phase pick performance (Experiment 7)

OnTime	AvgShipmentTimes	AvgTimeLeft
98,298%	00:43:30	03:40:47
Min	00:00:00	(08:08:21)
Max	11:07:22	03:40:47

Table 69: Phase pick performance (Experiment 4)

OnTime	AvgShipmentTimes	AvgTimeLeft
99,946%	00:41:28	06:26:07
Min	00:00:00	(04:30:54)
Max	08:03:21	14:50:06

Table 70: Sales pick performance (Experiment 7)

OnTime	AvgTimeLeft
97,64%	04:57:50
Min	(04:03:25)
Max	08:59:08

Table 71: Sales Pick performance (Experiment 4)

OnTime	AvgTimeLeft
99,982%	05:23:07
Min	(04:01:04)
Max	08:59:09

Table 70 shows that for the Sales orders the performance dropped as well. Just 97.64% of the sales orders is picked in time. Different from the Phase orders, the performance decrease for Sales orders in mainly in the On-Time score. The maximum lateness did not change much and the Average Time Left is also just slightly reduced. This tells us that the number of late Sales shipments is increased but an increase in length of the delay is limited. The main reason for this limited effect on the maximum lateness is the higher priority of Sales orders.

Table 72: 2Bin performance OSR (Experiment 7)

	2Bin Orders OSR
Picked	220
Still in Queue	1
Percentage not Picked	0,45%
Percentage Same Day	10%

Table 73: 2Bin performance at the OSR (Experiment 4)

	2Bin Orders OSR
Picked	221
Still in Queue	0
Percentage not Picked	0,00%
Percentage Same Day	96,380%

Table 72 shows that even with the outsourcing of the 2Bin orders, the system is not able to pick the remaining 2Bin orders at the same day as requested. The table shows that at the end of the simulation run just a single 2Bin order is still in queue. This is too little to conclude that the system is overflowing again.

Workload performance

Evidently the workload at the Central warehouse increases when the production numbers at one of the assembly halls increase. Table 72 shows the average utilization per area per day analysis for the system with 2Bin outsourced and an increased production at the HVA. The table clearly shows that the utilization of the OSR is again very high. Fridays are just as busy as the rest of the days at the OSR, showing that the system needs the Friday afternoons to catch up on the work left in queue.

Striking about comparing Table 74 and 76 is that for the areas other than the OSR the utilization figures seem not to increase that much or not at all. At first this might not make sense but the explanation is simple. The utilization is measured by the time needed to complete picking routes that are completed during the day. Meaning that the utilization is based on the work actually done. Because the utilization of the OSR is so large again, the rest of the aisle are waiting for the OSR to finish and therefore cannot continue to complete phase shipments

Table 74: Average utilization per area per day (Experiment 7)

	0	31	32	33	34	35	36	37	38	39
Monday	94%	58%	82%	64%	45%	57%	64%	49%	76%	68%
Tuesday	95%	54%	75%	50%	46%	63%	67%	51%	74%	71%
Wednesday	94%	54%	73%	60%	47%	60%	68%	57%	70%	74%
Thursday	95%	45%	76%	61%	46%	56%	72%	57%	73%	70%
Friday	94%	62%	82%	47%	44%	53%	63%	43%	56%	62%

Table 75: Average utilization per area per day (Experiment 4)

	0	31	32	33	34	35	36	37	38	39
Monday	82%	68%	85%	67%	49%	62%	60%	54%	77%	69%
Tuesday	80%	57%	70%	45%	41%	54%	61%	48%	62%	60%
Wednesday	76%	63%	66%	54%	43%	60%	53%	51%	64%	65%
Thurday	92%	58%	87%	73%	44%	55%	70%	57%	82%	70%
Friday	41%	66%	57%	37%	33%	40%	36%	37%	45%	40%

Conclusion on Experiment 7

The pick performance analysis supports the claims that the output speed of the Central warehouse is keeping the assembly from increasing their productivity. This could have been expected with an already overflowing system for the Base model, but even with a reduced workload at the OSR, the Central warehouse is not able to keep up with higher production numbers.

6.5.8. Experiment 8: Separate OSR from consolidation, 2Bin outsourced and HVA production increased

In this experiment we test the most successful combination of interventions for the current situation, that was presented in experiment 6, in a system with the raised production numbers at the HVA. Besides the reduced takt times at the HVA, the rest of the simulation settings are equal to those of experiment 6.

Shipment pick performance

Table 76 shows the pick performance of the phase shipments for the system with 2Bin outsourced, the OSR separated from consolidation and the production numbers at the HVA increased. The On-Time score immediately shows that outsourcing 2Bin and separating the OSR from consolidation is still a successful combination of interventions with a raised demand for assembly. The average shipment time is even lower compared with the same system with lower HVA demand (Experiment 6). The reasons is that the SKUs are in general allocated more efficiently over the pallet aisle for HVA shipments than LVA shipment. Therefore, a higher share of HVA shipments results in the shorter average shipment times. The same reason holds for the decrease of CPS. Because of the separated outbound of the OSR and the pallet aisles, the occupation of the consolidation area is limited (Table 84), giving the system the chance to quickly complete phase shipments.

Although the average shipment time decreases, the average time left shows that the workload for the system has increased. The shipments are completed quickly, however they cannot all be picked at the same time. This results in a lower average time left and one shipment close of being late, with just 3 minutes to spare.

Table 76: Phase pick performance (Experiment 8)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
100,000%	00:18:55	05:51:48	2,22
Min	00:00:51	00:03:27	
Max	05:04:18	16:49:53	

Table 77: Phase pick performance (Experiment 6)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
100,000%	00:20:00	07:12:53	2,30
Min	00:00:52	00:38:13	
Max	03:53:44	18:11:56	

Just as for experiment 6, not only the pallet aisles manage to pick all Phase shipments in time with the raised production numbers, the OSR is also still able to complete all phase shipments in time (Table 78). The average time left score shows the same decrease as for the pallet aisles due to the raised workload. However, striking is the high minimal time left (Table 78) that is a lot higher than for experiment 6 (Table 79). This result raises the suspicion that the performance increase for the Phase shipments is at cost of the performance in other categories. Table 82 confirms this suspicion, which will be reflected on later in this section.

Table 78: Phase pick performance at the OSR (Experiment 8)

OnTime	AvgTimeLeft
100,000%	04:54:21
Min	01:57:37
Max	11:46:28

Table 79: Phase pick performance at the OSR (Experiment 6)

OnTime	AvgTimeLeft
100,000%	06:45:18
Min	00:33:07
Max	14:50:28

Table 80 shows the Sales pick performance of experiment 8. The On-Time score is decreased a little bit, just as the average time left. The max lateness score however increased significantly. All the Sales shipments that are picked to late are Sales orders of the Friday afternoon. So the raised workload for Phase shipments results in more workload pushed to the Friday afternoons. On Friday afternoons, pick station 2 is the only station active in the combined configuration, meaning that this station needs to pick Sales, Phase and 2Bin shipments. The performance results shows that this single station is not able to complete all Sales shipments in time.

Table 80: Sales pick performance (Experiment 8)

OnTime	AvgTimeLeft
99,36%	05:28:02
Min	(01:17:18)
Max	05:59:06

Table 81: Sales pick performance (Experiment 6)

OnTime	AvgTimeLeft
99,988%	05:34:57
Min	(00:03:19)
Max	05:59:02

As expected by the Phase pick performance analysis for this experiment, the performance of the 2Bin category decreases. Comparing Table 82 with Table 83 shows that the system with increased HVA production is not able to complete all the work at the OSR in time. Just 34% of all the 2Bin orders are picked within the same day as requested.

Table 82: 2Bin pick performance at the OSR (Experiment 8)

	2Bin Orders OSR
Picked	219
Still in Queue	2
Percentage not Picked	0,90%
Percentage Same Day	34%

Table 83: 2Bin pick performance at the OSR (Experiment 6)

	2Bin Orders OSR
Picked	221
Still in Queue	0
Percentage not Picked	0,00%
Percentage Same Day	97,738%

Consolidation occupation

Table 84 shows that despite the increased workload, the pressure on the consolidation areas remains limited. This is the reason for the little effect of the production number increase on the phase pick performance at the pallet aisles. This illustrates that the pallet aisles are able to deal with higher workload as long as this area does not have to wait on the OSR. Table 85 shows that just 3% of the time an aisle is waiting for a consolidation area to be released. Table 76 shows that this waiting does not result in lateness.

Table 84: Consolidation area occupation (Experiment 8)

Value	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	439	1.20	67.19	-
1	935	2.56	5.7	17%
2	1048	2.87	1.95	6%
3	1242	3.41	2.48	8%
4	1532	4.20	2.52	8%
5	1945	5.34	3.26	10%
6	2729	7.49	2.52	8%
7	3923	10.76	2.48	8%
8	5307	14.56	2.66	8%
9	6213	17.04	2.65	8%
10	5859	16.07	3.15	10%
11	3970	10.89	2.25	7%
12	1315	3.61	1.2	4%

Table 85: Duration of fully occupied consolidation areas causing waiting time (Experiment 8)

Value	Duration [%]
false	96.63
true	3.37

Workload performance

Table 86 confirms the pick results for the OSR that we have seen earlier in this section. The increase in HVA production numbers resulted in an increase in workload that results in more work being pushed to the Fridays. This results in a high overall utilization for the OSR. Not just for the OSR but for all areas the utilization has been increased, as can be concluded from comparing Table 86 with 87. Other than for experiment 7, the utilization for the pallet aisles increased because they do not need to wait on consolidation, as we have seen by analysing Table 82. The Pallet aisle seem to be able to handle the increase in workload for the HVA based on the utilization figures and the pick performance analysis. Based on the figures in Table 86, aisle 32 is expected to be the next area that will face difficulties to complete all pick assignments in time.

Table 86: Average utilization per area per day (Experiment 8)

	0	31	32	33	34	35	36	37	38	39
Monday	93%	60%	81%	61%	45%	62%	63%	55%	78%	70%
Tuesday	96%	59%	87%	55%	53%	63%	70%	53%	74%	78%
Wednesday	94%	55%	74%	60%	49%	59%	69%	60%	72%	77%
Thursday	95%	52%	92%	75%	53%	63%	74%	59%	84%	81%
Friday	86%	55%	69%	34%	37%	36%	43%	32%	39%	42%

Table 87: Average utilization per area per day (Experiment 6)

	0	31	32	33	34	35	36	37	38	39
Monday	83%	56%	72%	66%	40%	53%	54%	44%	69%	58%
Tuesday	78%	58%	71%	49%	39%	50%	58%	47%	70%	57%
Wednesday	73%	54%	66%	55%	43%	54%	58%	56%	67%	64%
Thursday	91%	51%	84%	66%	40%	54%	72%	58%	82%	68%
Friday	40%	56%	64%	38%	40%	36%	37%	33%	41%	40%

Conclusion on Experiment 8

This experiment showed that the combination of reducing the workload at the OSR by outsourcing 2Bin together with the separation of the OSR form consolidation to reduce the waiting times on phase shipment, remains very effective for the system with increased production numbers for the HVA. Especially the pallet aisles are still able to complete all pick assignments in time. The OSR is struggling again, causing the 2Bin orders to be pushed back again. Deeper analysis of the simulation outcome showed that all late completion of Sales orders was for Sales orders with a logistics time on Friday afternoon and the great majority were OSR Sales orders. This showed that especially capacity on the Friday afternoon is a limiting factor for the OSR.

In the next experiment we therefore use the model of this experiment as the basis and only implement an intervention at the OSR.

6.5.9. Experiment 9: Separate OSR from consolidation, 2Bin outsourced, HVA production increased and 1.5 extra working hours at OSR

The results of experiment 1 showed that extending the workday is not very effective for all sections of the warehouse. The previous experiment showed that the system is very capable of dealing with larger production numbers when 2Bin is outsourced and the OSR is separated from the pallet aisles for consolidation. Only the OSR is facing difficulties again with the increased workload, resulting in lateness for the 2bin orders. The workload at the OSR is already decreased by outsourcing the 2Bin SKUs and since the OSR system is programmed by the supplier Knapp, it is impossible to make any changes to the operational process of the OSR picking system. Therefore, we decided for this experiment to increase the operational capacity at the OSR by extending the work hours with 1.5 hours. This means that from Monday to Thursday both pick stations are active until 18:00 instead of 16:30, and on Friday pick station one is active until 14:15 instead of 12:45 and pick station two is active till 18:00 instead of 16:30.

Workload performance

For this experiment it is more relevant to first look at the impact on the utilization rate of the operational capacity rather than the pick performance, since the total working hours are increased at the OSR and the Phase and Sales pick performance of the system for experiment 8 were already good.

Table 88 shows that the utilization rate for the OSR has decreased. This was to be expected since the operational capacity is increased as the only intervention. The table also shows that the additional 1.5 hours results in a significantly lower utilization rate at the OSR on the Fridays. This means that by increasing the operational capacity at the OSR by adding 1.5 working hours, less work for the OSR is taken to the next day and the system does not need to catch up on the queue on Friday. Because of the less pressure on the OSR on Fridays, the rest of the system has to wait less on the OSR resulting in higher utilization rates for most of the pallet aisles on Fridays.

Just as we have seen before, aisle 32 seems to become the next bottleneck after focussing on the OSR. In the next and last experiment, interventions are tested to see if the pressure at aisle 32 can be reduced as well with a combination of all previously mentioned interventions.

Table 88: Average utilization per area per day (Experiment 9)

	0	31	32	33	34	35	36	37	38	39
Monday	78%	56%	82%	67%	46%	59%	62%	50%	78%	68%
Tuesday	86%	56%	81%	54%	50%	58%	73%	51%	75%	72%
Wednesday	77%	57%	75%	58%	48%	61%	64%	59%	69%	72%
Thursday	90%	50%	91%	68%	53%	63%	75%	60%	82%	83%
Friday	37%	60%	66%	38%	41%	37%	42%	33%	43%	45%

Table 89: Average utilization per area per day (Experiment 8)

	0	31	32	33	34	35	36	37	38	39
Monday	93%	60%	81%	61%	45%	62%	63%	55%	78%	70%
Tuesday	96%	59%	87%	55%	53%	63%	70%	53%	74%	78%
Wednesday	94%	55%	74%	60%	49%	59%	69%	60%	72%	77%
Thursday	95%	52%	92%	75%	53%	63%	74%	59%	84%	81%
Friday	86%	55%	69%	34%	37%	36%	43%	32%	39%	42%

Shipment pick performance

Before we go to the last experiment we first have a look at the pick performance of experiment 9. Table 90 shows that although the average shipment time decreased, the maximum lateness increased from a minimum of 3 minutes left to almost 4 minutes late. This lateness is a marginal score which concerns a single shipment on a total of 15,556 shipments. The single late shipment occurred in the pallet aisles. Therefore the explanation for the system not to be 100% on-time anymore, is the stochasticity of pick times within the pallet aisles in the simulation model.

Table 90: Phase pick performance (Experiment 9)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
99,994%	00:18:47	05:53:43	2,21
	00:00:51	(00:03:51)	
	05:16:18	17:25:27	

Table 91: Phase pick performance (Experiment 8)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
100,000%	00:18:55	05:51:48	2,22
Min	00:00:51	00:03:27	
Max	05:04:18	16:49:53	

Comparing Table 92 with Table 93 shows that 1.5 hours extra at the OSR each day improves the sales pick performance. The on-time score increased and the maximum lateness decreased significantly. As was already stated in the previous section, all the late sales picks are sales orders for Friday afternoons for experiment 8. The increase in the on-time score is the result of the less workload pushed to the Friday afternoons, which is shown in the utilization analysis of this section.

Table 92: Sales pick performance (Experiment 9)

OnTime	AvgTimeLeft
99.977%	05:35:29
Min	(00:09:50)
Max	05:59:04

Table 93: Sales pick performance (Experiment 8)

OnTime	AvgTimeLeft
99,36%	05:28:02
Min	(01:17:18)
Max	05:59:06

Experiment 7 and 8 showed that an increase in workload at the central warehouse is at the expense of the OSR orders that have the lowest priority. With the raised production numbers for the HVA, the interventions of outsourcing 2Bin and separating the OSR from consolidation are not enough anymore to realise a sufficiently high On-Time score for every demand classification. However, different from the current situation the system did not overflow in experiment 7 and 8 and was still able to catch up on Friday afternoons. Table 94 shows that adding the 1.5 extra work hours to the OSR allows the system enough time to pick most of the 2Bin orders on the same day as requested during the week. Table 88 showed that this resulted in a lower utilization at the Fridays due to less work that has been pushed forward at the end of each day.

Table 94: 2Bin pick performance at the OSR (Experiment 9)

	2Bin Orders OSR
Picked	221
Still in Queue	0
Percentage not Picked	0,00%
Percentage Same Day	98,643%

Table 95: 2Bin pick performance at the OSR (Experiment 8)

	2Bin Orders OSR
Picked	219
Still in Queue	2
Percentage not Picked	0,90%
Percentage Same Day	34%

Conclusion on Experiment 9

The increase of the workload by raising the production numbers at the HVA can be managed by the central warehouse with the implementation of outsourcing the 2Bin, separating the OSR from consolidation and increasing the work hours at the OSR. This set of interventions are a combination of reducing the workload, improving the operational efficiency and increasing the capacity.

The increase of capacity remains a difficult intervention to implement, as mentioned before in the conclusion of experiment 1. The experiment shows that an extension of the workday by around 1.5 hours could potentially improve the systems output so that every task is fulfilled in time. However, this 1.5 hours is a difficult number to plan the workforce on. Suggestions are made to offer students a two hour evening job as OSR pickers at the central warehouse.

Furthermore this experiment showed that the OSR and aisle 32 remain the busiest pick areas. The relative utilization of capacity caused by sales orders is higher for aisle 32 than for the other pallet aisle, besides aisle 31 that is dedicated to sales. In the last three experiments we have only analysed the increase of Phase demand on the system. The spare part sales orders are also expected to grow when more vehicles are sold. With this in mind the OSR and aisle 32 could quickly reach the situation where they are not able to keep up anymore, resulting in waiting times for the rest of the system and eventually late completion of shipments. Unfortunately, one of the limitations of this research is that the increase in spare part orders is not tested to provide exact figures.

6.5.10. Experiment 10: Separate OSR from consolidation, 2Bin outsourced, HVA production increased, Relocating the SKUs, Malaysia order to Friday afternoons and 1.5 extra working hours at OSR

For this last experiment we combine all interventions that have shown to be effective in the previous experiments in one system. Compared to experiment 9, the intervention of relocating SKUs over aisle 32 till 37 and picking Malaysia orders on Friday afternoons are additionally configured in the simulation model. The relocation of SKUs is added to see whether the relatively large utilization in aisle 32 can be divided over the rest of the pallet aisles. Picking Malaysia orders on Friday afternoons is again implemented to limit the interference of this type of Sales orders on the completion of Phase shipments and make use of the relatively less busy Fridays.

Shipment pick performance

Table 96 shows that the system is able to complete all phase shipments in time. The additional interventions of relocating the SKUs and picking Malaysia orders on Friday do have a positive effect on the operational efficiency for Phase shipments. The average shipment time has decreases with more than one minute and the max lateness score has decreased from three minutes late to at least two hours left for each shipment.

The CPS score decreased as well as a result of relocating the SKUs over aisle 32 till 37 based on the outcome of the simulated annealing heuristic as explained in Section 5.3.2. The CPS score decreased by 9%. In experiment 3 the decrease in CPS was 6%. This shows that relocating SKUs for phase shipments using simulated annealing is even more effective when the production numbers increase.

Table 96: Phase pick performance (Experiment 10)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
100.00%	00:17:13	05:59:41	2.02
Min	00:00:52	01:59:26	
Max	05:33:44	17:42:01	

Table 97: Phase pick performance (Experiment 9)

OnTime	AvgShipmentTimes	AvgTimeLeft	CPS
99.994%	00:18:47	05:53:43	2.21
Min	00:00:51	(00:03:51)	
Max	05:16:18	17:25:27	

The performance of the Sales orders worsens slightly again when the Malaysia orders are all picked at Friday afternoons. Comparing Table 98 with Table 99 shows that the On-Time score decreases and the maximum lateness increases. All late Sales shipments where orders on Fridays for the pallet aisles. We have seen the same results in experiment 5. Removing pick activities for Malaysia orders from the rest of the week results in more efficient Phase shipment completion but at the same time increases the workload on Friday afternoon. As explained before in Section 6.6.1, the utilization figures of Table 100 might suggest that the system has operational capacity left on Fridays. However, only a single picker is left to complete the pick activities in the Pallet aisles. The shipment performance shows that the addition of intervention 3 and 5 are improving the outbound efficiency of the system from Monday to Thursday, but requires additional capacity at the pallet aisles on Friday afternoon.

Table 98: Sales pick performance (Experiment 10)

OnTime	AvgTimeLeft
99.965%	05:33:16
Min	(00:14:34)
Max	05:59:06

Table 99: Sales pick performance (Experiment 9)

OnTime	AvgTimeLeft
99.977%	05:35:29
Min	(00:09:50)
Max	05:59:04

Workload performance

The goal of relocating the SKUs for this experiment was to decrease the workload for aisle 32 and distribute the workload more evenly over the aisles. The colours of the conditional formatting in Table 100 show that especially for aisles 33 till 37 the workload is spread more evenly. The utilization of aisle 32 is still larger than for aisle 33-37 because of the higher share of Sales orders for this aisle. Although the utilization for aisle 32 is still larger than for aisle 33 to 37, the utilization did decrease for aisle 32. Table 100 shows that the utilization for aisle 32 is lower than 85% for each day and on average around 73%. With these figures the utilization at aisle 32 is not critical.

Table 100: Average utilization per aisle per day (Experiment 10)

	0	31	32	33	34	35	36	37	38	39
Monday	79%	60%	71%	65%	55%	53%	53%	57%	78%	74%
Tuesday	86%	54%	73%	57%	55%	57%	60%	59%	70%	73%
Wednesday	77%	55%	69%	61%	55%	55%	57%	64%	73%	72%
Thursday	89%	55%	84%	75%	57%	57%	69%	67%	87%	79%
Friday	39%	64%	72%	42%	43%	40%	35%	37%	47%	48%

Table 101: Average utilization per aisle per day (Experiment 9)

	0	31	32	33	34	35	36	37	38	39
Monday	78%	56%	82%	67%	46%	59%	62%	50%	78%	68%
Tuesday	86%	56%	81%	54%	50%	58%	73%	51%	75%	72%
Wednesday	77%	57%	75%	58%	48%	61%	64%	59%	69%	72%
Thursday	90%	50%	91%	68%	53%	63%	75%	60%	82%	83%
Friday	37%	60%	66%	38%	41%	37%	42%	33%	43%	45%

Consolidation occupation

As a result of the more evenly distributed workload and the resulting decreased CPS, the occupation figures for the consolidation areas improved as well. Table 102 shows that the duration of ten or more consolidation areas occupied is 14% of the time in which at least one area is occupied. Table 103 shows that without relocating the SKUs, the score was 21%. This is a 33% improvement. That is a more significant drop than we have seen in experiment 3, showing again that the relocation of SKUs is more effective for larger production numbers at the HVA.

Table 102: Consolidation area occupation (Experiment 10)

Value	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	507	1.39	68.02	0%
1	1092	2.98	5.45	17%
2	1241	3.39	2.4	8%
3	1445	3.95	2.58	8%
4	1763	4.82	1.92	6%
5	2289	6.26	3.35	10%
6	3221	8.8	3.74	12%
7	4475	12.23	1.62	5%
8	5664	15.48	3.81	12%
9	6041	16.51	2.52	8%
10	5024	13.73	2.18	7%
11	2951	8.07	1.61	5%
12	874	2.39	0.79	2%

Table 103: Consolidation area occupation (Experiment 8)

Value	Frequency	Frequency [%]	Duration [%]	Occupated Duration
0	439	1.20	67.19	-
1	935	2.56	5.7	17%
2	1048	2.87	1.95	6%
3	1242	3.41	2.48	8%
4	1532	4.20	2.52	8%
5	1945	5.34	3.26	10%
6	2729	7.49	2.52	8%
7	3923	10.76	2.48	8%
8	5307	14.56	2.66	8%
9	6213	17.04	2.65	8%
10	5859	16.07	3.15	10%
11	3970	10.89	2.25	7%
12	1315	3.61	1.2	4%

The comparison of Table 104 and 105 shows a similar drop in the total time that the pallet aisles need to wait for a consolidation area to be released.

Table 104: Duration of fully occupied consolidation areas causing waiting time (Experiment 10)

Value	Duration [%]
false	97.64
true	2.36

Table 105: Duration of fully occupied consolidation areas causing waiting time (Experiment 8)

Value	Duration [%]
false	96.63
true	3.37

Conclusion on Experiment 10

In this last experiment, we have seen that the combination of five interventions to the system are very effective to make the system able to deal with increased production numbers at the HVA. The pick performance is nearly 100% in-time for all demand classifications. The workload is distributed evenly over the pallet aisles that showed a positive effect on the shipment pick efficiency and the occupation of the consolidation areas. Furthermore, the relocation of SKUs is shown to be more effective with higher production numbers resulting in a larger share of Phase shipments.

However, the intervention of moving the Malaysia orders to the Fridays is causing lateness in the pallet aisles. A 99.965% On-Time score and a maximum lateness of just 14.5 minutes is a very good performance that not requires a dramatic change, but it shows that the Friday afternoons could become the next critical element of the system.

The 1.5 extra working hours at the OSR remains a difficult intervention to implement as explained before. Considering the issues on the Friday afternoon it might be an option to move the picker at OSR pick station one from the OSR to the pallet aisles after 14:15. In this way, a second picker can help completing the shipments at the pallet aisles in time and it allows Terberg to provide this worker with a complete working day of 8 hours.

7 | Conclusions & Recommendations

This chapter provides the final conclusions in Section 7.1, based on the outcomes of this simulation study. In Section 7.2. we reflect on the positives and limitations of this research. Based on the conclusions, we provide the Logistics Management of Terberg Benschop with a few recommendations in Section 7.3, suggesting how to improve the operational efficiency of the outbound process within the central warehouse.

7.1. Final Conclusions

Based on the outcomes of the base model in Section 6.1, we conclude that the central warehouse in the current situation is not able to process the entire workload. The OSR currently is the bottle neck. Not because the pick process at the OSR itself is too slow but because the workload for the OSR is significantly larger than for the pallet aisles, which is presented in chapter 3. The OSR was not able to keep up with the pick assignments, which resulted in the system overflowing, as can be derived from Table 106. The table shows that 115 2Bin orders are still in the queue after 200 simulation days while two 2Bin orders per day are requested. Furthermore the high utilization at the OSR resulted in the rest of the warehouse waiting on the OSR to complete the shipments. The OSR being late was presented in Table 3 in chapter 3 and the resulting waiting time could be retrieved from the simulation base model outcome, which is presented at the bottom of the first column of Table 106.

Table 106: Overview of experiment results with current production levels

	26 vehicles per week at HVA						
	Base	**1**	**2**	**3**	**4**	**5**	**6**
% On-Time Phase	99.798%	99.977%	92.735%	99.899%	99.946%	99.977%	100%
Max Lateness Phase (hh:mm:ss)	(08:05:28)	(01:19:04)	(03:27:34)	(02:42:46)	(04:30:54)	(01:18:40)	00:38:13
% On-Time Sales	99.613%	99.544%	96.346%	99.361%	99.982%	99.927%	99.988%
Max Lateness Sales (hh:mm:ss)	(06:48:43)	(04:11:30)	(04:42:39)	(06:33:48)	(04:01:04)	(04:04:07)	(00:03:19)
% On-Time 2Bin	2.66%	100%	100%	0.00%	96.380%	98.19%	97.739
# Still in Queu	115	0	0	165	0	0	0
% Full Occupation Consolidation	26%	17%	22%	30%	13%	17%	4%
% Waiting time	19.34%	15.23%	19.81%	23.39%	10.44%	11.84%	2.31%

In the first experiment, the negative effect of the large utilization was tried to be limited by increasing the operational capacity by making the end of the working day dependent of the assignments still in queue with a deadline on the active day. This had a direct positive effect on the 2Bin orders, since the deadline for completion of the 2Bin orders is at the end of the requested day. Because the extension of working days allowed the system to complete more shipments on one day, less work was taken to the next day, having a positive effect on the shipment pick performance due to lower peak demand. The simulation showed that allowing the system to have a variable end of the working day, results in overtime for the pallet aisles in over 50% of the days and for the OSR in over 75% of the days. For most pallet aisles, the variable end of the working day also resulted in a later start the next morning, and therefore shifting the entire working day. Although the 2Bin performance improved, the variable end of the working day did not improve the efficiency of the pick process. The system was still showing a large waiting time percentage due to a fully occupied consolidation area as shown in Table 106. The option of extending the working days is not considered to be a durable option.

The second experiment showed that the addition of switching priority to the variable working day did not solve the problem but only shifts the problem from 2Bin orders to Phase and Sales shipments. Table 106 shows that the 2Bin orders are picked 100% in-time while the pick performance for Phase shipments dropped to 92.7%. Switched sorting does not improve the pick efficiency only the order in which the shipments are picked. The 2Bin orders are now started early during the day, pushing forward the Sales and Phase shipments. The overall performance worsened by including the switched priority intervention. Therefore we conclude that it is best not to change the priority rules in the way that we have tested in Experiment 2.

The relocation of SKUs in experiment 3 did improve the workload division and pick efficiency at the pallet aisle. However, the positive effect is limited since this intervention does not influence the utilization or pick process of the OSR. The pallet aisle still needs to wait on the OSR to finish its share. Table 106 shows that for experiment 3 the waiting time at the pallet aisles increased as a result of more efficient picking at the pallet aisles while still waiting on the OSR.

Based on the first three experiments, we conclude that the utilization of the OSR in the current situation is too high. Experiment 4 was designed to test the system with a reduced workload for the OSR by outsourcing the 2Bin. The outcomes of experiment 4 show that the reduction of workload at the OSR by outsourcing 80% of the 2Bin orders is effective. Both the On-Time and the maximum lateness score of the Phase and Sales shipments improved compared to the base model, the waiting time on the OSR decreased and the OSR is not overflowing anymore. 96.4% of the 2Bin orders are now picked in-time. The addition of picking Malaysia shipments on Friday afternoons, as tested in experiment 5, could potentially improve the efficiency for Phase orders during the week. However, the operational capacity at the Friday afternoon is not sufficient for the extra workload resulting in lateness for Sales and Malaysia orders at the pallet aisles specifically.

The most surprising outcome of the simulation study was the significant performance improvement after separating the outbound flow of the OSR and the pallet aisles. For the first time, the On-Time score of the Phase shipments was 100% and a maximum lateness of just 3 minutes for Sales shipments. The separation of both outbound flows strongly reduces the pressure on the consolidation areas because the time to complete a shipment was reduced by more than 50%. The implementation of this intervention requires development in the warehouse management system of which we should evaluate the possibilities.

Table 107: Overview of experiment results with increased production levels

	40 vehicles per week at HVA			
	7	8	9	10
% On-Time Phase	98.298%	100%	99.994%	100%
Max Lateness Phase (hh:mm:ss)	(08:08:21)	00:03:27	(00:03:51)	01:59:26
% On-Time Sales	97.640%	99.360%	99.977%	99.965%
Max Lateness Sales (hh:mm:ss)	(04:03:25)	(01:17:18)	(00:09:50)	(00:14:34)
% On-Time 2Bin	10%	34.00%	98.643%	99.095%
# Still in Queu	1	2	0	0
% Full Occupation Consolidation	10%	4%	4%	2%
% Waiting time	9.30%	3.37%	2.91%	2.36%

After observing the results of the interventions on the system with the current production numbers, experiments were done with increased production numbers at the HVA. This increase in production numbers immediately showed that the decrease in workload at the OSR by outsourcing 2Bin is not sufficient for the system with increased production number (experiment 7). Table 107 shows that for experiment 7 the 2Bin On-Time performance dropped to 10% and the Sales and Phase On-Time score dropped to 97.6% and 98.3% respectively, which is lower than the base model performance without any intervention. The max lateness scores increased to numbers similar to the base model. So, for higher production demand the outsourcing of 2Bin is not sufficient anymore.

Experiment 8 again shows the positive effect of separating the outbound flow from the OSR and the pallet aisles. Even with the increased demand, the On-Time score for Phase shipments is 100%. The Waiting time at the pallet aisles on consolidation is also limited to just 3.37% of the time. However the Sales and 2Bin at the OSR performance are not sufficient. Section 6.9.2 explained that the late Sales order are mainly OSR orders on Friday. This result together with the 2Bin performance at the OSR show that especially the OSR has difficulty keeping up with the workload, causing work in the queue to be pushed to the Friday afternoon were the limited operational capacity results in lateness.

Experiment 9 was designed with a focus on the capacity issues at the OSR. By adding 1.5 hours to the working day at the OSR, the Sales and 2Bin performance improved to acceptable numbers again. The maximum lateness for Sales is less than ten minutes and only 3 2Bin orders are not picked completely by the end of the day. This outcome shows that by increasing the operational capacity at the OSR with 18%-20%, the system is able to keep up. If 100% of the work can be completed in 120% of the time, than 83% of the work can be completed in 100% of the time. This means that either the capacity at the OSR should be increased with 20% or the workload for the OSR should be decreased by 17%.

The last experiment showed us that the effect of relocating the SKUs over the pallet aisles based on simulated annealing is larger for a system with higher production numbers at the HVA. The combination of relocating the SKUs within the pallet aisles and the separated outbound flows for the OSR and the pallet aisles, did result in a significant improvement of the phase pick shipments at the pallet aisles because it is not dependent on the OSR anymore. The On-Time score is 100% and the minimal time left is almost two hours. So, experiment 10 shows the potential of relocating the SKUs over pick areas by using simulated annealing based on the future production schedule. The Malaysia orders on Friday afternoon give the same results as for experiment 5. This intervention could be useful if the operational capacity at the pallet aisles is slightly increased on Friday afternoons.

The outcomes of experiment 9 and 10 show promising results for the intended production increase at Terberg Benschop and show that, although in the current situation the warehouse has reached its maximum capacity, the warehouse has the potential to increase its outbound levels by implementing interventions that decrease the workload at the OSR, increase the operational capacity at the OSR or improves the operational efficiency. Especially the latter interventions category has shown to be effective, OSR separation from consolidation and SKU relocation, but are also most interesting because they do not require capacity expansion or outsourcing.

The experiments have shown that anticipating to the dependencies within different areas of the warehouse and an equal distribution of workload over the different areas, are important factors to increase the outbound efficiency of the warehouse as a whole.

7.2. Discussion

In this research we have shown that by using discrete event simulation we were able to provide a strong representation of the Central warehouse at Terberg Benschop. This allowed us not only to evaluate the system using the current KPI's, but provided additional system data which is not available in the historic data. By creating a performance indicator with measure in time units, we were able to compare the performance of multiple pick areas with different characteristics. With the simulation model and the additional data we were able to evaluate the central warehouse as a whole and the dependencies between the different areas. Furthermore, the simulation helped us evaluate the robustness of the operational capacity of the central warehouse with increased production numbers by running multiple experiments.

However, there are some limitations to the simulation model and the use of simulation in general. The simulation model is not an exact representation of the real warehouse but an approximation of the system as is explained in Section 4.2. Therefore, the outcomes of the different simulation experiments should be considered as indications of potential performance changes rather than exact outcomes. The outcomes of experiments should always be evaluated as relative results from a starting solution. Therefore, we first modelled and validated the base model and compared the outcomes of each experiment with the base model or a preceding experiment, rather than the historic data set.

Besides the limitations of the simulation model that are listed in Section 4.3.2, this research itself has some limitations. We have focussed solely on the outbound movements within the warehouse and within that scope mainly analysed the pick and consolidation activities of the phase and Sales shipments. Little to no attention was given to the inbound flow, packing of Sales orders and the distribution of shipments from the warehouse to the assembly halls, while all these elements are an import part of the supply process. Furthermore, the increase of production levels at the assembly was translated into an increase in shipments and utilization for the pickers. Due to a lack of SKU volume data and items per pallet, we were not able to anticipate on a potential increase of on hand inventory and evaluate the utilization of the physical capacity.

Lastly, this research lacks the evaluation of cost factors. Although the explored implementations probably will not require massive investments, it would also have been interesting to evaluate the process improvements in revenue benefits rather than just throughput and pick performance figures.

This research however, showed some initial directions to improve the outbound efficiency of the central warehouse and ruled out some interventions that turned out not to be successful. The outcome of this research shows the Logistics Management of Terberg Benschop a short list of possible operational changes that could each be explored in more detail if desired.

7.3. Recommendations & Future work

In this last section we provide Terberg Benschop the most important recommendations to improve the outbound performance of the central warehouse. These recommendations are based on the conclusions of this research. First we formulate three recommendations that are strictly necessary to implement for Terberg Benschop to reach their production goals. Furthermore, we provide Terberg with a few other potential performance improvements and suggest topics for future research.

7.3.1. Recommendations for immediate implementation

- **Outsourcing 2Bin:** The outcomes of the performance analyses and the experiments within the simulation model clearly show that the utilization of the OSR is too high. It should either be decreased by outsourcing two Bin, or by reallocating SKUs at the OSR over the pallet aisles. The option of outsourcing two bin is known to be possible, since Terberg is familiar with suppliers offering this service. Moving SKUs to the pallet aisles is probably less useful since the characteristics of the SKUs were the reason to place them in the OSR in the first place. Therefore the first recommendation for Terberg Benschop is to start exploring the options of outsourcing two bin supply.
- **Separating the outbound flow of the OSR and the pallet aisles**: Separating the OSR from the pallet aisles eliminates the wait on the OSR at consolidation, reducing the load at the consolidation areas and improving the outbound flow efficiency. This system change showed surprisingly strong results and therefore we recommend Terberg to implement this change. Although it requires a development change in the WMS system, this is a one-off implementation that does not require large investments or third party efforts.
- **Increase capacity at the OSR by extending the working hours with 1.5 hours:** In the experiments with the increased production numbers, in combination with the above mentioned changes, it became clear that the system was able to complete Sales and Phase shipments in time. However, due to the current priority rules, the Two Bin orders are falling behind. The simulation showed that after outsourcing 80% of the Two Bin SKUs, the OSR still requires around 1.5 extra working hours each day to complete all the Two bin orders before the end of the day. We recommend Terberg Benschop to explore ways to extend the working ours only at the OSR with 1.5 hours, to make sure the central warehouse is able to keep up with increasing production numbers.

7.3.2. Future work

- **SKU re-allocation:** Relocating the SKUs over the different storage areas using a slotting heuristic like simulating annealing has shown to potentially improve the pick efficiency of the order consolidation system. However, in this research we assumed that each SKU within aisle 32 until 37 could be freely moved, ignoring possible storage restrictions like special shelving or distance between rack beams. Furthermore, some SKUs that are used in assembly are sold as spare parts as well. Therefore it is not possible to make the hard distinction between spare parts SKUs and production SKUs as we did. Including the spare parts in the slotting approach, could be interesting as well to see if the strategy of storing most of these SKUs in aisle 31 is indeed a good approach.

When Terberg decides to re-allocate the SKUs over the areas, it is important to maintain these allocations. Meaning that Terberg should then also consider to implement system directed inbound instead of allowing the pickers to freely store the goods within the pallet aisles.

So, this research showed that re-allocating the SKUs over the different storage aisle is a potential performance improver for Terberg Benschop, but it requires further research.

- **SKU location optimization within the pallet aisles:** Not just the allocation of SKUs over the different storage areas could be analysed, also the locations of the SKUs within the pallet aisle could be optimized. This however was not critical at the start of this research since the OSR, and not the pallet aisles, was identified as the area causing delays.
- **Malaysia orders to Friday:** Pushing the Malaysia orders to the Friday afternoon, reduces the disturbance of these order type on the pick process for the local production orders. However, we have seen that moving these order to Friday results in a large workload on Friday afternoon. We do recommend Terberg to further evaluate this option and suggest to leave the second pick station at the OSR manned until 14:30 and move the picker to the pallet aisle afterwards until 16:30.
- **Third pick station at the OSR:** Another option for future research is the addition of an extra pick station at the OSR. The throughput at the OSR is not just determined by the speed of the pickers but by the output speed of the storage system as well. It is interesting to simulate an extra pick station to see if the system is quick enough to provide all three stations with totes, and not causing idle time for the pickers because the pickers turn out to be quicker than the system can provide.
- **Batch picking:** For this research we accepted that a growth in production numbers results in an immediate increase in shipments and picking routes for the warehouse. It could be valuable for Terberg to critically evaluate the shipment picking process and review options like batch picking. Batch picking could potentially decrease the total time spent on initialization of a picking route and decrease movements within the aisles (Yu and De Koster (2008)).
- **Reducing the total number of SKUs:** Lastly, the physical storage capacity was explained to be an issue. Terberg is offering a large variety of vehicle types and additional options in specifications. These all require different parts, resulting in a huge amount of unique SKUs that all require a storage location. Less unique SKUs result in less stress on the physical capacity and makes it easier for a slotting algorithm to come to a strong solution. Therefore we advise Terberg to always monitor turnover rates of each SKU to identify dead stock and give feedback to the design and sales department about potential superfluous parts and design options.

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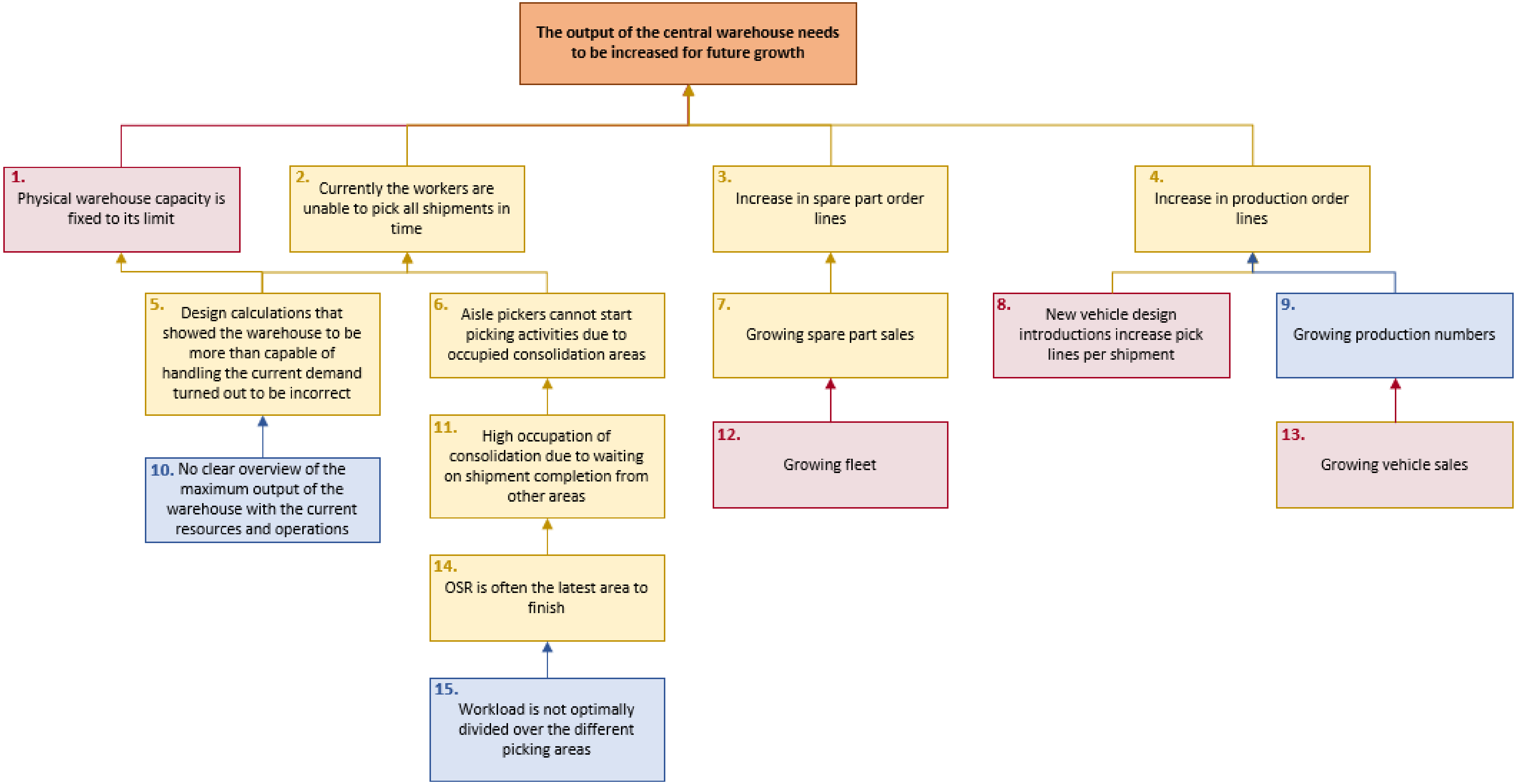
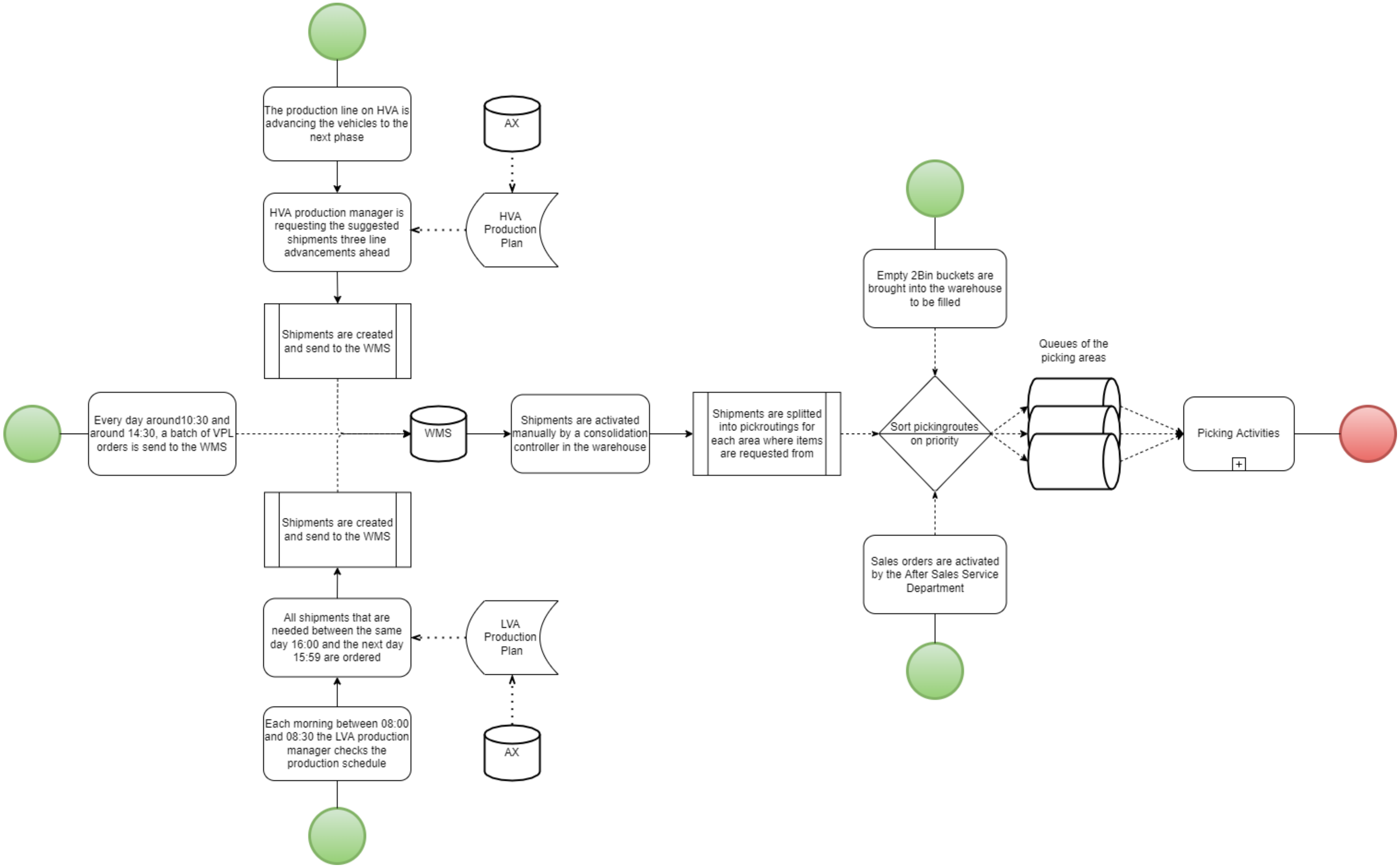
Appendices

Appendix 1: Problem cluster



Appendix 2: Process flow of the demand creation and activation of the different demand types including the IT support



Appendix 3: MILP Model

1. Problem Description

The goal of the MILP is to assign items to aisles, so that for each shipment as little aisles as possible need to be visited and the workload is equally divided over the aisles.

For this problem the items can be stored in 6 different aisles. Pickers and a crane are assigned to each aisle and only perform pick activities within this aisle. This means that if items for a shipment are stored in different aisle, they need to be consolidated after each individual picker has completed the route within his aisle. Data analysis showed that the completion time of a shipment is mostly determined by waiting for other areas to complete their route before consolidation. Therefore we want to limit the aisles per shipment, but at the same time we want to level out the workload over the aisles.

2. Partial problem formulation

Sets:

s	set of future shipments	∊ S
a	Aisles of the warehouse	∊ A {32, 33, 34, 35, 36, 37}
i	Items to divide over the aisles	∊ I
j	Indicator for absolute value variables	∊ J {1, 2, … , 11, 12}

Parameters:

$iteminshp(i,s)$	{0,1} relation between item *i* and the future shipment *s*
M	Big M equal to 1000 that is used in the constraints
S	Total number of future shipments

Variables:

$SHPtoAisle(s,a)$	{0,1} variable that reflects whether Aisle *a* needs to be visited for Shipment *s*
$ItemsPerAisle(a)$	Number of Items that is assigned to Aisle *s*
$SHPperAisle(a)$	Number of shipments that visit Aisle *a*
TotAisleSHP	Total number of aisles visited for all shipments
$ItemError$	Sum over all aisles of the deviation of items in the aisle compared to the average items per aisle
$SHPError$	Sum over all aisles of the deviation of Shipments in the aisle compared to the average shipments per aisle
T_j	absolute value parameter for Item per aisle error
G_j	absolute value parameter for shipment per aisle error

Decision Variable:

$ItemToAisle(i, a)$ {0,1} decision to assign Item *i* to Aisle *a.*

MILP goal Function:

$$\text{min:}\ \ TotAisleSHP + ItemError + SHPError$$

Subject to:

$$ItemsPerAisle(a) = \sum_i ItemToAisle(i, a)\,, \qquad \forall a$$

$$\sum_a ItemToAisle(i, a) = 1, \qquad \forall i$$

$$SHPtoAisle(s, a) * M \geq \sum_i ItemToAisle(i, a) * iteminshp(i, s)\,, \qquad \forall a, \forall s$$

$$SHPperAisle(a) = \sum_s SHPtoAisle(s, a)\,, \qquad \forall a$$

$$TotAisleSHP = \sum_a SHPperAisle(a),$$

$$T_{j=a-31} - T_{j=a-25} = ItemsPerAisle(a) - \frac{\sum_a ItemsPerAisle(a)}{6}\,, \qquad \forall a$$

$$G_{j=a-31} - G_{j=a-25} = SHPperAisle(a) - \frac{\sum_a SHPperAisle(a)}{6}\,, \qquad \forall a$$

$$SHPError = \sum_j G_j$$

$$ItemError = \sum_j T_j$$

Appendix 4: Simulated Annealing code

```
var i, j, OldLoc, NewLoc : integer
var Item : string
var Rnd : real

setInfiniteLoopDetectionTimeout(0)

while Temp >= 0.2                   //stopping criterium
    for var m := 1 to Markov        //Markov chain
        i := z_uniform(1, 1, 419)               //Draw random number to find a random SKU to relocate
        OldLoc := ItemLocaties[2, i]            //Select current location
        Item := ItemLocaties[1, i]              //select item
        if OldLoc = 37
            ItemLocaties[2, i] := 36
            NewLoc := 36                        //Select new location
        elseif OldLoc = 32
            ItemLocaties[2, i] := 33
            NewLoc := 33                        //Select new location
        else
            j := z_uniform(1, 0, 2)
            if j = 0
                ItemLocaties[2, i] := ItemLocaties[2, i] - 1
                NewLoc := ItemLocaties[2, i]    //Select new location
            else
                ItemLocaties[2, i] := ItemLocaties[2, i] + 1
                NewLoc := ItemLocaties[2, i]    //Select new location
            end
        end
        ItemSHPdataAisles[OldLoc-31, 1] := ItemSHPdataAisles[OldLoc-31, 1] - 1      //Decrease the total number of items in the old area with 1
        ItemSHPdataAisles[NewLoc-31, 1] := ItemSHPdataAisles[NewLoc-31, 1] + 1      //Increase the total number of items in new area with 1

        for var n := 1 to ItemShipment.YDim      //If the SKU is the first SKU of a certain shipment to enter the area, the shipment to area binary should become 1
            if ItemShipment[1, n] = Item
                ItemShipment[2, n] := NewLoc
                ShipmentToAisle[NewLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := ShipmentToAisle[NewLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] + 1
                ShipmentToAisle[NewLoc-25, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := 1
                ShipmentToAisle[OldLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := ShipmentToAisle[OldLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] - 1
                if ShipmentToAisle[OldLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] = 0   // If the SKU moved from the current area was the last of a certain shipment, the shipment to area should be changed to 0
                    ShipmentToAisle[OldLoc-25, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := 0
                end
               ShipmentToAisle[13, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := ShipmentToAisle.Sum({7 ,ShipmentToAisle.getRowNo(ItemShipment[3, n])}..{12, ShipmentToAisle.getRowNo(ItemShipment[3, n])})
            end
        next

        for var y := 1 to 6
            ItemSHPdataAisles[y, 2] := ShipmentToAisle.sum({y+6, 1}..{y+6, *})
        next

        // Update all variables
        ItemError := abs(ItemSHPdataAisles[1,1] - AvgItems) + abs(ItemSHPdataAisles[2,1] - AvgItems) + abs(ItemSHPdataAisles[3,1] - AvgItems) +
            abs(ItemSHPdataAisles[4,1] - AvgItems) + abs(ItemSHPdataAisles[5,1] - AvgItems) + abs(ItemSHPdataAisles[6,1] - AvgItems)
        AvgSHP := ItemSHPdataAisles.meanValue({1,2}..{*,2})
        TotSHP := ItemSHPdataAisles[1,2] + ItemSHPdataAisles[2,2] + ItemSHPdataAisles[3,2] + ItemSHPdataAisles[4,2] + ItemSHPdataAisles[5,2] + ItemSHPdataAisles[6,2]
        SHPError := abs(ItemSHPdataAisles[1,2] - AvgSHP) + abs(ItemSHPdataAisles[2,2] - AvgSHP) + abs(ItemSHPdataAisles[3,2] - AvgSHP) +
            abs(ItemSHPdataAisles[4,2] - AvgSHP) + abs(ItemSHPdataAisles[5,2] - AvgSHP) + abs(ItemSHPdataAisles[6,2] - AvgSHP)
        AvgCPS := ShipmentToAisle.meanValue({13,1}..{13,*})

        Neighbour := TotSHP + ItemError + SHPError   //Objective function
```

```
        if Neighbour < Solution         //If new outcome is better than current, accept new location
            Solution := Neighbour
            StoreSolutions
            if Neighbour < CurrentBest      //if new location is better than the best outcome so far, update best outcome.
                CurrentBest := Neighbour
                CurrBest.insertList(2,1,ItemLocaties.copy({2,1}..{2,*}))
            end
        else
            Rnd := z_uniform(1, 0, 1)           //If de outcome is not better than current situation, draw random number between 0 and 1.
            if Rnd <= pow(e,(Solution-Neighbour)/Temp)  //If random number is lower than cooling parameter, deny new outcome else accept
                Solution := Neighbour
                StoreSolutions
            else                                        //return values to current solution becaus outcome was denied.
                ItemLocaties[2, i] := OldLoc
                ItemSHPdataAisles[OldLoc-31, 1] := ItemSHPdataAisles[OldLoc-31, 1] + 1
                ItemSHPdataAisles[NewLoc-31, 1] := ItemSHPdataAisles[NewLoc-31, 1] - 1
                for var n := 1 to ItemShipment.YDim
                    if ItemShipment[1, n] = Item
                        ItemShipment[2, n] := OldLoc
                        ShipmentToAisle[OldLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := ShipmentToAisle[OldLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] + 1
                        ShipmentToAisle[OldLoc-25, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := 1
                        ShipmentToAisle[NewLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := ShipmentToAisle[NewLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] - 1
                        if ShipmentToAisle[NewLoc-31, ShipmentToAisle.getRowNo(ItemShipment[3, n])] = 0
                            ShipmentToAisle[NewLoc-25, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := 0
                        end
                        ShipmentToAisle[13, ShipmentToAisle.getRowNo(ItemShipment[3, n])] := ShipmentToAisle.Sum({7 ,ShipmentToAisle.getRowNo(ItemShipment[3, n])}..{12, ShipmentToAisle.getRowNo(ItemShipment[3, n])})
                    end
                next

                for var y := 1 to 6
                    ItemSHPdataAisles[y, 2] := ShipmentToAisle.sum({y+6, 1}..{y+6, *})
                next
            end
        end
    next
    Temp := Temp * Alpha  //update cooling parameter / cooling parameter
end
```