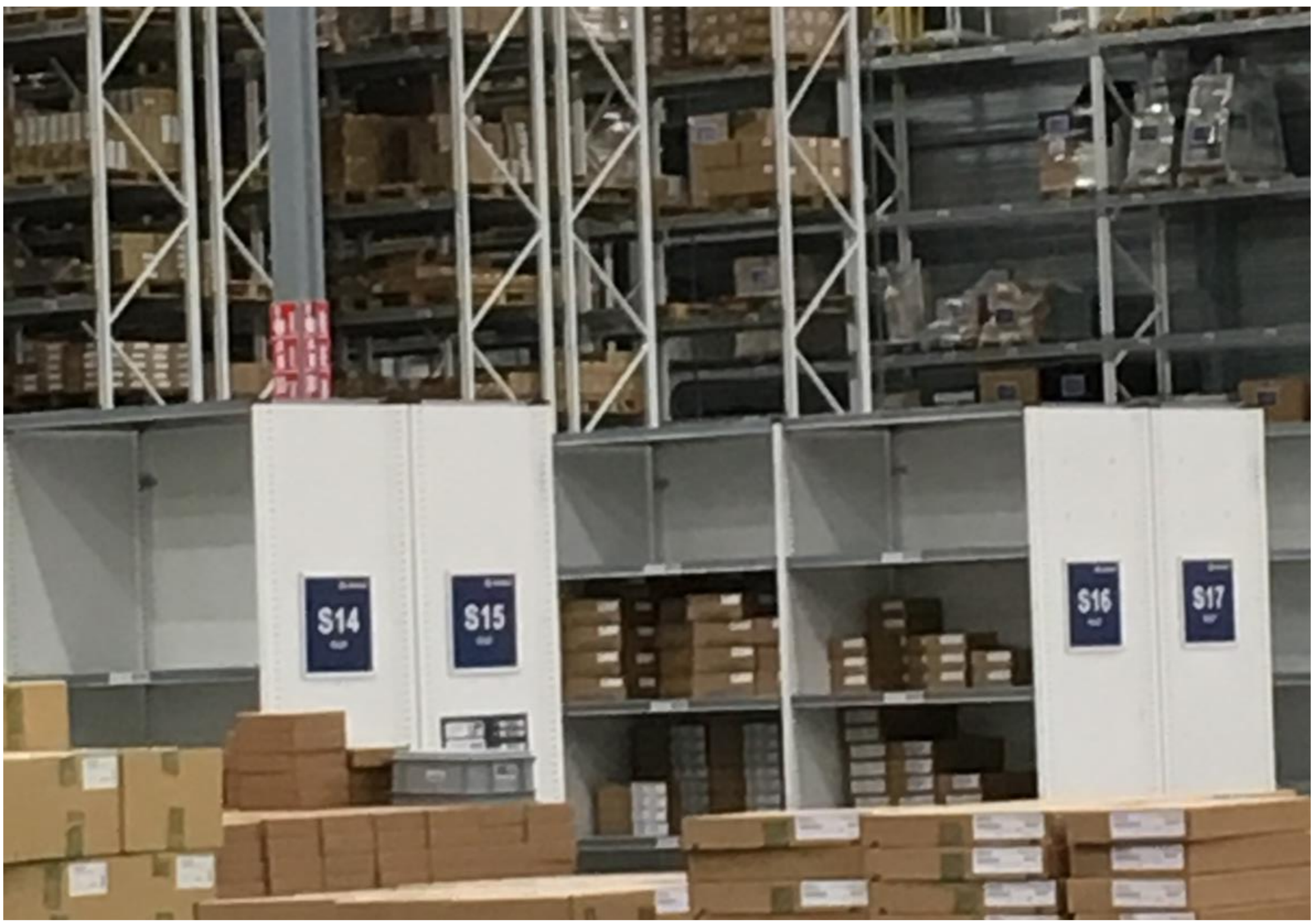
Matching workload and workforce requirements using simulation in FlexSim



DB SCHENKER

UNIVERSITY OF TWENTE.

Linda Nijland - s1383728 - M Industrial Engineering and Management – Production and Logistic Mana

DATE:

28-09-2019

AUTHOR:

Linda Nijland, BSc

SUPERVISORS:

Y.M.M.J. van den Berg (External supervisor and Logistics Engineer at DB Schenker Breda)
dr. P.C. Schuur (1st supervisor of University of Twente)
Ir. W. de Kogel - Polak (2nd supervisor of University of Twente)

Preface

With this report, I am finishing my master Industrial Engineering and Management and therewith also my life as a student. I look back on an amazing time in which I have learned a lot academically, but even more on a personal level. This would all not have been possible without the support of a few important people in my life, to whom I would like to express my gratitude.

First of all, I would like to start to thank Jeroen Velthuizen, for giving me the opportunity to conduct my research internship at DB Schenker Breda for the department of Logistics Support. I want to thank all my coworkers at the latter department for making my time at Schenker pleasant and fun. I especially want to thank Yuri van den Berg, who was my daily supervisor at Schenker but also acted as an excellent and inspiring mentor, often understanding my needs better than doing myself.

My choice for this graduation assignment led to a relocation to Breda. I want to thank my new roomies Inge, Maartje and Sophie for all the fun and support and, above all, for making me feel at home.

During this assignment, I have received valuable feedback and support from my first supervisor Peter Schuur in our monthly meetings. As much as I want to thank Peter for his academic guidance, I want to thank him for his enthusiasm, our fun conversations and his outstanding Netflix recommendations (please keep them coming!). At a later stadium, I also received feedback from my second supervisor, Wieteke de Kogel – Polak, which definitely helped me to enhance the quality of this thesis. Finally, I wish to thank both Wieteke and Peter for their great flexibility.

I want to express a special thank you to Ir. Steven Hamoen from TALUMIS B.V. for his FlexSim support and education. It is safe to say that this thesis would not have been possible in this form without his help.

Last but not least, I want to thank my family and friends. My parents, for their ongoing, unconditional love and support. My close friends, Annemiek, Auke, Bastiaan, Bob, Femke and Joanne, for their motivational talks and listening to my thesis struggles and complaints. And finally, my fellow students of “Eetclub + Darsh”, for all our collaborations and for making my time as an IEM student a lot more fun.

I look back on the last year of my studies as a challenging, yet enjoyable time. I am proud to present this thesis as the last, final and completing part of my master education. Enjoy reading!

Linda Nijland

Breda, August 2019

Management Summary

This research has been performed for DB Schenker's business unit "Contract Logistics" in Breda. Schenker's Breda location handles returned consumer electronic products. On site, phones are repaired and replacement or replenishing orders for all electronic products are shipped throughout West-Europe. Before outgoing orders can be shipped, orders need to be picked and packed according to specific rules depending on order type and destination. This is done at department DEPTG-out, where outgoing orders of working products are handled and shipped to (end)customers.

Recently, Schenker Breda's management has purchased a new simulation package called FlexSim. With this new software, management wanted to carry out an improvement project on one of its most urgent problems: structural overtime at DEPTG-out.

We started this research by creating a problem cluster that indicates what core problems lie at the root of the observed overtime. Our most important finding was that Schenker Breda experiences problems in matching the right number of personnel to the expected workload. This problem originates from:

1) An inaccurate forecast
2) A lack of insight in the relation between workload and necessary workforce

Since the opportunities for a simulation study are limited for the first problem, we chose for the second to be the topic of this research. We developed a central research question accordingly:

> *'How can simulation in FlexSim help to better match workload and resources at DEPTG-out?'*

To get a better idea of the problem, we started with analyzing the current situation. We found that the current forecast is made in units: parts or bundled products that together for a stock keeping unit (SKU). An example of a unit is a phone: though the unit "phone" comprises a phone, charger, cable, manual and ear phones; it is called a unit since the whole package can be picked at once. The number of units does not correlate with the amount of overtime that we observe. Moreover, due to batch picking and the ability to easily pack multiple units in one order, we decided to take the amount of orders as indicator for workload rather than units. We found that the workload strongly

depends on the distribution channel that orders come from and that the due dates differ amongst carriers, but for all carriers Schenker aims to maintain a 100% service level. Finally, orders arrive in batches. This induces idle time which also complicates the planning of personnel.

With the system having these characteristics, we looked into literature for solution methods for workforce scheduling problems. We found that most often mathematical programming models are used, followed by improvement heuristics and simulation. The benefits of mathematical programming models over simulation are short computation time, but using simulation it is easier to incorporate uncertainty factors.

Since we limit ourselves to simulation in FlexSim, we continued to determine the most suitable type of simulation for this problem: Discrete Event Simulation (DES). DES allows for modelling of systems that change over time and with stochastic processes. FlexSim is a DES package.

We determined the performance measures of focus to be the service level: we look for a staff configuration in which we are sure the service level can be attained. A conceptual model was constructed and approved by operational experts. Accordingly, a simulation model in FlexSim was built. We ran experiments with the model by levelling up the workforce with 2 full time employees (fte.) per weekday and found that the current workforce lacks four full time employees to perform at a 100% service level. If the workload would increase 5%, six extra ftes should be hired and we recommend to increase the workforce with 10 fte. in case of a 10% increase.

Workload Level	0	+5%	+10%
Expected Number of Weekly Orders	35669	37656	39346
Recommended Resource Level Compared to Baseline	+ 4 fte.	+ 6 fte.	+ 10 fte.

We also experimented with the shift start times of the workforce to check the benefits of order consolidation in batches. It turns out that an optimum occurs at a pick shift start at 10:30 (and pack shift start at 11:30), which induces a 3% increase in service level. The time difference is small compared to the current shift start 10:15, but the legal effort it would take to change contractually agreed shift times is high, we do not recommend Schenker to implement this recommendation.

Meanwhile, Schenker has scaled up the workforce with 5 fte. on own behalf. This action has eliminated overtime for workers and therefore, the conclusions from our research seem to be reliable. Yet, we make remarks on these outcomes since overtime occurs significantly more on Mondays and Tuesdays and Fridays (1140, 383 and 348 overtime hours in three months) than on other weekdays (183 and 108 overtime hours in three months). In our experimental design, we have levelled up the workload for all weekdays equally, which results in an overestimation of the workforce shortage. We recommend Schenker to continue experimentation with part-time employees that scale up the workforce on days where necessary.

Finally, we assessed the suitability of FlexSim as simulation package for DB Schenker Breda and conclude that for the time, the simulation package is sufficiently appropriate. Employees have no, or limited experience in conducting simulation studies and therefore they can start building simple models in FlexSim with their own method of preference (modelling or programming). The advanced graphics of FlexSim can help to convince operational management teams of the power of simulation. Yet, if the simulation skills increase in the company, we recommend Schenker to switch to another package. Other packages pay less attention to 3D graphics, but save time in running experiments, provide more flexibility and are much cheaper in terms of purchasing costs.

List of Figures

List of Tables

Table of Contents

Glossary

Concept	Description	Introduced at Page
B2C	Distribution channel, consists of orders that are shipped directly to end-customers.	24
B2B - SERVICEPROVIDER	Distribution channel, consists of orders that are shipped to Client Authorized Service Providers.	24
B2B - Telco	Distribution channel, consists of orders that are shipped to Telecom companies.	24
Central Planning	Part of the LS that determines the distribution of personnel over all operational departments.	27
CRQ	Central Research question, main question to be answered in this research.	5
Distribution Channel	Indicates from which customer segment the order stems from. Can either be B2C, SERVICEPROVIDER, Telco, STO or Retail.	23
DOE	Design of Experiments, research area that focusses on ways to carry out experiments in simulation studies.	52
DEPTB	Known Bad Boards, department that handles returned products with defects.	2
DEPTB-in	DEPTB inbound, part of DEPTB that handles defective incoming products	2
DEPTB-out	DEPTB outbound, part of DEPTB that handles shipment of defective products back to the manufacturer	2
DEPTG	Known Good Boards, department that handles spare parts and new products for replacement.	2
DEPTG-in	DEPTG inbound, part of DEPTG that handles incoming, functioning products	2
DEPTG-out	DEPTG outbound, part of DEPTG that handles shipment of outgoing, functioning products for replacement.	2
Line	An order line indicates the product ordered and its quantity. An order can exist of multiple order lines.	22
LS	Logistics Support, department at Schenker Breda carrying out improvement projects	13

OFAT	One-Factor-at-a-Time, method for running experiments, where only one factor is changes at a time keeping other input variables constant	52
Order	An order exists of at least one order line and one unit.	22
Retail	Distribution channel, consists of orders that are shipped to companies.	23
SAP	The ERP system used at Schenker Breda.	10
STO	Distribution channel, a Stock Transfer Order is requested by The client with the goal to equalize stock between distribution channels or to move stock to where it is most needed.	23
The client	The customer for which the contract logistics business unit Schenker Breda handles the logistics for. Anonymized due to confidentiality reasons.	3
Unit	A Stock Keeping Unit: a unit may comprise several parts, but are always stored at one pick location and consolidated in one box.	22
UPH	Units Per Hour, handled units per hour for a process	16

CHAPTER 1 | INTRODUCTION

In the framework of completing the Master Industrial Engineering and Management at the University of Twente, this research is performed at DB Schenker, location Breda. Schenker Breda requested to conduct an improvement project at their outbound department that will contribute to reducing overtime.

In this introductory chapter we introduce DB Schenker and its activities performed in location Breda specifically. We provide the motivation for this research after which we will dig into what is causing the overtime in chapter two, the problem analysis.

1.1 | COMPANY INTRODUCTION

Below we introduce DB Schenker and its Business Unit (BU) Breda. In this report, we will refer to BU Breda as ‘Schenker Breda’.

1.1.1 | DB SCHENKER AND BU BREDA

The general company of DB Schenker can be described as a global logistics provider, supporting industry and trade through land transport, air and ocean freight, contract logistics and supply chain management. Overall, DB Schenker employs over 72,000 employees worldwide distributed over about 2000 locations.

The Breda location of DB Schenker is part of the contract logistics branch (3PL). It offers warehousing and handling of returned products for a consumer electronics company. This company is the only Client that is serviced in Breda, and their returned products comprise notebooks, tablets, smart watches but mainly smartphones. The latter is also being repaired at the Breda site when possible. This is one of the offered value-added services of DB Schenker Breda specifically and is considered its core business. Other value added services are repackaging, relabeling and recharging of phones.

1.1.2 | DEPARTMENT DEPTG-OUT

Schenker Breda’s business takes place in two separated halls that are schematically displayed in Figure 1 . Schenker Breda distinguishes their products and activities between those involving returned *defective* items:

Known Bad Boards (DEPTB), and those involving *new* functioning items: Known Good Boards (DEPTG).

In the first hall, defective products (DEPTBs) are handled. They are received (DEPTB-in), being screened and, if possible, repaired. DB Schenker only Repaired products leave the process and are sent back to end customers and the second hand market. Products that are considered non-repairable at the Schenker Breda site are stored and shipped to the original equipment manufacturer (OEM) in China when demanded (DEPTB-out). At the OEM, more advanced repair- and recycle options are available. In the non-repairable case, the customer receives a new product for replacement.

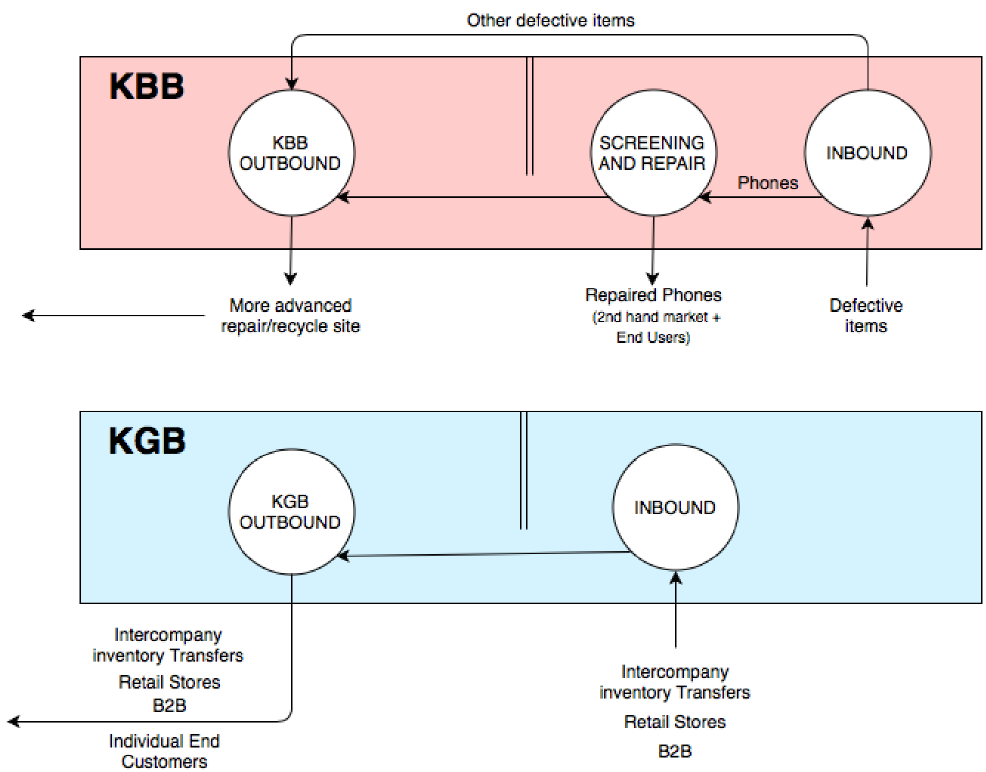


FIGURE 1 DEPTB/DEPTG PRODUCTS UNDERGO DIFFERENT PRODUCTION STEPS.

Processes related to receiving and shipping new products take place in the second hall and involve receiving of new goods (DEPTG-in), storage of new goods (DEPTG-Bulk) and picking of outgoing orders (DEPTG-out). In this thesis we will focus on the processes taking place in the DEPTG hall.

The 8-diagram in Figure 2 displays products flows. Starting at the left bottom, we find the customers: SERVICEPROVIDERs, TELCOs and End-Users. SERVICEPROVIDERs are companies that are authorized by Schenker

Breda's Client to provide service, whereas TELCOs are an abbreviation for telecom companies who function as an intermediate between The client and End-Customers. Finally, the last type of customers are the End-Users self, who can also directly contact the services of the client via the website.

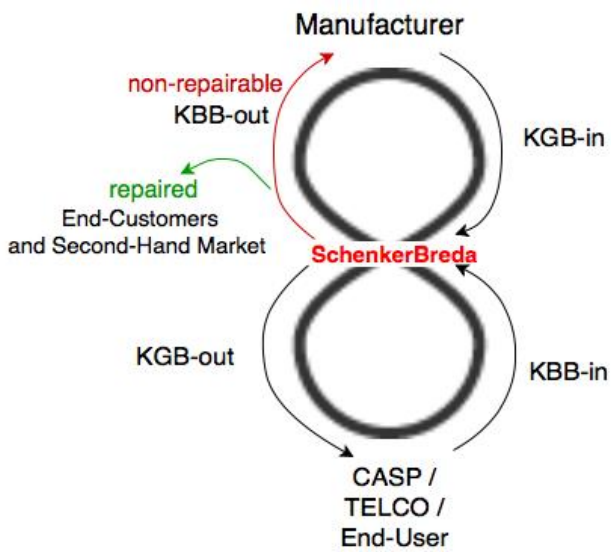


FIGURE 2 STAKEHOLDERS OF SCHENKER AND THEIR RELEVANT PROCESSES

When a defective item is sent to Schenker Breda by one of the customers, it is received by DEPTB-in and assessed whether it can be repaired or not. Most products (…%) are non-repairable and are temporarily stored at Schenker Breda (middle of diagram). Subsequently, DEPTB-out forwards the defective products to the OEM when requested (red arrow). The products that could be repaired at Schenker Breda are shipped to the second-hand market or directly to the End-Customers (green arrow). Schenker Breda needs provide a replacement for all products that are not directly returned repaired to the End-Customer. This is where the department DEPTG-in comes in: the OEM sends new, working products back to Schenker Breda which are received at DEPTG-in. At DEPTG-in, they are received and sometimes their composition is changed. After that, the new products are stored until DEPTG-out needs them to ship back to the SERVICEPROVIDER, TELCO or End User.

1.2 | MOTIVATION FOR RESEARCH

Recently, the department Logistics Support (LS) at Schenker Breda purchased a simulation software package called 'FlexSim'. Schenker Breda wishes to examine how simulation in FlexSim can help to improve efficiency at DEPTG-out.

Currently, the workers at DEPTG-out are struggling to finish their work in time. Management has noticed that the employees at DEPTG-out need to work in overtime quite regularly to finish all orders in time. The situation is considered to be undesirable, since working in overtime has a negative impact on their employee satisfaction and motivation. Moreover, work in overtime has to be paid at a 130% rate of the regular salary. Schenker Breda indicates that it has been hard to find new (temporary) workers willing to support.

For this reason, Schenker Breda wishes to gain insight in how much resources are necessary given an expected workload at DEPTG-out. Since the requirement of management is to use simulation in this study, the research will be carried out by a simulation study in FlexSim.

1.3 | Conclusion

In this chapter we have introduced the company DB Schenker and its location Schenker Breda and gave information on the department of focus for this research: DEPTG-out. We found that DEPTG-out struggles with its low capacity: employees at the department often have to work in overtime. Management wishes to study how it can determine the capacity requirements based on the available forecast. So, the question that rises is: How should capacity match workload requirements? As requested by management, the study will be carried out by modelling the operations at DEPTG-out in FlexSim. In the following section, we will describe the research questions we set up to carry out this study.

Chapter 2 | Research Design

In the previous chapter, we have briefly introduced the problem to be researched and introduced the demanded solution method: simulation in FlexSim. This section, we start with introducing our research goal (2.1). Next, we introduce a central research question (CRQ) that will be answered in this thesis. Following from this central question, we developed sub- research questions in correspondence to the question to be answered in the CRQ. For each of these sub-questions, we provide a plan of approach on how we are going to answer them (2.2). When all questions are described, we continue by delimiting the research such that it fits into our scope (2.3) and finalize the chapter with a description of the deliverables (2.4) that this research is going to provide.

2.1 | Research Goal

Our research goal is to gain insight on what resource requirements apply to DEPTG-out to run operations without workers having to work in overtime. The method should take the stochastic external weekly demand and irregular demand between weekdays into account.

2.2 | Research Questions and Approach

Now that we have determined our research goal we will present the corresponding research questions in this chapter. In order to state a clear main research question we used the SMART method. Our target area for improvement (Specific) is operational planning and resource management at DEPTG-out, which must be improved such that no overtime occurs and the Service Level Agreement (SLA) of 100% is attained (Measurable). We allow a violation of the latter constraints in 5% of the cases to keep our goal Realistic. The project remains Achievable by focusing on planning and workforce allocation only at DEPTG-out and its core activities (picking and packing). The project must be finished within six months (Time-bound), the time set for a master thesis research by the University of Twente. Based on these requirements we have followed the following main research question:

> *'How can simulation in FlexSim help to better match workload and resource requirements at DEPTG-out?'*

Related to this main research question we have defined a number of sub-questions that will help us to approach and answer the main research question in a structural way. Each sub-question corresponds to a chapter in this thesis.

1. *What problems lay at the root of the occurrence of overtime? (Ch. 3)*
   Schenker has observed an unwanted mismatch between workload and capacity, resulting in overtime. In this chapter, we analyze what problems lay at the root of the observed overtime and what factors have an influence on its magnitude. We also examine of there are other ways, e.g. efficiency improvements that could reduce the problem of overtime as well.
   Sub-questions answered in this chapter are:
   a. *What factors play a role in the mismatch of workload and capacity?*
   b. *What are possible solutions for reducing overtime?*

2. *What does the current situation look like? (Ch. 4)*
   In Chapter 4 we analyze and map the current process at DEPTG-out. We describe the current supporting management activities and analyze the order arrival process and its impact on workforce productivity. Furthermore, we assess the quality of current practices by calculating KPIs such as forecast errors, idle time and productivity. Sub-questions answered in this chapter are:
   a. *What does the current planning process look like?*
   b. *How is resource planning and workforce allocation managed?*
   c. *How is resource planning linked to the forecast?*
   d. *How do orders arrive?*
   e. *What is the influence of the order arrival process on KPIs?*
   The information presented in this chapter is gathered by conducting interviews and data analysis.

3. *What methods are suggested in literature to improve workforce planning and allocation? (Ch. 5)*
   In this chapter we present our findings of the literature review. The literature review focusses on simulation as a solution method for workforce scheduling problems and compares this to other solution methods described in scientific literature.

4. *How can DEPTG-out apply simulation to better match workload and capacity to reduce overtime? (Ch. 6)*
   In this chapter we provide a solution design: what should be the scope of the simulation and to what are important modelling requirements. We argue why we think the designed solution is suitable for Schenker Breda. Sub-questions related to this chapter are:
   a. *What should be the scope of the simulation study?*
   b. *What variables are important?*

   With these questions answered, we construct a conceptual and simulation model in the next chapter *(Ch. 7)*. Before we start experimenting with this model, we verify the model and check its validity. In chapter seven we discuss the sub questions:

   c. *Is the conceptual model correctly transformed into a simulation model?*
   d. *Is the final model valid?*
   e. *What are interesting experiments? How can these best be conducted?*

5. *How do proposed solution(s) perform? (Ch. 8)*
   After the validation the experiments can be carried out. We present the results of the experiments and compare them to the current situation. We discuss the results and draw conclusions.

6. *How can Schenker Breda implement the proposed solution? (Ch. 9)*
   The last chapter provides recommendations on how the solution can be implemented at Schenker.

2.3 | SCOPE

In this research we focus on the core processes happening at DEPTG-out, which basically entails the picking of orders stored in the pick-area and packing them according to the requirements of the shipping company that will transport them. We thus assume that the process is finished as soon as an order is packed. We exclude supporting processes such as receiving goods at DEPTG-in, inventory replenishments by the DEPTG-bulk team and loading the packages into the truck (docking). This entails that we limit the workforce to employees solely trained for picking, packing or both. Supporting DEPTG-out personnel such as team leaders, shift leaders and wave planners are not considered as part of the workforce.

We do take into account the internal deadlines, the cut-off times. At a cut-off time, the corresponding carrier leaves the dock, which means that all (packed) orders must be ready and loaded into the truck. The previously mentioned 100% SLA is based on these cut-off times and will be maintained in this research by preference of the logistics- and operational management.

Lastly, we will restrict ourselves to recommendations on the implementation of the outcomes of this research. The responsibility of actual implementation and training lies with Schenker Breda.

2.4 | Deliverables

Logistics Support demands simulation in FlexSim to be used as solution method. Although our literature study will explore other solution methods as well, we have agreed to a simulation study as one of the deliverables. The following requirements apply to the model:

- The delivered model should provide an advice on how much capacity is required and how resources (personnel) can best be allocated.
- The delivered model should be flexible: it should be able to adapt to a changing forecast or workload.
- The delivered report should provide a practical implementation plan and instructions on the model use.
- The simulation models must be provided in the program FlexSim
- A user manual on how to use the simulation must be provided for the employees of Schenker.

2.5 | Conclusion

In this section we provided an outline for this research. We described how the research is structured and to what questions it will provide answers to. We have provided a short description of how we have demarcated the research to fit into the given timespan, and ended the chapter by stating which deliverables will be provided by this research. In the next section, we provide an analysis of all problems that have an influence on the high amount of overtime at DEPTG-out. We make a selection of problems with high priority and examine if they are suitable for simulation.

Chapter 3 | Problem Analysis

In this chapter we present the results of our problem analysis. By conducting interviews with members of Logistics Support and operational staff of DEPTG-out, we found many factors that contribute to the overtime problem at DEPTG-out. The chapter starts off with giving a more elaborate description of the context in which the activities are performed at DEPTG-out (3.1) and provides an overview of currently occurring problems in section 3.2. The problems in this overview are described in more detail in section 3.3. We conclude the chapter with a conclusion on the most urgent problems to be solved in order to reduce overtime (3.4) and their suitability for a simulation study.

3.1 | Problem Context

The activities performed at DEPTG-out can generally be divided into picking and packing. First, the pickers collect the orders on a cart or pallet after which they bring it to the packers. At the packer station, orders are packed and sealed according to the requirements of the carrier that they will be shipped with. At the end of the day, all orders need to be handed over to their carriers for the workday to be finished. To make things more complicated, each carrier handles its own “cut-off time”: an external deadline set by the carrier at which the last struck leaves the dock. All orders that are not prepared by then are considered late and need to be handled the next day.

At 9:15, the first few employees of DEPTG-out arrive. These early birds are the “wave planners”: wave planners have the responsibility of releasing orders to the pickers. The wave planner starts his day with checking what orders are present in the ERP-system SAP. Some of these will present a warning that an order batch cannot be released yet due to insufficient inventory. The wave planner releases these orders to the DEPTG-bulk team, triggering a replenishment order. The first pickers arrive at 10:15 and start picking immediately. At 11:15, most packers start their job. The last shift starts at 12:15 and includes mostly temporary employees who also perform picking.

The availability of pick orders in SAP is not uniformly distributed over time. Orders arrive during the day, but specifically around 9:30, 11:30, 13:30, 15:30 and 17:15 when the so-called ‘order drops’ take place: the arrival of many orders in a short time interval (batch arrivals). This irregularity in order arrivals causes idle time when too many workers are present at low demand time intervals, but on the other hand provide opportunities for order consolidation.

3.2 | Choosing the Core Problem

All problems that we could retrieve from interviews were put together in the problem cluster presented in Figure 8. As can be seen, the problem overtime is presented at the far right, the initial reason of our research. Moving to the left, we find problems that are causing the successive problem.

The “Algemeen bedrijfskundige aanpak” (Heerkens, 2012) defines we should always take a problem without any successors as our core problem. Many potential core problems remain. Therefore we asked the operational management of DEPTG-out to indicate what kind of research they would be most interested in. They remarked that they struggle most with matching the appropriate number of personnel to the expected workload. We see that this is, amongst others, caused by inflexible contracts (Problem 14) and a shortage of personnel (Problem 15). With the current labor availability and legislation, these problems are hard, or impossible to solve and therefore will not be the focus of this research. We can, however, study what how the stochastic demand (Problem 1) interacts with workforce size and variable worker productivity (Problem 17). Due to the presence of stochasticity, this problem is suitable for simulation as well. So, we take the mismatch of workload and personnel as our core problem. When we have time left, we will also study the interaction of different shift starts with the service level (Problem 16).

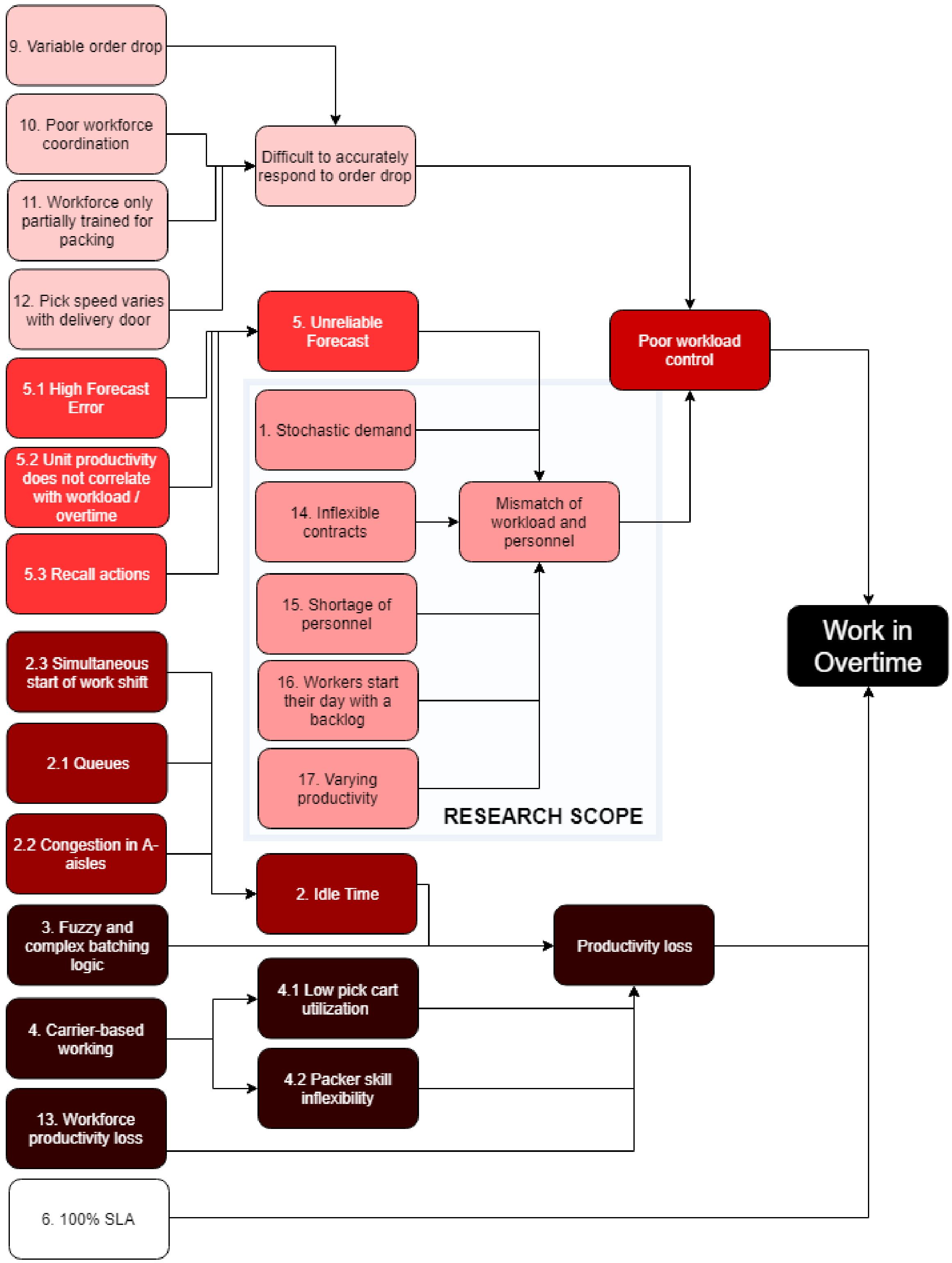


Figure 3 Problem Cluster

3.3 | Interview Results

To get an overview of the problems at DEPTG-out, we have conducted interviews with members of the Logistics Support (LS) team, the operational management and employees of DEPTG-out. We also interviewed the supporting employees from SAP Support, who provide data to the analysts at LS and construct data summaries on operational processes.

A wide variety of problems have been identified. They will serve as the input for the problem cluster presented in section 3.3, from where we will determine the most suitable problem for our simulation study.

3.3.1 | Logistics Management - Logistics Support Team and SAP Support

The Logistics Support (LS) team performs improvement projects for operations at Schenker Breda. In this team, each member has its own specialization based on a topic (productivity reports, IT, planning), and often also a department (DEPTB or DEPTG) on his/her responsibility. In the SAP Support Team we find, as the name may reveal, the SAP Experts of Schenker Breda. They have knowledge of the implemented logic in the SAP system, DB Schenker's ERP system. Since LS has knowledge about various topics, it is a good start for our problem analysis. The following problems were identified by conducting interviews:

1. Highly varying workload over weekdays

Analysts at LS argue that the workload varies over the weekdays. On Mondays, the workload is always significantly higher than on other weekdays.

2. Idle time

Batch arrivals of orders induce an erratic arrival pattern of orders during the day. Due to this unlevelled workload, it is expected that workers have high rates of idle time. This concerns a suspicion of LS and is not (yet) a proven, quantified problem. We performed a data analysis in order to estimate how big the problem of idle time really is, which is shown in the next section (4.3). However, when carefully observing the warehouse operations we were able to retrieve the following sub problems that contribute to idle time:

> **2.1 Queues at the wave planning station and activity check-in desk**
>
> Wave planners hand out the order batches to the pickers. It occurs quite frequently that there are lines at the wave planner desk where

pickers wait to receive orders. The same holds for the activity check-in desk, where pickers have to check-in at the start of each shift and after each break to track the time they have spent working.

2.2 Congestion of pickers at A-item aisles
Product locations in the warehouse have been determined according to the ABC-logic. The aisles where A-products are stored are wider than those for B- and C- products. However we still observe congestion in the A-aisles specifically. Pickers are then not able to easily overtake each other on their pick routs.

We saw that both observed problems to relate to the fact that large groups of pickers start their shift at the same time: they all need orders from the wave planner, to check-in at the activity desk and are subsequently all sent to the same A-aisles. So we conclude that a third problem occurs being the root of (2.1) and (2.2):

2.3 Many pickers start simultaneously
Since all pickers have the same order of activities, the simultaneous shift start causes queues and congestion.

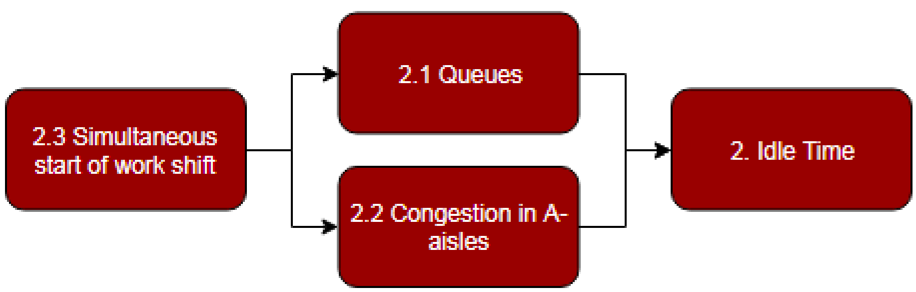


FIGURE 4 PROBLEMS RELATED TO IDLE TIME

3. Fuzzy and complex batching logic.

DEPTG-out's pickers perform batch picking: walking one route through the warehouse, they pick multiple orders. Employees that know about the SAP batching logic argue that the implemented logic was made up based on experience and common sense rather than proven methods. Moreover, at the time, it had to be constructed quickly, and so many improvements needed to be made afterwards. LS and SAP members can hardly explain the current implemented batching logic, since it uses many rules and exceptions. It is therefore considered fuzzy and LS members suspect that is likely to be a sub-optimal method, resulting in a productivity loss.

4. Carrier-based working limits flexibility.
An important element of the current batching logic is that it batches are always created based on carrier: the company that transports the goods to the designated end customer. This is an important limitation that is expected to result in a lower utilization of trolleys than desired. Furthermore, packers are often trained for only a selection of carriers.

4.1 Low trolley utilization.
An observation that is quite easy to make, is that not all trolleys are fully utilized. Trolleys with totes for batch picking, contain either 1, 4, or 20 totes. Especially the OUT 3 trolleys, which we will explain in more detail in 4.3.2 often have many empty bins in the 20 bin trolley. Because picking is always done per carrier, less opportunities for consolidation of orders arise than if we would assume all orders equal.

4.2 Packer skill inflexibility.
Packers told us that when the workload is high and cut-off time is close, they help each other out by packing from the same cart (sharing a job). But many packers are trained for only a selection of carriers. Thus, there are limited possibilities to shift resources to the highest priority carrier.

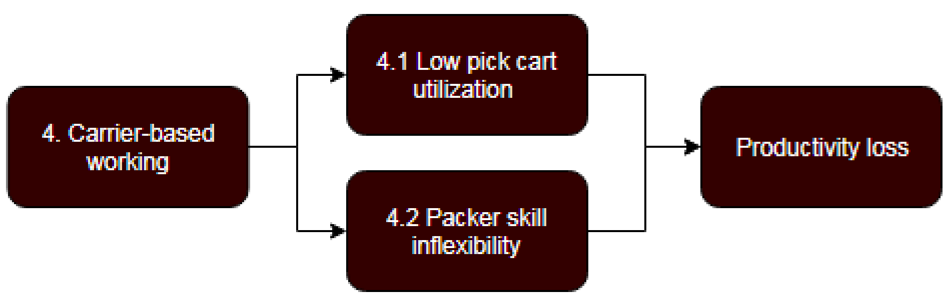


FIGURE 5 PROBLEMS RELATED TO PRODUCTIVITY LOSS

5. Unreliable forecast
Planning specialized LS members remark that they base the necessary amount of working hours on a forecast provided by the client. This way, they partially hand over responsibility of capacity planning to the client. Even

though this forecast can be rather unreliable at times. We identified three possible explanations for the unreliable forecast:

5.1 High forecast error

The forecast error is quite high. On average, the absolute forecast error is 13%. This can be both an over- or under estimation of the real demand.

5.2 It is hard to translate the forecast into resource requirements

The current forecast estimates the amount of units that will need to be handled for the upcoming week. The way Schenker currently translates this unit forecast into resource requirements is to take the total amount of expected units and to divide this by the unit productivity per hour (UPH) to get an estimation of the required man-hours.

However, as we will see in section 4.1.1, a one-to-one relation between unit productivity and required man hours is doubtful. We thus expect that the forecast can be improved to better match resource requirements.

5.3 Recall actions occasionally cause a temporary higher workload

When it turns out that (a part of) the products that have been sold to customers contain significant errors, the client can decide to withdraw these products from the market. Such withdrawals imply more work for DEPTG-out, since they need to be replaced by a working product. The impact of such a recall action is hard to forecast.

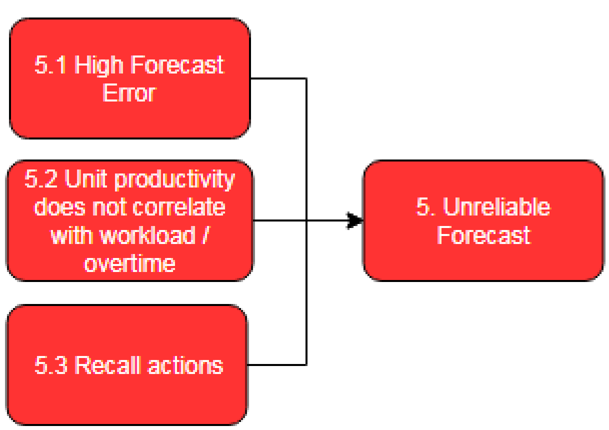


FIGURE 6 PROBLEMS RELATED TO THE FORECAST

3.3.2 | Operational Management - Department Chief, Shift Leaders and Wave Planners

The operational management of DEPTG-out consists of the department chief, shift leaders, wave planners and senior employees. Their main task is to ensure that daily operations run smoothly, therefore they were an interesting group to interview. The problems listed in this section also contain problems that followed from our own observations and interviews with operational staff members (pickers/packers).

9. Order drop induces uncertainty on workload over the day.

An important factor that complicates operations at the shop floor is the order drop (batch arrival). At the start of each day, it is always uncertain how many order drops there will be, how large they will be and when they will 'drop'.

When order drops turn out to be larger than expected, shift leaders try to respond as accurately as possible to manage this increase in workload as best as possible to reduce the chance of overtime. Yet some factors complicate the response, these are listed in point 10, 11 and 12.

10. Lack of coordination of multiple skilled workers.

When the order drop turns out to be larger than expected, shift leaders try to control the situation as good as possible by assigning multiple skilled workers to the activity with highest priority (picking/packing). They coordinate their workforce based on experience and usually reactive to the order drop. It is unclear what the best response to an order drop would be. We observed that also outside order drop moments multiple skilled workers switch activities when they run out of work at their carrier or, sometimes, when they feel like it.

11. Not all workers are trained for both picking and packing

The composition of the workforce also limits the flexibility to adequately respond to the whims of the order drop because not all employees are trained for both picking and packing. This can sometimes result in the packers being the bottleneck.

12. Pick speed is highly dependent on OUT

Orders in the order drop are grouped together according to a batching logic implemented in ERP system SAP. Our data analysis will reveal that the pick speed is highly dependent on the so called "OUT", which is all explained in

Chapter 4. Sometimes, this batching logic can be overruled by wave planners in order to work faster, but this is not always possible.

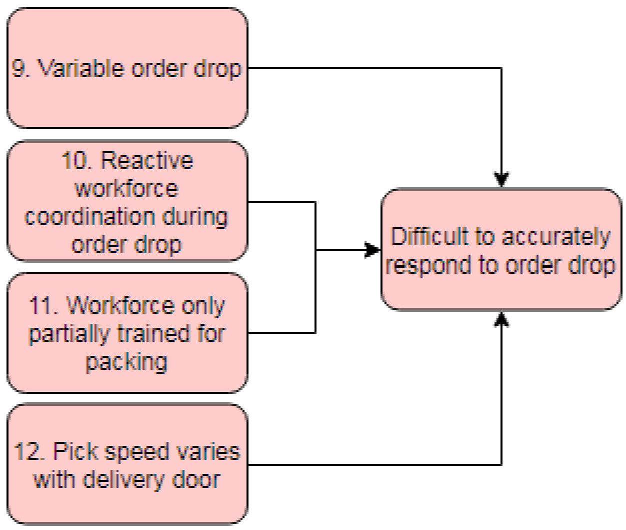


FIGURE 7 PROBLEMS RELATED TO ORDER DROP

All of these make it hard for shift leaders to accurately respond to variations in the order drop. Moreover, shift leaders stress that not all employees are as productive as Schenker Breda needs them to be:

13. Workforce productivity loss

Some employees at the DEPTG-out warehouse do not meet the desired productivity of the shift leaders. Reasons for this loss include:

13.1 Many employees have physical complaints

The department chief has indicated that many of his workers suffer from physical injuries. Though in Schenker Breda only light production work is performed, physical complaints can become a serious problem at later age.

13.1.1 Bad ergonomics

The warehouse design barely takes into account ergonomics. The work is performed standing and pickers need to stretch or bend over frequently to pick the right products. Moreover, the carts that they need to push can become rather heavy. This is likely to have a negative effect on the already vulnerable workers.

13.1.2 Previous heavy production jobs

The department chief believes that injuries find their root in previous jobs of the workers that are considered as heavy production work.

13.2 Aged workforce

Although the high average age cannot be officially confirmed with data due to confidentiality reasons, shift leaders and wave planners have indicated that the productivity of DEPTG-out's personnel is negatively affected by the high average age.

13.3 Unmotivated employees

Shift leaders and wave planners both indicate that they often miss motivation of some employees in the workforce. With new employees, they feel a disinterest in learning the job and with some long-time employees they feel unwillingness to try to finish the job as quickly as possible.

13.4 High temperature

Pickers and packers remark that often the temperature in the factory hall is high. Because they have to move a lot, this makes the work tough.

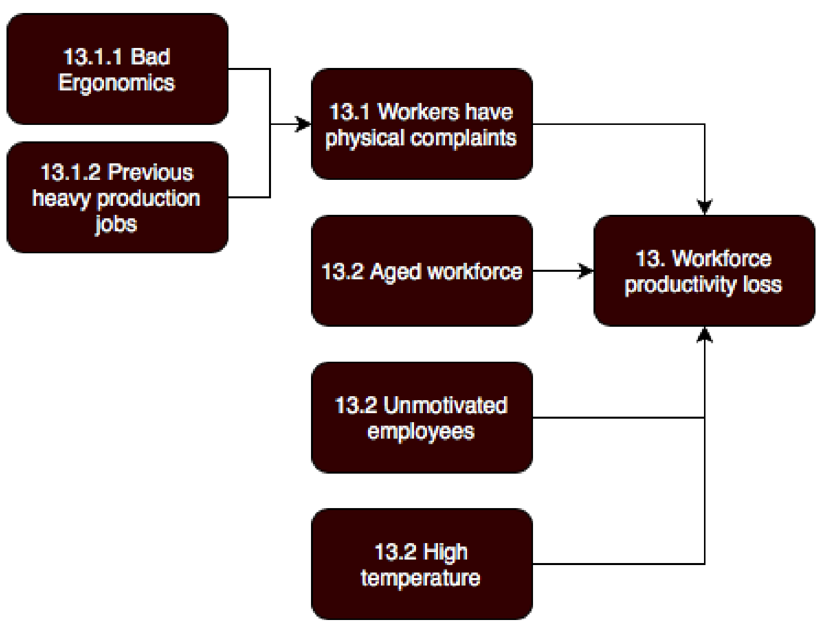


FIGURE 8 PROBLEMS RELATED TO WORKFORCE

14. Inflexible Contracts

The workforce of DEPTG-out can roughly be divided into employees with a fixed or temporary contract. In the fixed contracts the working hours of the employee are defined and thus inflexible. The majority of DEPTG-out's workforce has such a fixed contract (61%) and so the workforce is partially constrained to the agreed working hours. The other part of the workforce is flexible, they can start at any of the shifts starting at 9:15, 10:15 or 11:15.

15. Insufficient workers available.

When asking about how the operational management thinks the overtime problem can be solved, they all answer that they need more personnel, especially on Mondays. They do not believe that an efficiency improvement will solve the complete problem, though they are up for improving their work methods.

16. Workers start their day with a backlog.

It turns out that before the first pickers arrive, already around 25% of the orders have arrived. These orders are then waiting for workers to arrive to be processed. We asked LS why Schenker chose for such a late shift start. LS expects that this postponement will reduce idle time: pickers will not have to wait for orders to arrive. On the other hand, right now, the current workforce size is often not able to catch up with workload during the day and thus we conclude that the strategy of starting with a backlog is a problem.

17. Varying productivity

The amount of units that can be picked per hour (UPH) is not constant. It varies with the employee that is picking them: shift leaders suggest that productivity is highly dependent on the employment agency that the worker is coming from, but also with the trolley type, the distribution channel and order composition. Due to this variation it is hard to accurately translate a forecast into how many additional (temporary) workers are necessary.

3.4 | Conclusion

In this chapter, we explored all the problems that occur at DEPTG-out and relate to the problem of workers having to work in overtime. We found many problems of which the mismatch of personnel and workload is the most urgent one according to the operational management. The mismatch is caused by both an insufficiently accurate forecast and a lack of insight in how factors such as variable productivity and stochastic demand interact. We summarize the latter as the lack of insight in the relation between workload and necessary workforce, and choose this as the focus of our research. In the next chapter, we zoom in on the factors that complicate the matching of workforce and personnel that have been introduced in this chapter.

Chapter 4 | Current Situation

In this chapter, we will have a detailed look on the processes conducted at DEPTG-out. We start off with examining the orders that are processed at the department. Where do they come from? How are they composed and what requirements apply? We discuss these questions in section 4.1. In the following section, we describe how Schenker currently creates a forecast, from which resource requirements are deduced (4.2). Subsequently, we check how orders are released to the shop floor on their day of arrival (4.3). We will see that they not only arrive in batches, but also are processed in batches. The latter topic is discussed in section 4.4. We finish the chapter with a quantitative analysis of idle time and order wait time (WIP) to get an idea of the departments efficiency of operations.

4.1 | Order Characteristics

In this section we describe the composition of orders, their origin and what other properties are relevant for successful processing.

4.1.1 | Orders, Lines and Units

At Schenker Breda, an order can consist of multiple (order)lines that define the products in the order. The lines in turn indicate the number of units ordered of that product (see Figure 9). Orders that have only one line, ordering one unit are called “one-liners”. As we will see in section 4.3.2, this type of order is always batched into a group to enable batch picking.

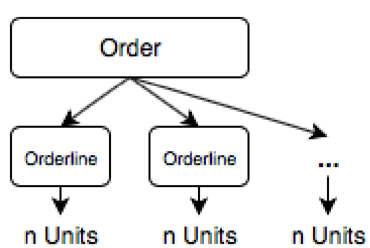


Figure 9 Order Composition

Currently, Schenker Breda measures the workload in units. We question if the unit-based workload is a valid measure to base the staff planning on. The red bars in Figure 10 display the workload in both orders and units per weekday, while the black bars represent the total amount of overtime that has occurred until now on that weekday.

We see a peak of overtime on Monday, after which it decreases on the rest of the weekdays until Friday. The amount of units shows a different pattern: here, the peak is on Wednesday, on which relatively little overtime occurs. A similar pattern (Monday peak, decrease for every next weekday) shows in the amount of orders and order lines, except for the Friday peak. On Fridays, the least orders are handled while overtime is rather high. The most likely cause for this is the smaller workforce on Fridays. Most part-time employees have their day off on Friday.

It seems that units are not the best indicator for workload. In the next sections, we find explanations for why this is the case.

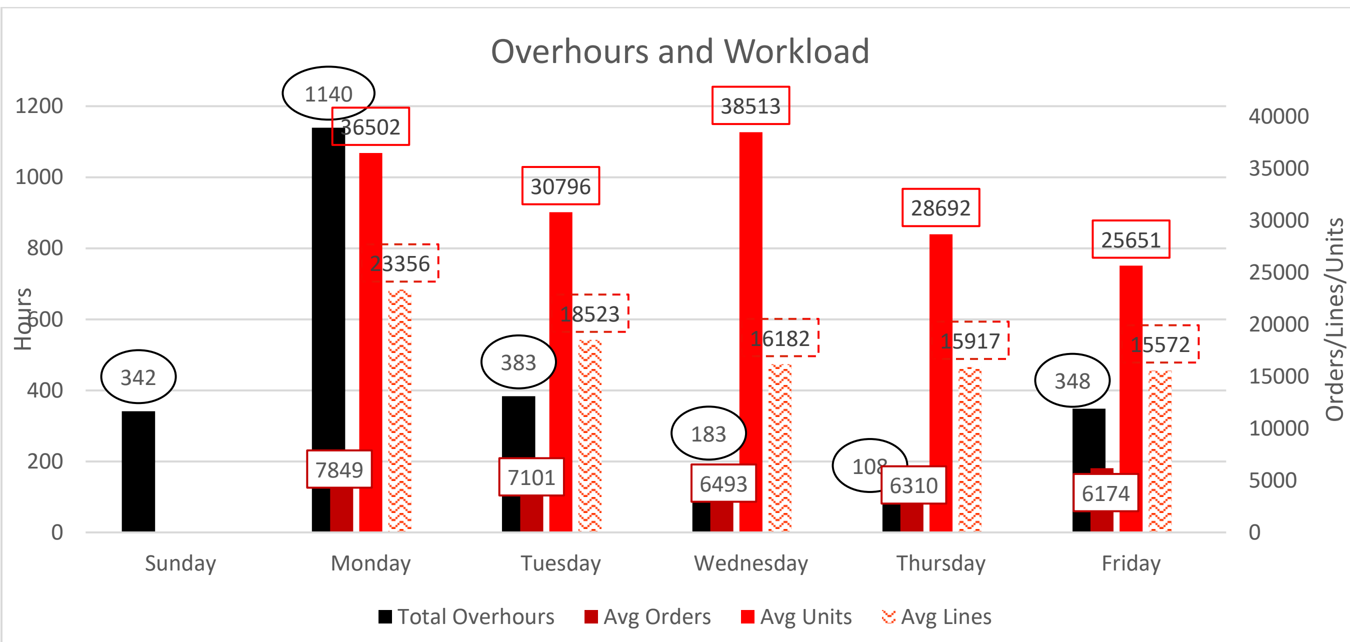


FIGURE 10 OBSERVED OVERTIME VS. WORKLOAD IN ORDERS/UNITS/LINES MEASURED OVER 3 MONTHS (JUNE, JULY, AUGUST 2018)

4.1.2 | DISTRIBUTION CHANNELS

Incoming orders at DEPTG-out can be distinguished based on 'distribution channel.' The distribution channel indicates the customer segment from which the order came from. Schenker Breda's Client differentiates between five distribution channels: SERVICEPROVIDER, TELCO, Retail, Customers and STO.

1. The Business-to-Business (B2B) distribution channel **B2B - SERVICEPROVIDER** is an abbreviation for Client Authorized Service Providers. SERVICEPROVIDERs include, as the name may reveal, companies that have permission to provide repairs and service to Schenker Breda's clients' end-customers.
2. The second B2B channel **B2B - Telco** includes telecommunications companies that, most importantly, sell the phones of Schenker Breda's client, but also take in returned products.
3. The **Retail** distribution channel groups the retail stores that are managed by The client itself.
4. The **InterCompany** distribution channel involves stock transfer orders to equalize stock between Schenker Breda and other distribution centers (intercompany). Schenker Breda does not manage the STOs itself; the client makes the STO arrangements.
5. Finally, the business channel **B2C** remains, this channel is concerned with returned products of individual end-customers.

In the rest of this report, we will refer to distribution channel as Order Type. Order types come with different characteristics. B2C orders, for instance, are pretty much always one liners. The arrival of B2C orders during the day barely fluctuates with time, whereas orders of the B2B channels are mostly released during four specific time intervals of the days in batches. The latter will be further analyzed and explained in section 4.3. The order's internal deadline is another characteristic that differs between order types. For most orders, the internal deadline (cut-off) is on the same day. InterCompany orders are an exception, it is known that their cut-off is more flexible: up to six days forward. An exact analysis of InterCompany deadlines can be found in Appendix G. Nevertheless, Schenker always processes these orders the same, or the next day. Table 1 provides an overview of the order type characteristics.

Warehouse employees indicate that the InterCompany orders, though often high in unit quantity, do not take much handling time. Usually, they can be picked with boxes and pallets at the same time. On the other hand, the pack process takes significantly more time for these orders than for others.

	B2B - SERVICEPROVIDER	B2B - Telco	Retail	InterCompany	B2C
Order Deadline	Same Day	Same Day	Same Day	Flexible	Same Day
Order Composition	Variable	Variable	Variable	Mostly single line, high unit quantity	Mostly one unit orders
Order arrival	Batch arrivals	Batch arrivals	Rather constant	Rather constant, significantly more arrivals on Tuesdays	Rather constant

TABLE 1 DISTRIBUTION CHANNELS AND THEIR ORDER TYPE CHARACTERISTICS

4.1.3 | CARRIERS

We have seen that most orders face an internal deadline on the same day that they were released. The exact time of this deadline depends on the carrier with which the order is shipped. Carriers have their own cut-off time: the deadline when the truck leaves the dock. All orders must be picked and packed and loaded into the truck by this time. Cut-off times can also vary with destination for the same carrier. A list of carriers and their cut-off times is provided in Table 2. STO orders are shipped with different carries and therefore also have different cut-off times.

	Vervoerder	Truck Lane	Cut off Time
Standaard vervoerder	UPS	COL	20:30
		EHV	19:00
		TIL	19:00
		SAB	19:00
		DOM	19:00
	TNT	EHV	19:00
		LGG	19:00
	OWN	OWNAC	18:00
	DHL	TDI	20:30
		TDIWPX	19:00
STO	SCA	SCHAIR	17:00
		SCHORE	17:00
	KNL	KNAC	21:00
	WIL	WILSON	17:00
	SCH	SCHAC	17:00

TABLE 2 CARRIERS AND THEIR CUT-OFFS

Schenker Breda has an agreement with the client that orders that have dropped at least two hours before the cut-off time need to be handled the same day. If they have been released during these two hours or after the cut-off time, their deadline is the next day at the same cut-off time.

4.2 | Forecasting and Planning

The forecast is the first step in the process of planning. The client provides a forecast to LS, of which the planning-specialized members convert the forecast to an amount of required resources in cooperation with DEPTG-out's team leader. This chapter gives details on what the forecast looks like and how it is translated to a workforce planning.

4.2.1 | Forecast Accuracy

The forecast is constructed on product level: it makes individual forecasts for the outgoing orders of product categories like Phones, MP3 Players, Tablets, Computers, Smart Watches, Earphones and Accessories in units. The final forecast is retrieved by simply adding up the individual forecasts, and thus is in units as well. Based on this final forecast, a planning is constructed.

Schenker Breda does not know exactly how the forecast is constructed: The client wishes not to disclose its methods. Figure 11 shows that over the last

36 weeks, the final forecast has on average absolute forecast error of 13% (Mean Average Deviation, MAD) from the realized order amount. Remark that since Schenker Breda's Client has started forecasting in week one, a learning effect seems to have occurred. A downward trend is clearly visible in the forecast error.

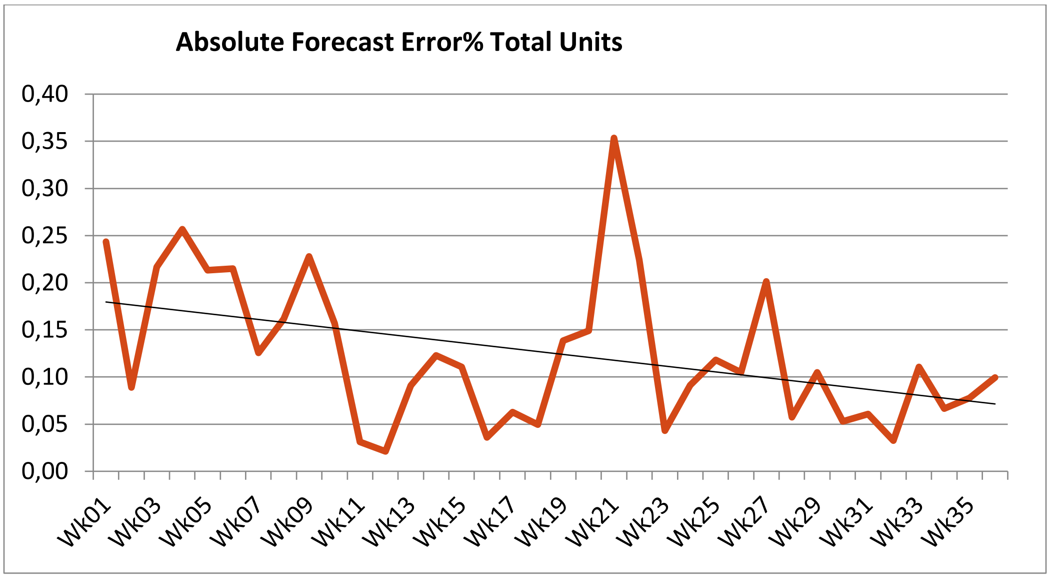


FIGURE 11 ABSOLUTE FORECAST ERROR

The forecasts on product category on average have a MAD of 12.5% to 60% from the actual ordered units. It is notable that none of the individual product category forecasts achieve an absolute error as low as the accumulated one for the final forecast. Thus, individual forecast errors are compensating one another in the total forecast.

When finished, the final forecast provides the total units that is expected to be ordered for the upcoming week. It does not distinguish between weekdays. This forecast is handed over to the Central Planning department, which is responsible for deciding how much personnel is needed and how they are allocated over the weekdays. Here, all units are considered to have an equal workload.

4.2.2 | MATCHING FORECAST WITH RESOURCE REQUIREMENTS

After Central Planning has received the final forecast for the next week, the weekly number is translated to expected daily requirements. They do this by assigning weights to each weekday based on historical data of the past 5 weeks. The weekday weight is calculated as the average fraction of the realized units on that day, compared to the total units that week. The forecast per weekday is then obtained by multiplying the ‘weekday weight’ with the new forecast.

Unfortunately, this daily forecast of required personnel is often not met. Due to the lack of personnel, it is usually not possible to adapt the planning to the provided forecast. Therefore the planning department always assigns as much man hours as possible, but usually this is not sufficient to meet the calculated daily requirement. The difference between the assigned and actual work force size is about 300 to 400 man hours per week (~ max. 10 fte.).

The planning department considers four different skills: picking, packing, packing IMC and packing STO. The requirements per skill have been calculated based on a mean value analysis. The actual allocation of the workforce over these activities is determined during the day itself by shift leaders. They assign multiple skilled personnel over activities based on their experience and the realized order drop on that day.

LS members have analyzed productivity rates for picking and the three different packing activities and concluded that the realized man hours should suffice for the weekly workload, despite the observed overtime. This has raised strong suspicions of high rates of idle time amongst workers.

4.3 | Order Release: The “Order Drop”

In this chapter we further explain the term “order drop” and zoom in on the effects order drops have on productivity and idle time. Briefly, an order drop can be described as the arrival of many orders in a short time interval (e.g. half an hour). Only orders coming from distribution channels B2B - SERVICEPROVIDER and B2B - Telco arrive in order drops, other channels tend to arrive with little variability during the day. First, we will show these properties of the order drop, after which we continue to describe how orders are batched before they are actually released to the shop floor.

4.3.1 | Order Drop

At Schenker Breda, the order drop can generally be described as the arrival of many orders in a short time interval. In literature this is called “batch arrivals”. In this thesis we use the term order drop for batch arrivals. In the

B2B channels, orders arrive mainly in drops, whereas in other channels they arrive more distributed over the day. Figure 12 displays an example of the order drop pattern of all channels during the day.

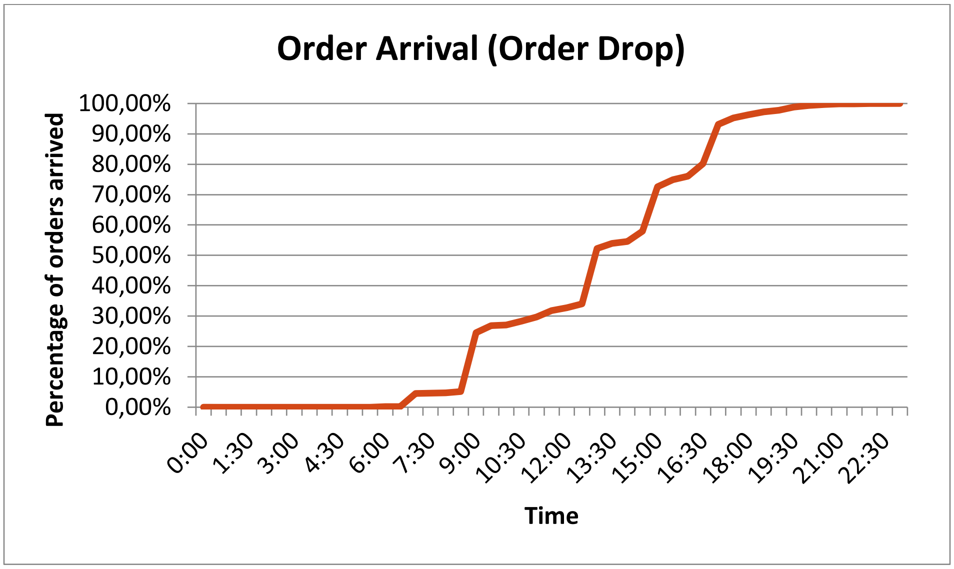


Figure 12 Example of Order Arrival Process with Drops (Batch Arrivals)

As can be seen, a large share of the total orders for that day (about 30%), has already arrived before the first pickers start their shift at 10:15. Though the order drop always happens at fixed time intervals, it complicates shop floor operations due to its unpredictability in size. When the order drop is larger than accounted for, it may result in overtime and high levels of orders waiting for processing. On the other hand, when the order drop is smaller than expected, it may result in idle time and low space utilization of trolleys.

4.3.2 | Order Batching and Release

Being part of the order drop or not, orders first arrive in the SAP system during the day. The SAP systems performs batching on the orders it contains. SAP automatically puts certain orders into the same batch based on volume and order composition.

The system distinguishes several batch options based on order volume, and maps each batch type to a so called “OUT”. There are four different OUTs (1, 2, 3 and 4), that each correspond with a type of trolley. Order batches assigned to OUT1 are usually picked with a 2-level trolley (see Figure 13) and usually carry one large order. OUT2 batches are picked on a 4-level trolley and can contain up to 4 orders. OUT3 batches are picked on a 20-bin trailer, and thus can contain up to 20 orders. At last, in OUT4 orders are batched together that comprise only one unit. Since all orders contain one unit, they do not need to be separated by levels or bins and therefore also do not have a maximum number of orders they can contain. D04 Orders are therefore usually picked on a pallet or 2-level trolley.

It is important to remark that each OUT is subject to its own delivery speed. For OUT 2 and 3 the picker needs to perform an extra handling step when picking (Figure 17). He/she has to scan the correct tote that corresponds to the right order. If the product is also needed in another order, the picker needs to repeat the process of picking the right number and scanning the right tote. The picktime per order is therefore lowest in OUT 1 and 4, and higher in OUT 2 and 3.

FIGURE 13 4 DIFFERENT TROLLEYS: D01: 2-LEVEL TROLLEY, D02: 3-LEVEL TROLLEY, D03: 20 BIN TRAILER, D04: PALLET TRUCK OR 2-LEVEL TROLLEY

Once orders have been placed into a batch, the batch can be released to a picker at the shop floor. The wave planner manually decides when and which batches are released. Batches are always formed with orders for the same carrier, and so trolleys are always filled with orders for the same carrier that have the same packing requirements.

The order drop therefore also influences the batching process: if many orders are present in SAP, it is more likely that a batch can be formed for a carrier that fills the complete trolley. The opposite holds as well: if little orders are present in SAP, the utilization of trolleys will be low. We speak of a “consolidation trade-off”: the longer the wave planner postpones the release of a batch, the higher the space utilization of trolleys, but waiting until the full cart can be filled might also result in high rates of idle time of employees.

4.3 | Order Processing

Now that we know how orders are batched and released, we will zoom in on how the orders are actually processed. As already briefly introduced, they are first picked and then brought to a packing station to be packed. In this section we will therefore first discuss the picking process, after which we continue with the packing process.

4.3.1 | Warehouse Design

In section 1.1.2 we briefly discussed the difference between DEPTG and DEPTB. Both processes take place in physically separated warehouses. We now discuss the product flows in the DEPTG Warehouse. Incoming goods are received at the DEPTG-in department. Most incoming goods are prepared for storage in the bulk area, but at DEPTG-in also some “value added services” can be conducted to the products. An example of such a value added service is the preparing of products to be a replacement products, take for instance phones. DEPTG-out receives phones that freshly come from the manufacturer ready to be sold. However, if they will be shipped to a customer to replace a broken phone under warranty, certain parts of the new phone package such as the included charger, head phones and cables should be removed. The spare phone and the parts are put in new boxes and stored under individual product code. When repackaging is done, the items accumulated with similar product codes and stored in the bulk area. In the bulk area, products wait to be replenished to the forward area at DEPTG-out, where they will be stored in cabinets for picking.

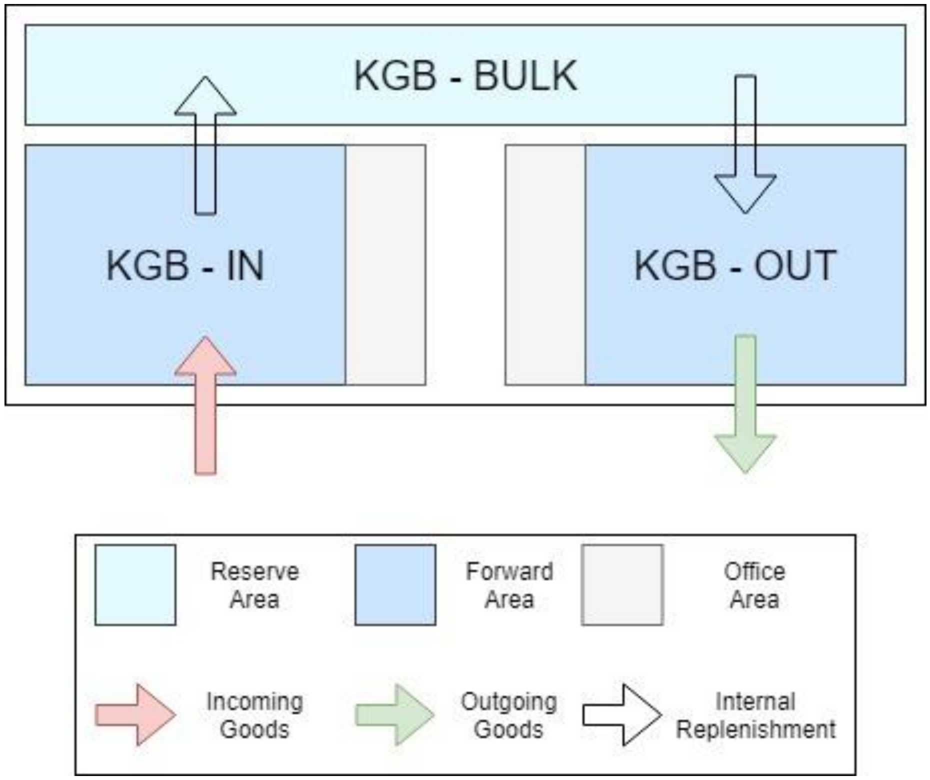


FIGURE 14 PRODUCT FLOWS IN THE DEPTG WAREHOUSE

In the layout of the picking area some design logic is applied (see Figure 16). Schenker Breda has applied ABC slotting to enable pickers to walk short distances when picking mostly fast movers. Aisles where A-items are stored have a wider aisle than aisles where B or C items are stored, because more pickers are likely to be present in this area. Furthermore the A aisles are closely located to the wave planner desk and trolley pick-up (yellow boxes in Figure 16), such that for orders only containing A-items the picker walking route is short. Behind all A-aisles, the B-aisles are located and finally, the C items are located in the back of the warehouse. B-aisles are smaller than those for C-aisles.

As can be seen in Figure 16, the reserve area of the warehouse contains two cross aisles. The pick route starts with an S-shape through all A-aisles. Subsequently, in the B- and C- aisles, the S-shape continues over the storage locations above the lower cross aisle. The route then returns in S-shape to left front of the warehouse over the storage locations below the lower cross aisle. This route has been implemented this way to enhance the chance that the picker's last pick will be close to the pack stations, where he/she will need to deliver the trolley with picked orders. In practice pickers do not have to stick with this route, it is simply to determine the sequence of the pick locations that they will see on their pick device (Figure 15). Pickers are free to take shortcuts but cannot change the order sequence. When pickers have many different items to pick, the pick device will automatically send them in this S-shape through the warehouse.

FIGURE 15 EXAMPLE OF A PICK DEVICE

4.3.2 | PICKING

The picking process starts as soon as the order is handed out by the wave planner to the picker. Figure 17 represents the flow charts for the pick processes in all outs. As mentioned earlier, in the multi-order OUTs OUT2 and OUT3, extra steps are required to maintain the distinction between orders. In OUT4, multiple orders are picked as well, but since they are all one-liners do not need to be put in separate totes.

The picker is sent through the warehouse based on the order in which products occur on the predetermined pick route. A schematic overview of the warehouse area and pick routing is displayed in Figure 14 . Walking routes are determined according to the S-shape travelling route. In practice, pickers do not have to follow a picking route or logic; they walk the route they consider fastest. Though, when they have many different items to pick, the scanner will automatically send them in this S-shape through the warehouse.

Another S-shape route over the third row of cabinets routes back to the front of the warehouse (left side in figure). Schenker Breda chose for this design because the third row is located closest to the packing stations. This way, they figured that they could reduce the distance pickers have to travel from their latest pick to the pack station.

FIGURE 16 WAREHOUSE LAY-OUT AND ROUTING

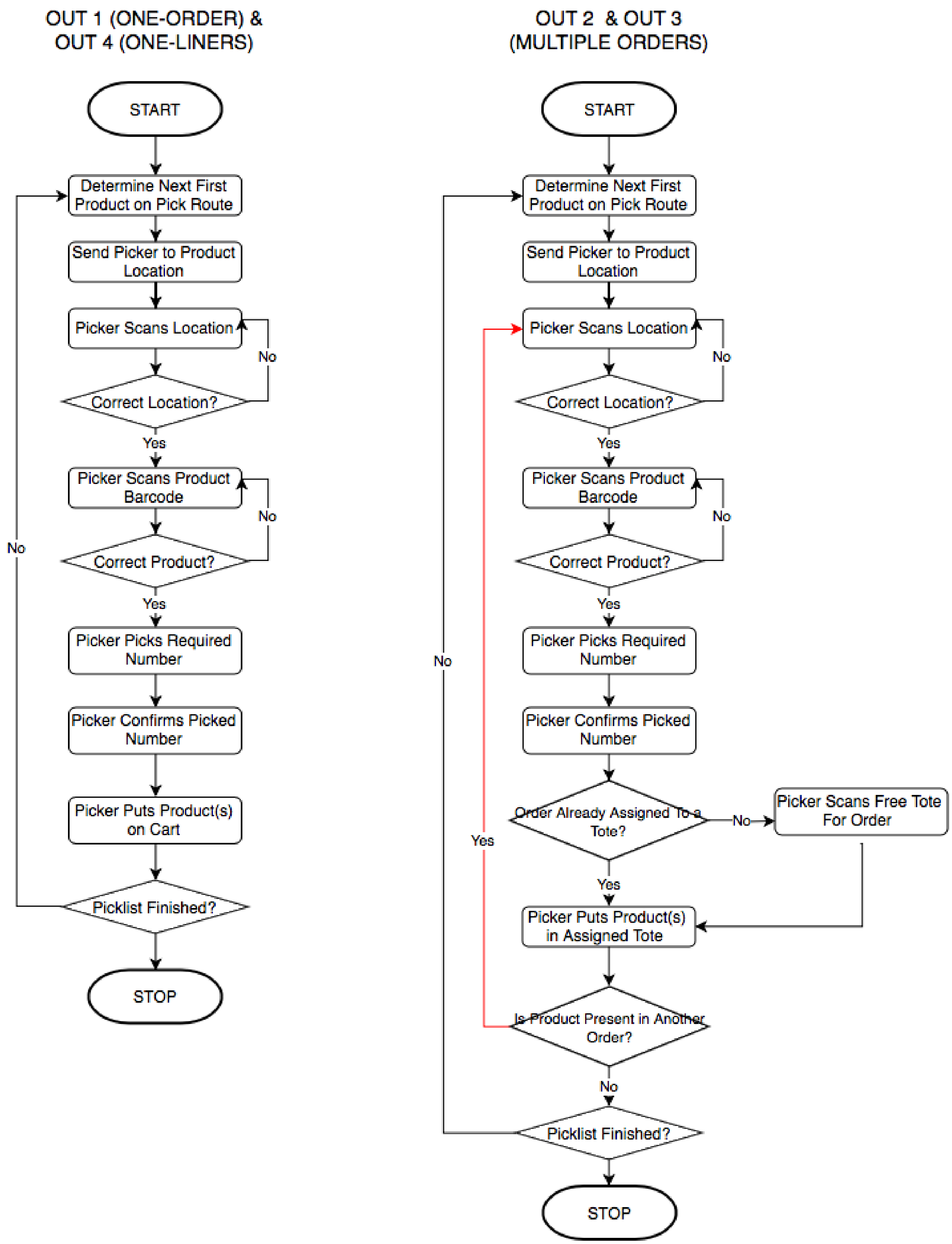


FIGURE 17 PICKER ROUTING

4.3.3 | Packing

Once the picker has finished picking an order batch, he/she brings the trolley to a packing station corresponding to the carrier the products were picked for. If the packer is idle, he/she will start packing the orders on the trolley immediately, but in most cases the trolley will have to wait for its turn. Packing stations are dedicated to a carrier and thus the amount of 'servers' is limited to the amount of packing stations and available packers that know the skill of packing for that carrier. We can distinguish three different packing "skills":

- Regular Packing
- Packing for IMC
- Packing for STO

The most important factors that distinguish these three groups are their order size and destination. As Figure 18 shows, the average number of units in an order is remarkably higher for Stock Transfer Orders (STO) orders than for regular pack orders. InterMarket Company (IMC) orders are often also larger in size, but are always shipped to NON-EU destinations that apply more strict packing requirements. We will discuss the exact details in the next paragraph.

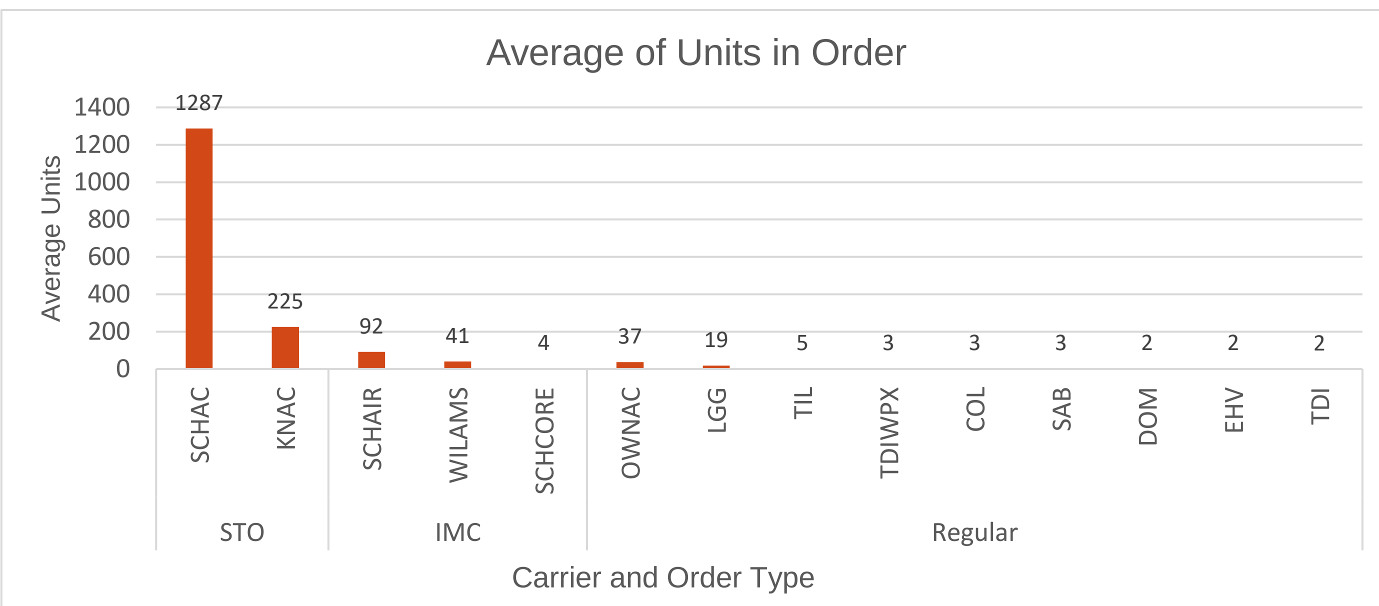


Figure 18 The Average Units per Order in STO Orders Is much Higher Than in Other Order Types

Regular Packing entails all carriers for regular shipments. Under regular shipments we understand those orders of which the shipping does not has to fulfill any special requirements. The volume of these orders does not exceed requirements for special shipments and their destinations are within European Union. A nice example of orders that are always shipped with regular carriers are end-customer replacement orders. Think of the customer that lost/broke his phone under warranty. Regular packages are thus often small and only contain a few items. Figure 19 displays an example of a regular order. Figure 20 displays a picture of a workbench for regular orders.

--- Confidential ---

Figure 19 An Example of a Package Packed for Regular Carriers

Figure 20 Packstation Regular Packing

Figure 21 Packing of Large STO Orders

--- Confidential ---

STO (Stock Transfer Orders) orders are shipped to other DCs and may also be shipped to NON-EU destinations. Yet, since it concerns an internal stock shipment (within the client's logistic network, not to customers), STO orders are always high in unit number.

IMC is an abbreviation for Inter Market Company and, as opposed to STO, can comprise shipments to any NON-EU customer destinations such as Israel, US, Australia and Singapore. IMC packing is considered more complex due to the larger variety of destinations and requirements. For both STO and IMC it holds that orders are usually large relative to regular orders. The same administrative tasks need to be executed for IMC and STO orders. Units in

STO and IMC orders need to be sealed, packed into larger cartons (Figure 21), or crates (Figure 22) These new packages may not exceed certain weight and volume requirements, and thus also need to be weighted and measured. Furthermore, products that contain batteries need to be packed separately form products that do not. Products that contain batteries must be separated further into categories "Phones and Tablets" and "Parts and Accessories". When an STO/IMC order is packed, it is forwarded to an area reserved for waiting for confirmation from the receiving party and an internal quality check.

Packing stations are grouped together based on the carrier that orders will be shipped with. This has been done because each carrier has different packing requirements and so requires specific packing materials. Therefore it logistically makes sense to group packing stations with the same supplier.

For packing, processing times differ slightly per carrier due to different requirements, but significant differences can be seen between the previously stated 3 packing destinations (Regular, IMC, STO). Packers always pack per order. When (parts of) the order are packed, they are put in a bag or on a conveyer belt that brings them to the docking area.

4.4 | Operational Problems

Previously we described how operations are run at DEPTG-out. It may have become clear that although the general process at DEPTG-out is simple (an order drops, is picked and is packed), there are exceptions and variability in order deadline, arrival process and handling speed. Moreover, each weekday is likely to require a different strategy since the composition and volume of the order drop differs per weekday. All these factors make it hard for the planning department and shift leaders to plan and control personnel. Problems such as idle time and waiting orders arise. In this chapter, we analyze and quantify the impact of these problems.

4.4.1 | Idle Time

Because orders do not come in at a constant rate, the shift leaders have to estimate the best allocation of personnel. Usually, right after an order drop, a

Figure 22 Packing and Weighting of an IMC Order

lot of personnel is allocated to picking. Orders waiting to be picked diminishes fast and shift leaders reassign personnel to packing. Sometimes it happens that personnel is allocated inefficiently and queues exist for packing, while little orders are waiting for picking. These situations result in pickers spending their time idle or working at a very low speed. In this chapter we try to gain insight in how much time the employees of DEPTG-out spend idle.

Before we present our findings, we will define how we will treat idle time in this research. We consider *idle time* as the time spend on activities that are not of value to the customer. Example: when a picker is picking orders, he is working to collect the right mix of products for the customer so we say he is *operative*, but other activities that follow from, or enable this core picking activity we will define as idle, even though they are necessary to keep operations running(!), since the customer is not willing to pay for these activities. For pickers, they include:

- Changing trolleys
- Waiting to be assigned an orderbatch
- Non-work related activities e.g. meetings, personal care etc.

For packers, idle activities entail:

- Cleaning the workstation
- Returning an empty trolley
- Non-work related activities e.g. meetings, personal care etc.

To get an idea of the current worker idle time, we took a sample of 26 workers (about 40% of the daily workforce) of whom data was available over a recent three week time span, and calculated their individual productive hours. Although this is a rather trivial measure defined by data availability, it will give us an indication on what weekdays most idle time occurs. The data consisted of the following time measurements:

- Start time of a pick order
- Finish time of a pick order
- Start time of a pack order
- Finish time of a pack order

Since workers have to sign out when they take breaks or perform other activities than picking or packing, we can safely assume that the time between these time marks was spent productive. If we divide this by the total time the worker was present on the shop floor that day, we get the individual fraction of time the worker was productive per day, from which we derive the average fraction spent idle on a day as follows:

$$Avg\ fraction\ of\ time\ spent\ idle = \frac{1}{26} \sum_{worker=1}^{26} \frac{time\ spent\ productive}{total\ time\ spent\ at\ shopfloor}$$

Equation 1 Calculation of Idle Time

We calculated the average fraction of time spent idle for 15 days, divided over 3 weeks. The results are shown in Table 3.

Observation	Monday	Tuesday	Wednesday	Thursday	Friday
1	0,18	0,21	0,23	0,22	0,17
2	0,14	0,16	0,24	0,19	0,23
3	0,16	0,15	0,21	0,19	0,2
Average	0,16	0,17	0,23	0,20	0,20

Table 3 Average Fraction of Time Spent Idle Measured over 15 Days (Week 26, 27, 28 in 2018)

According to this data, the workforce spends a significant part of the day idle, but these fractions also include time spent on necessary activities. Schenker estimates necessary activities to take large part of the calculated idle time. It is remarkable that on the days where overtime occurs most frequently (Mondays and Tuesday), on average, the lowest rates of idle time are realized. Therefore, it is more reasonable that the overtime problem at DEPTG-out is due to insufficient capacity than idle time.

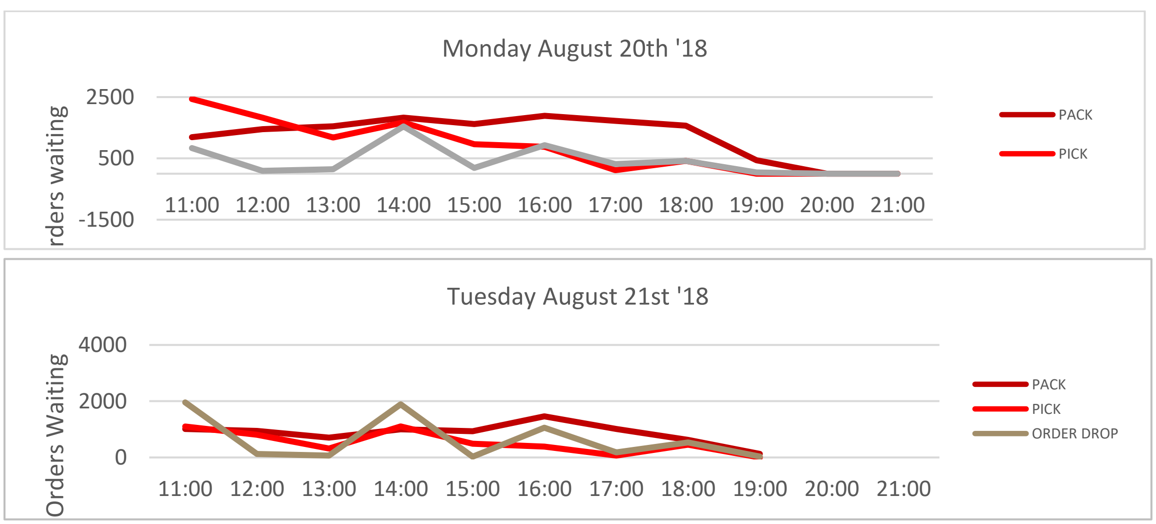
4.4.2 | Work-In-Process

Previously we have seen that on Mondays and Tuesdays worker idle time tends to be low, whereas on the other weekdays, especially Wednesdays, time spent idle is significant. Idle time is likely to be correlated to the amount of orders waiting to be processed (WIP): if there are no orders waiting to be handled, an operator is likely to be idle. In return, if there are many orders waiting to be processed operators are probably all occupied. In a similar fashion, WIP relates to the order drop. When many orders are released at once, there is a higher chance that they will have to wait to be processed. In this Chapter we will review the WIP and order drop during all five weekdays.

We distinguish ‘WIP – Picking’ and ‘WIP – Packing’, orders waiting to be picked or packed respectively. WIP – Picking are orders that remain invisible in SAP waiting to be released. Orders waiting for packing, WIP – Packing, are actual carts containing orders that wait at a pack station until a packer finishes his/her current order. Figure 23 shows plots of WIP – Picking, WIP – Packing and the order drop during the day. WIP is tracked by the wave planners on an hourly basis.

The first important observation that we can retrieve from this graph is that on Wednesday (high idle time) WIP - Packing fluctuates around zero for a large part of the day. Likewise we see that on Monday and Tuesday, where we have observed low idle time, that WIP fluctuates around a rather high level during the day.

Furthermore, we see that both WIP – Picking and WIP – Packing fluctuate with the order drop. Thus, the order drop has a significant influence on the running of operations and on idle time as well: on Wednesday and Thursday we see that WIP – Picking hits zero. The complete pick force is then either idle or finishing a job with no new one waiting.



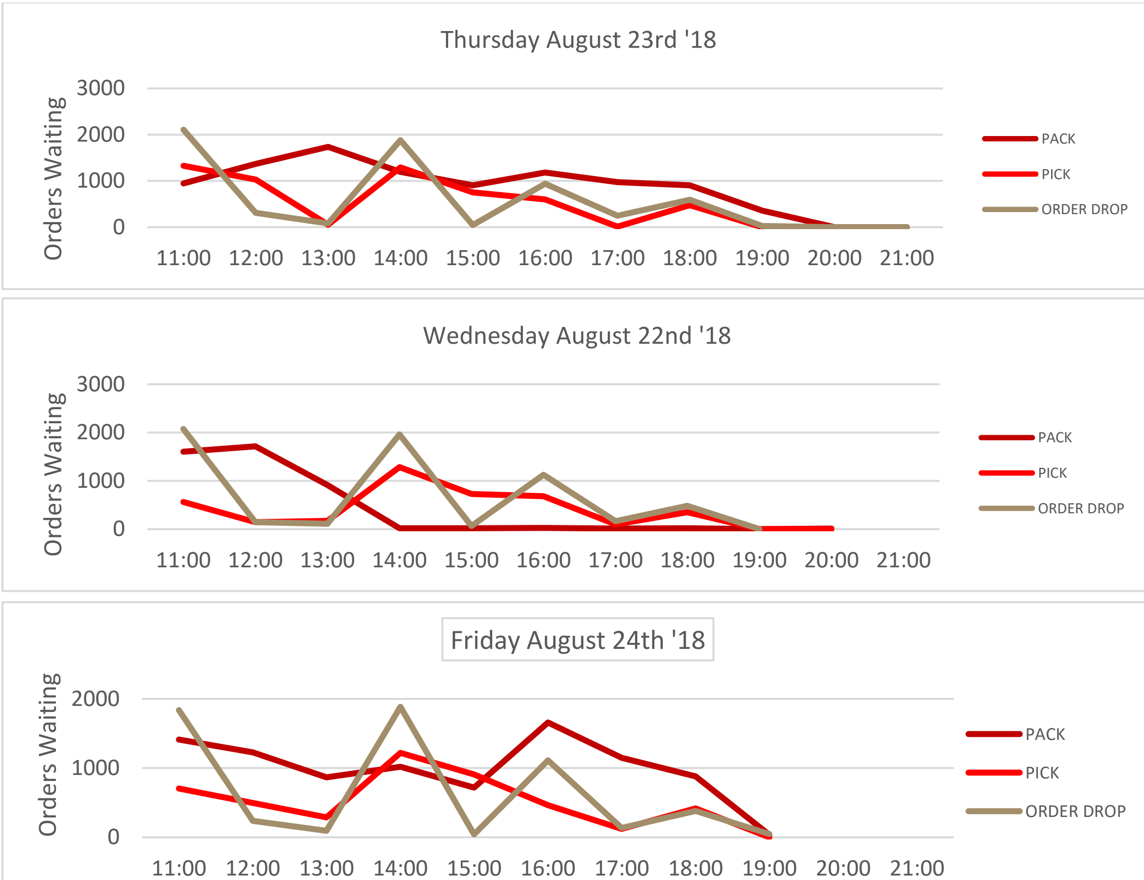


Figure 23 Graphical Representation of Order Drop and WIP at Different Weekdays

	Monday	Tuesday	Wednesday	Thursday	Friday
Idle Time	Low	Low	High	High	Low
WIP	Very High (no zero hits)	Moderate (no zero hits)	Low (zero hits)	Low (zero hits)	High

Table 4 Idle time and WIP at Different Weekdays (Summary of Findings from Table 3 and Figure 23)

4.4 | The Resulting Overtime

Overtime has been a structural problem at DEPTG-out; it has occurred every month, even every week. Figure 24 shows the course of overtime per weekday over the past months. Recently, the management of DEPTG-out has decided to start working on Sundays, which is always considered overtime. On Mondays, the workload consists of all orders that came in on Friday evening, Saturday and Sunday. Since this has often resulted in overtime on the Monday after, management has decided to work in advance on Sundays against a higher pay-rate. We see that the overtime is an increasing problem.

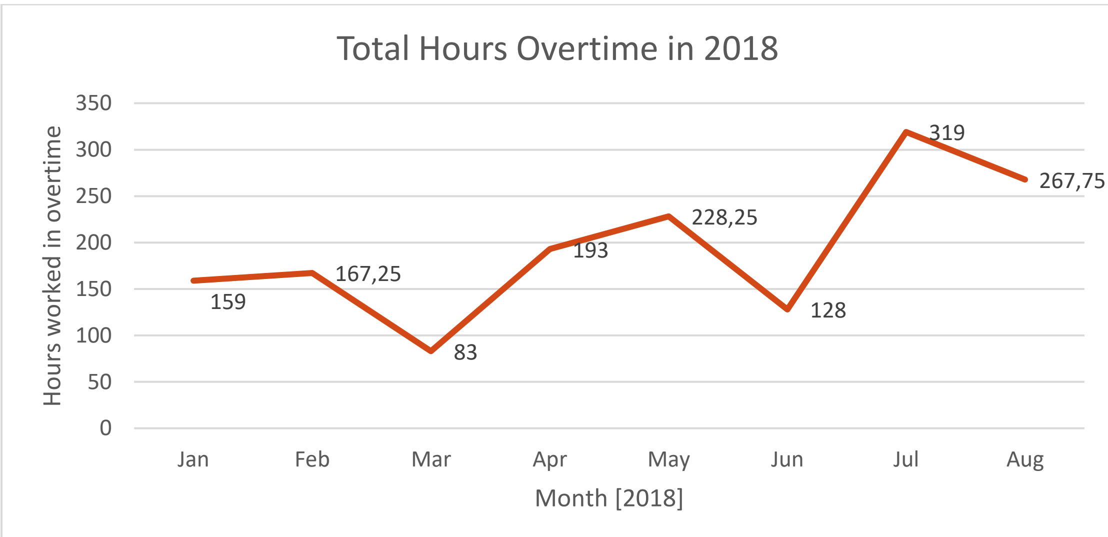


Figure 24 Overtime in 2018

4.5 | Conclusion

In this chapter, we have examined the processes at DEPTG-out. We saw that an order is composed of order lines, and a number of units associated an order line. We remarked that in the current situation there seems to be a batter correlation between workload and orders / orderlines than units. The unit productivity varies highly and is dependent on the ordertype, for which we distinguish SERVICEPROVIDER, Telco, B2C, Retail and STO orders. Schenker forecasts the expected workload in units per week, rather than lines or orders, and does not distinguish between ordertype.

Orders first arrive in the SAP, from which they are grouped into a batch by the wave planners. Batches are created based on the order characteristics volume and carrier. We saw that in the batching process a trade-off applies:

the later the shift starts, the more orders have arrived and thus, more orders can be consolidated into a batch. Due to batch picking, batches with a higher occupation will result into less movement of pickers and thus an increase in efficiency and probable reduction of idle time, but having workers start their shifts later also implies a higher risk of missing the cut-off deadline.

To get a quantitative indication idle time and efficiency in the current situation, we studied idle time of employees and WIP during five working days. We found that worker idle time tends to fluctuate between 14 and 24% and is generally lower on Mondays and Tuesdays than on other weekdays. These findings match our analysis of WIP: on Mondays and Tuesdays we see that work tends to accumulate more before it can start process steps picking and packing. This is partially due to the order drop: batch arrivals of some distribution channels that induces a variable workload during the day.

CHAPTER 5 | LITERATURE REVIEW

In this chapter, we reviews what is written about simulation in scientific literature. We examine what is written in scientific literature about planning and scheduling problems (5.1). Next, we dig into one of the solution methods that matches the required use of FlexSim: simulation (5.2). We end the chapter with a conclusion (5.3) .

5.1 | STAFFING AND SCHEDULING PROBLEMS IN LITERATURE

Scheduling problems are a well discussed topic in scientific literature. Van den Bergh et al. (2012) wrote a literature review on personnel scheduling problems in in which they distinguish four different perspectives to classify literature on personnel scheduling:

1. Personnel characteristics, decision delineation and shift definitions
2. Constraints, performance measures and flexibility.
3. Solution method and uncertainty incorporation
4. Application area and applicability of research

For the purpose of searching suitable solution methods, we examined the first and third category. In the first category, suggestions for modelling worker skills are proposed. In the previous chapter we saw that DEPTG-out's employee pool entails different skill classes: not every worker is perform every task. Van den Bergh et al. (2012) consider two different approaches for skills modelling: hierarchical and definable skills. In hierarchical skills levels are applied whereas in the latter it is assumed that he scheduler has the freedom to define skills for every personnel member in the set.

The third category discusses solution methods and the uncertainty incorporation. Van den Bergh et al. state that the most researched measures in personnel scheduling are often related to cost, e.g. personnel cost, cost per skill, overtime cost and cost of hiring temporary resources. Mathematical programming is stated as the most frequently used solution method, followed by application of improvement heuristics. An often referred model is the set covering model, which is described by Daskin (2008) as a model to find the minimum amount of facilities to cover all demands. Uncertainty of demand/workload, arrival time and capacity are stated as important factors to consider stochastic approaches.

Since the uncertainty of demand and workload plays an important role in our research, we dismiss the use of mathematical programming as a solution method this often involves a deterministic approach. Yet, mathematical programming models can be extended with so-called “chance constraints” to incorporate uncertainty. A nice example of the application of chance constraints to incorporate workload uncertainty is provided in Mabert (1979). In a later stadium of this research we found that the use of improvement heuristics is not supported by FlexSim (as will be explained in chapter 11). The use of FlexSim was a hard requirement for this research, and so we continue with discussing the use of simulation as a solution method and how simulation studies should be carried out.

5.2 | Simulation

There are several ways to solve operational scheduling problems. Van den Bergh et al. (2013) show that mathematical programing models are most often used as solution method for scheduling problems. Selection of the most suitable method is, however, always dependent on the situation. Mathematical programming models such as Linear and Integer Programming models it is hard or even impossible to, for example, account for random machine failures, precedence relations or unpredictable variability.

Robinson (2014) argues that simulation is a valid approach to analyze queueing systems when the variability, interconnectedness and complexity of a system is high. A distinction is made between predictable- and unpredictable variability. An example of predictable variability in our system is the amount of workers present at different weekdays. Though this factor is not constant, we can influence it. Unpredictable variability on the other hand, can be found in DEPTG-out in the arrival of orders.

5.2.1 | Types of Simulation

Many different types of simulation exist: Law (2014) describes that the most appropriate simulation approach is dependent whether a system is

- Deterministic or stochastic: Deterministic models do not contain any randomness / stochasticity, whereas in stochastic models the system can be viewed as a random variable that in turn consists of a set of random variables each having their own random input.

- Static or dynamic: static models show a system state at certain point in time, whereas dynamic models show a system that changes its state over time.
- Continuous or discrete: In continuous models, the system state changes continuously, whereas in discrete models this only happens at discrete points in time.

DEPTG-out faces stochastic order arrival and processing times. Its state changes over time as orders arrive, are processed and finished and so a performed simulation should be dynamic. Since state changes can be described according to events we will focus on models that are discrete.

With these requirements, Discrete Event Simulation (DES) is an appropriate simulation method for our study. Figure 25 provides an indication of where in the taxonomy of different simulation approaches we find discrete event simulation. In DES, only the points in time at which the state of the system changes, so called events, are represented (Robinson, 2014). Events can either be booked or conditional: booked events are scheduled to occur at a point in time while conditional events are state changes that are dependent on the conditions of the model. Whereas booked events commonly relate to arrivals or the completion of an activity, conditional events change the state of the system depending on the model's conditions. Conditional events often are related to the start of new activities. Product routings are often modelled with conditional events.

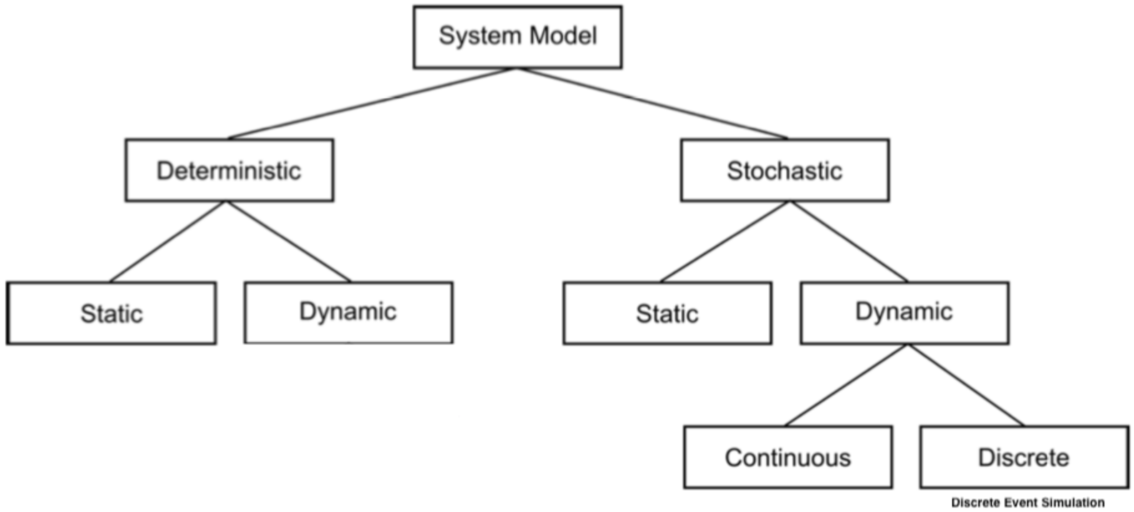


FIGURE 25 SIMULATION METHODS TAXONOMY OF SAWICKI ET AL. (2016)

5.2.2 | MODEL DESIGN AND VALIDATION

With inserting booked events and setting conditions on events, we can build a simulation model that mimics the real system. Shannon (1975) describes that simulation models should be used with the purpose to either increase the understanding of the behavior of the system or for evaluating strategies for the operation of the system. To make sure that the outcomes of experiments are reliable, the model must be validated with the real system. A valid simulation model can only be developed when design decisions are carried out with consideration.

Beaverstock et al. (2011) argue that for models designed for experimentation, the developer must consider in an early stage how he/she perform the experiments. The model design should enable the to be conducted experiments. Beaverstock therefore proposes six key activities for preparing a simulation model to be effectively used for analysis:

1. **Identify and define the experimentation variables**
   The model must be developed in a way that facilitates the changing of key inputs: the decision variables. The output will describe the performance of the set of input variables, and should be measured and stored in predefined KPIs. KPIs should therefore be identified early in a simulation project.
2. **Establish the type of system**

Early in a simulation project, the model developer must determine whether the system being considered is a *terminating* or *non-terminating* system. Terminating systems have well-defined starting and ending points. Typically, these points correspond to specific times, e.g. opening and closing times. Terminating systems often do not reach *steady-state conditions,* where the distribution of the performance measures settles down and approaches a constant. Non-terminating systems have, in contrast to terminating systems, the time to settle and reach steady state conditions.

3. **Determine the number of replications**
   In order to avoid drawing conclusions on a single, possibly extreme value of the output variables, an experiment setting must be replicated a number of times. Formulas are available with which the number of replications can be determined. We discuss this topic further in section 7.3.3.
4. **Define the starting or initial conditions**
   The configurations with which a systems starts can, especially in the case of terminating systems, impact the performance measures. Starting conditions could affect the time a non-terminating system takes to reach steady state.
5. **Define the run length**
   For terminating systems, determining the run length is usually straightforward. The simulation runs until the terminating event occurs. Determining the run-length of a non-terminating system is harder, but since the activities at DEPTG-out can be considered terminating (as we will explain in chapter seven) we will not discuss this method in this thesis.

When the simulation model has been developed, pilot runs should be used to check whether the model is valid. The model can be considered valid if model performance output and the performance of the real system with the same settings sufficiently overlap. Furthermore, Law (2014) suggest that Subject-Matter Experts (SMEs) should review the model results for correctness. Finally, sensitivity analysis can be used to determine what model factors have a significant impact on performance measures and, thus, have to be modelled carefully.

5.2.3 | Design of Experiments (DOE)

Once a valid model is obtained, experiments can be executed. Typically, there are a lot of different configurations that can form a possible set of input variables. Therefore it is, in most cases, not possible to carry out experiments for all configurations and is a strategy for conduction experiments desirable, we call this Design of Experiments (DOE). In DOE, input variables are referred to as factors, and output or performance variables as response variable. The major goal of experimental design in simulation is to determine which factors have the greatest effect on a response, and to do so with the least amount of simulating. This is often called factor screening or sensitivity analysis.

In the early stages of experimentation, *2^k factorial designs* is an efficient method to get a feel for the interaction between variables. 2^k factorial designs require that we choose just two levels for each factor and then calls for simulation runs at each of the 2^k possible factor-level combinations. Though under the assumption that responses are linear, 2^k designs often are a lot more time-efficient than the *one-factor-at-a-time (OFAT)* approach (Law, 2014).

5.3 | Conclusion

In this section we explored what is written on staffing and scheduling problems in literature. Two approaches are proposed to model worker skills. We consider the approach of definable skills as most suitable for the three packing skill (STO/IMC/regular), since it does not require large time investments for Schenker to train employees for the different packing skills. The skill difference between pickers and packers should be considered hierarchical. We found that the use of simulation as solution method is the most convenient option for problems containing uncertainty. Though many simulation types exist, we conclude discrete event simulation (DES) to be the most suitable for this research. Beaverstock (2011) defines five steps for construction and validation of models using DES. Finally, when a model is constructed, users of DES should pay attention to the design of experiments. We discussed two common designs, OFAT and 2k.

CHAPTER 6 | SOLUTION DESIGN

In this chapter we discuss the requirements the simulation model needs to satisfy in order to accurately answer our stated research questions. We start with the overall objectives of the simulation study and its scope. We continue with discussing which indicators will measure the effectiveness of a tested solution. We finish the chapter by introducing the simulation software in which we will build the model, FlexSim.

6.1 | MODEL OBJECTIVE

Needless to say, the simulation model should provide us an accurate representation of operations at DEPTG-out and allow us to play with its configurations. With the model, we examine how a change in workload affects staff requirements. Furthermore, we want to be able to assess the initial help question of management: are the current shift times appropriate? Summarized, the simulation model should help to answer the following (research)questions:

- When should shifts start?
- How many workers should start in each shift?

The main goal of the simulation is to find a set resource requirements for varying workloads with which DEPTG-out will be able to run its operation without having employees work in overtime. We will assess whether we favor a configuration over another configuration based on the KPI's presented in section 6.3.

6.2 | MODEL SCOPE

In the previous section we have stated which questions the model need's to provide answers to. Of course we want the simulation model to resemble reality as accurately as possible, but since the time for this study is limited to six months and not all activities are relevant to our research questions we build a more generic representation of DEPTG-out. In this chapter we explain the focus of our simulation model and where we have made assumptions.

6.2.1 | SCOPE

The model should focus on the core process of DEPTG-out: picking and packing of orders. The goal is to analyze how much personnel is needed to eliminate overtime for pickers and packers. In the model consider configurations where overtime occurs as invalid.

Activities of supporting personnel such as wave planners and supervisors are not modeled. Similarly we also do not model the activities of related departments DEPTG-Bulk and DEPTG-out. We assume that DEPTG-Bulk has finished the replenishment when the first workers of DEPTG-out start their shift.

Considering our goal to eliminate overtime at DEPTG-out, we do not model the acquisition of personnel to work in overtime. In practice, shift leaders start asking personnel of the first shift to stay after the end of their shift when they anticipate that the cut-off time may not be met with the regular capacity. Since we want to find a solution in which overtime does not occur, we do not model workers working overtime, but rather measure the decrease or increase in SLA that the configuration inflicts. Though this is in contrast to reality, we do consider this modelling assumption valid since it is in line with the scope of our research. In the next section we discuss the other modelling assumptions that we have made.

6.2.2 | Modelling Assumptions and Level of Detail

Besides the modelling assumption personnel will not stay after the end of the shift to work in overtime, we have made some other additional assumptions to ease the modelling:

- **Three shifts or less:** Currently, the employees at DEPTG-out start in one of the three shifts. Due to practical considerations and in consultation with shift leaders we decided to not consider options where more shifts are necessary.
- **Capacity remains unchanged during the day:** Opposed to reality, we assume that the assigned capacity remains constant over the day. If possible, in reality additional pickers are attracted from other departments in the company when the workload is high.
- **Packers work with fixed priorities:** We know that each packer has a priority list of the carriers he/she works for. We assume these individual priority lists are fixed over days and hours and are equal for all weekdays.

- **Pickers do not run out of trolleys:** We also assume trolleys to be sufficiently available such that running out of them is a non-existing problem.
- **Pickers do not encounter stock-outs:** Since pick jobs with any kind of errors in them, including insufficient stock, are not released by wave planners, we have assumed that pickers are not bothered by finding insufficient stock during their work.
- **One queue:** In reality, orders are grouped in SAP in three so called “queues”. Orders in the same queue cannot be mixed with orders from other queues when forming batches, even though carrier and OUT are equal. These special cases do not occur frequently and have a minor impact on operations. More about queues will be explained in section 7.1.2.
- **No productivity differences amongst workers**: Not every picker and packer has the same productivity. For the sake of simplicity, we do not model these individual productivity differences, but we do take into account variations in processing times on a general level. The processing time will be determined by a continuous distribution, which indirectly incorporates productivity differences.
- **Workers do not work overtime:** In our model we will not work with overtime. Management has clearly stated to look for a configuration where overtime is not an issue: thus, where capacity is always sufficient. Therefore we will model workers to be available within their working hours. Outside working hours no orders will be processed.
- **Packers never run out of workbenches:** In reality, each carrier has its own number of pack stations. Although most workbenches for carriers in the same category (STO/IMC/regular) provide the same materials and are therefore not carrier specific, workbenches are dedicated and thus, limited in number.
- **Waving is a systematic process and occurs at fixed time intervals:** To ease the modelling, we assume that wave planners release order batches at fixed time intervals. In the real system this process is not that strict and therefore hard to model. Based on their experience, wave planner wave orders and release batches when they consider the timing to be appropriate. This way, they are more flexible compared to the simulation to respond to what is happening on the shop floor, e.g. idle workers.

All these modelling assumptions were agreed with members of operational management (SMEs) and considered to be valid and in scope.

6.3 | Performance Measures

If we want to answer the previously stated questions, the output of the simulation model should be measured carefully in order to be able to compare system configurations with one another. In this chapter we will state which output measures are relevant for comparing and ranking distinct configurations.

SLA / Late Orders: Another very important measure is the SLA. We want to find a configuration in which all orders meet their deadline. The 100% SLA can be considered a hard constraint, all configurations in which the SLA is not met on a (semi-)regular basis, are considered invalid.

Cost of Personnel: Naturally, we prefer low-cost configurations over more expensive ones. The cost of personnel will be calculated rather easily: as requested by Schenker's management we assume that all staff members earn equal pay, regardless of their experience, age or training. Since Schenker Breda wishes not to disclose any information about worker salary the focus of this research is centered on eliminating overtime rather than reducing costs.

Average Lead Time: Measuring the average lead time gives us an indication of the efficiency of a configuration. The shorter the lead time, the less waiting time between process steps and thus a higher efficiency.

Other performance measures that are interesting for the effectiveness of the system are idle time and WIP. Unfortunately, we were not able to measure and track these variables in FlexSim.

Worker Idle Time: We wish to find a configuration in which work spreads equally over the day. Meaning we find little or no idle time.

Average WIP: Therefore we prefer configurations with low average WIP over ones with high average WIP. Lower levels of WIP indicate shorter waiting times and thus higher efficiency.

6.4 | FlexSim

Now that we have defined the objective and model scope and have defined KPIs, the next decision is, evidently, the choice of a suitable simulation package. As previously introduced in Chapter 2, management demands the use of FlexSim. In this chapter, we elaborate on FlexSim's capabilities and unique selling points.

FlexSim is 3D simulation software designed for modeling processes such as manufacturing, packaging, warehousing, material handling, supply-chain and many others. In contrast to many other simulation packages, FlexSim allows for direct modelling in 3D rather than having a 3D post-processor included. Another factor that distinguishes FlexSim from many other simulation software packages is that it has recently implemented an additional modelling tool named 'Process Flow'. The process flow functionality was made to reduce the amount of programming necessary to build logic into the model and works separately from the 3D model. However, FlexSim enables the user to connect both models to each other rather easily.

We also had Siemens Tecnomatix Plant Simulation to our availability, but since Schenker Breda is not in the possession of Plant Simulation and wants to use the model afterwards for own purposes, they required the model to be built in FlexSim. Schenker Breda has already purchased the FlexSim package and therefore we limit ourselves to this package. In Chapter 10 we will compare these packages and review which package would have been most suitable for DB Schenker's situation.

FIGURE 26 SNAPSHOT OF A FLEXSIM MODEL

6.4 | CONCLUSION

In this chapter we defined the scope of the simulation model that we are going to build. The most important modelling assumption is that we configure the model in such a way that work in overtime is not allowed. The most important

KPI in our research is the SLA: we search for a configuration that maintains the SLA of 100%, with minimal personnel cost and lead time. The model will be built in FlexSim.

Chapter 7 | Simulation Model

In this Chapter we present the final simulation model in FlexSim. However, before we got to this model, we first sketched out what logic the model should contain in order to correctly resemble reality. We drew out these 'sketches' in flow charts and proposed them to the SMEs: DEPTG-out's management (department chief, shift leaders, wave planners, data specialists and senior employees) for verification before building the final model in FlexSim. These flow charts form the conceptual model and are presented in 7.1. After the conceptual model description we continue to describe the data that was used to populate the model in section 7.2. We present the final model in Flexsim in 7.3 and finish the chapter with the verification and validation of both models (7.4).

7.1 | Conceptual Model

Here, we present our conceptual model. We start by providing a general model (7.1.1) that gives an overview of how we distinguished three core activities to be modelled. In the subsequent sections, we describe for each core activity how exactly it is modeled.

7.1.1 | General Model

In this section we present the general model of the DEPTG-out process that will be simulated. As we described before, the basic process at DEPTG-out is rather simple and consists of two major steps: orders are picked and packed. Before orders can start the pick-process, they need to be assigned to a batch. Depending on picker availability, a batch with orders has to wait or gets processed immediately. Between picking and packing, orders are likely to have to wait again if no packer is available. Figure 27 displays the flowchart of the general process.

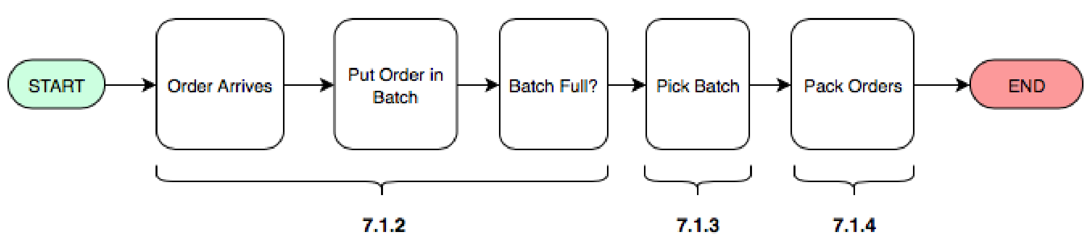


Figure 27 General Model

We distinguish three core processes that are analyzed further in the next sections: order arrival and batching process (7.1.2), picking process (7.1.3) and packing process (7.1.4).

7.1.2 | Order Arrival and Batching Process

In order to retrieve an accurate representation of reality, we model the order arrivals as well as the batching of orders. Schenker's Breda location only stores data on orders of the last 6 months. Historical data that goes back longer, can only be retrieved by special request from the headquarters in Essen of which the lead time can take up. Due to this limited data availability, we were not able to determine distributions for the arrival time of orders. Therefore we decided to use an empirical distribution that determines in which time-interval of one hour an order will arrive during the day. Accordingly, the exact arrival time in minutes and seconds is determined randomly. Thus, we use pre-fixed arrival times that are determined at the start of a new day. Similarly, we also predetermine the total amount of orders that will arrive during the day, the DayQuantity, based on a statistical distribution derived from historical data (Appendix E). Figure 28 displays the logic implemented in the final model that creates and schedules order arrivals.

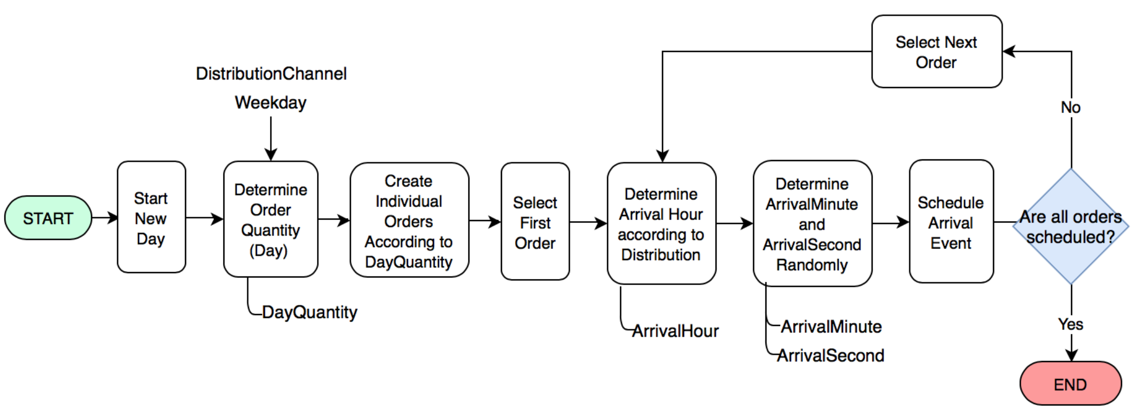


Figure 28 Daily Order Scheduling Process

The next Figure 29 displays the logic flow chart for order batching. In reality, a wave planner decides whether a batch is ready for release or not. The wave planner can decide to wait with releasing a batch until it has an acceptable "fill rate”. There are, however, no rules nor agreements made about consolidation or fill rate. Each wave planner acts as how he/she considers best in the moment, e.g. releasing a low fill rate batch because pickers are falling idle, or saving it for a higher fill rate. The existence of different waving queues (regular OUTs, PRIO and PROJECT) further complicates the modelling of batching, therefore we made the assumption that there is only one queue. Thus, orders with the same carrier and OUT can be batched into the same group.

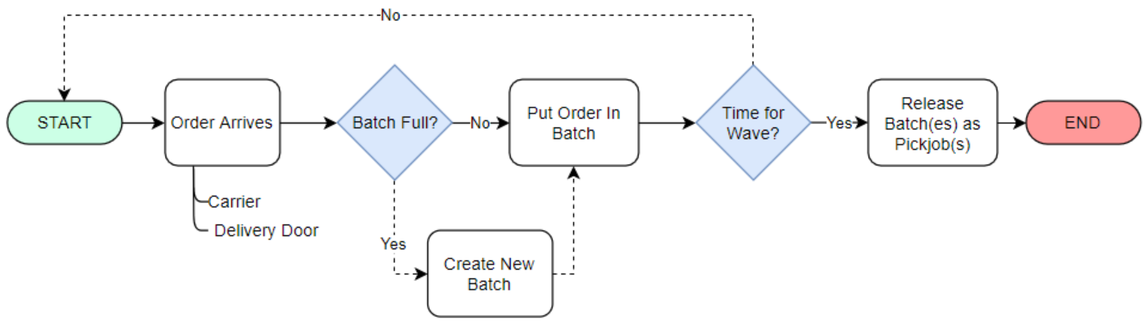


Figure 29 Conceptual Model - Batching

In the model, we defined a variable called “waveInterval”. Depending on the value of the this variable, the system triggers a wave: all batches currently available are released as pickjobs. In reality, this does not happen for all carriers and OUTs at once but manually according to the waveplanner’s judgement. Nevertheless, this approach was approved by the SMEs and an initial estimate of 45 minutes was applied. After a wave, the batch is released to the pickers and ready to be picked when a picker is available. In section 7.4.2 we check whether the fill rates that result from this approach match the fill rates observed in reality.

7.1.3 | Picking Process

As soon as an order batch is matched to an idle picker, the pick process can start. Of course, pickers are only available during their shift and since we consider work in overtime as no valid option the pickers are sent home at the end of their shift. Figure 30 presents the flowchart of the pick process. Naturally, we start checking if a picker is available as soon as there is at least one open pickjob. A picker is only available to process jobs when he/she is not occupied, on a break or outside shift times. When pickjobs are available, the picker is assigned a job according to a dispatching rule: earliest due date (cut-off). The picker starts picking and, when finished, brings the complete batch to the carrier corresponding packing area.

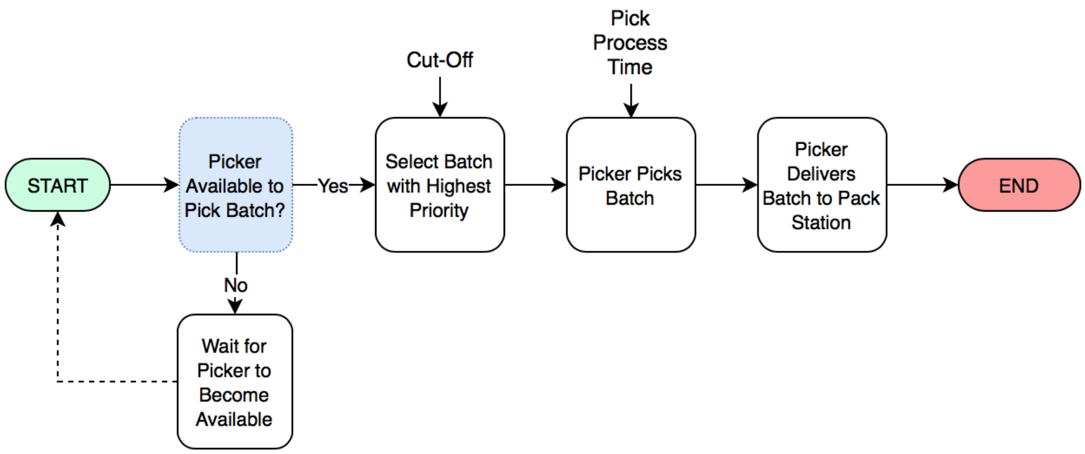


Figure 30 Conceptual Model - Pick Process

The order batch is now moved to the packing area, where the next process ‘packing’ will start. We describe this process in the next section.

Assumptions made in the pick process are, amongst others, that pickers always finish their pickjob before going on a break. In practice, pickers can decide to pick up a ‘on break’ sign to put on the trolley so they can go on a break on their assigned break-time. Since the latter requires continuously checking the simulation run time we chose this method because it is easier to implement. The same assumptions hold for going home, pickers first finish their current job and never go home early.

7.1.4 | Packing Process

The next step in the process is packing the individual orders in the batch. The most important factor that distinguishes packing from the picking process is that this process should account for task prioritization. Unlike pickers (in our model), packers will not just stand idle waiting for work when there is none at their first priority work station. Most pickers have been assigned a second priority or even a third priority carrier that they will pack for in case they run out of work at their first (for exact data see Appendix H). Moreover, every packer is able to help picking if there is nothing to pack.

TABLE 5 CARRIERS AND THEIR REQUIRED PACK SKILL AND CUT-OFF

Skill	Carrier	Carrier-Destination	Cut-Off Time
Regular Packing	UPS	COL	20:30
		EHV	19:00
		TIL	19:00
		SAB	19:00
		DOM	19:00
	TNT	EHV	19:00
		LGG	19:00
	OWN	OWNAC	18:00
	DHL	TDI	20:30
		TDIWPX	19:00
IMC	SCA	SCHAIR	17:00
		SCHORE	17:00
	WIL	WILSON	17:00
STO	KNL	KNAC	21:00
	SCH	SCHAC	17:00

Furthermore, not all packers have the skills to pack for certain carriers. In consultation with shift leaders and seniors we have distinguished three skills: regular packing: each packer has this skill, IMC: packing of usually large, international orders and STO: packing of large transfer orders meant for other DCs. Table 5 shows the carriers that are enabled for packing when a packer possesses a certain skill and their cut-off times.

After conducting interviews with DEPTG-out's team leaders and senior operators, we were able to model the logic of packer task prioritization as displayed in Figure 31. We see that when an order batch arrives, we first check if an order drop is going on. If this is the case, a number of packers are claimed to help out the pick force, after which we check for an available packer for the pack station where orderbatches are waiting. Requirement is of course that the packer is skilled for the pack station. If positive, the orders can be packed by the available packer. In the second swimlane of Figure 31, the logic directing the packers is displayed during a shift.

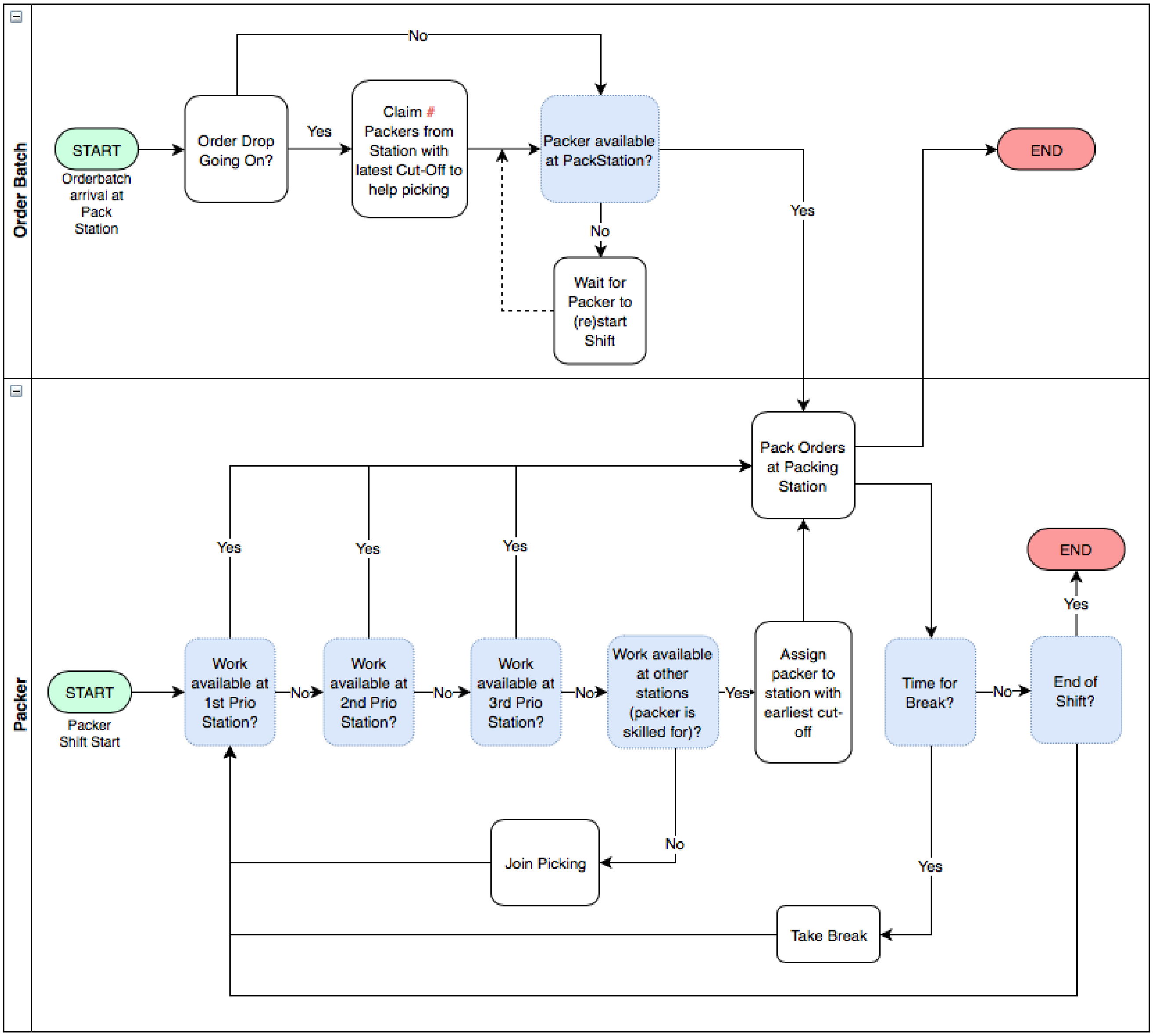


FIGURE 31 CONCEPTUAL MODEL - PACK PROCESS

7.2 | MODEL DATA

Now that we have defined the logic that must be implemented in our model, we need to populate it with data. For this study we had the data from Q3-Q4 in 2018 to our availability. Schenk Breda's ERP system SAP only saves data up to half a year in the past. This data was used to model random input variables including the order drop, pick processing times and pack processing times. Our general approach in the data analysis was to try as much as possible to find theoretical statistical distributions to model random input variables, which is also described as the most desirable option by Law (1991) since it smooths out irregularities in data and allows values to occur that have not been registered in the used data set. This is better in correspondence with reality, in which the system usually is not bound to any values either.

Unfortunately, we were not always able to fit statistical distributions to our data and often had to go with empirical distributions. Furthermore, we had to take into account the time restriction for this research which does not allow us to spend too much time on data study. Our findings are presented in the section “Verification” (7.4) of this report. There, we discuss used distributions and their performance in simulation test runs.

7.3 | Model in FlexSim

In this section we introduce the model we made in FlexSim. We start off with showing how the model looks and what functionalities are built in. We then discuss how the logic was implemented in the FlexSim feature ProcessFlow. Finally, we finish the chapter with an outlook to the next by introducing the initial conditions of the model. These need to be set before we continue with verification and validation in section 7.4.

7.3.1 | Model Look and Logic

The model consists of two parts: the 3D model and the model in ProcessFlow. In the latter, all logic is implemented which, in turn, triggers events in the 3D model when connected properly. As an alternative to PF, logic can also be programmed in objects in the 3D model instead of ProcessFlow. FlexSim reacts to a local programming language named FlexScript, which is similar to C++. When more advanced logic needs to be built in ProcessFlow, the common building blocks do not suffice and the user must extend the model with a “custom code” block.

Figures 32 and 33 display screenshots from the 3D model. The 3D model does not actually contribute to the purpose of simulation, but it’s visualizations are powerful for two reasons. First of all, one of the reasons Schenker decided to purchase FlexSim was because of its advanced graphics. It was expected that a realistic looking model would help to persuade the operational management of the outcomes of the study. But besides persuasive purposes, the 3D model is also very useful for debugging. With complex and large models, the ProcessFlow feature easily becomes messy and chaotic.

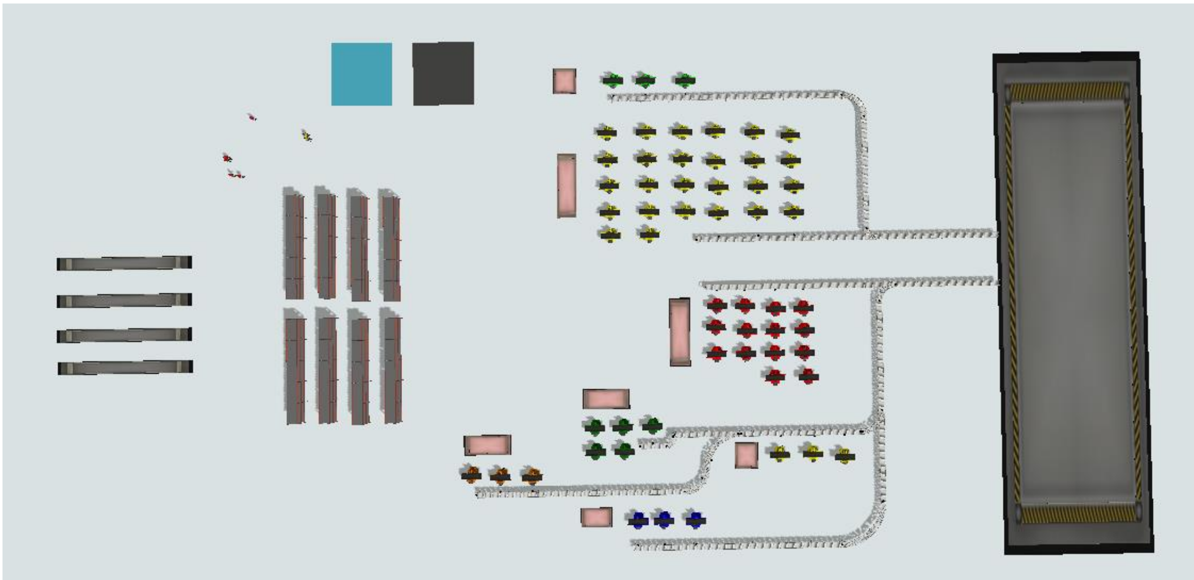


Figure 32 Top View of the 3D Model

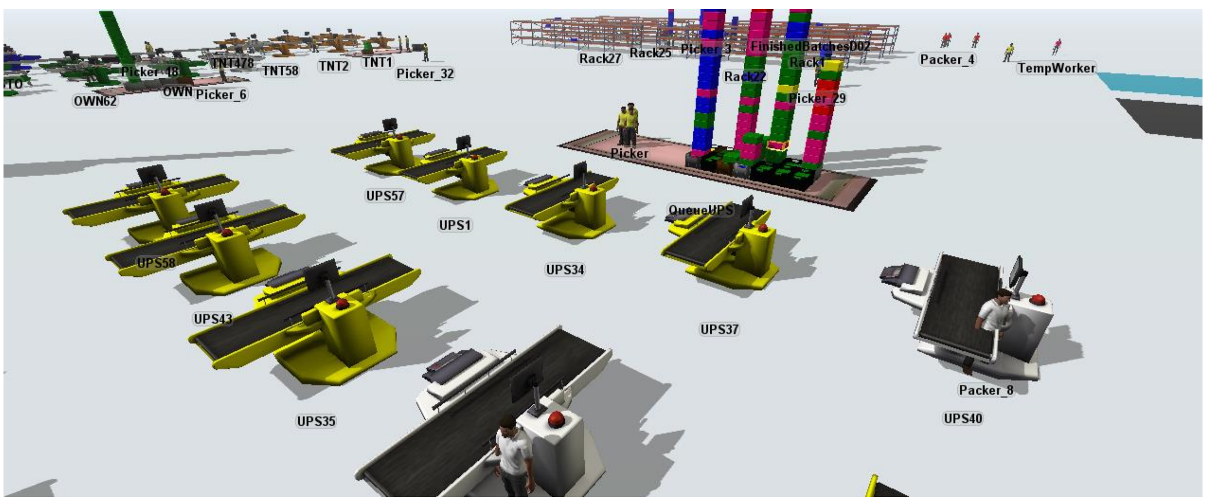


Figure 33 Snapshot of the 3D Model

Figure 34 (next page) shows an example of modelling in the process flow. In this caption we modelled all activities a picker goes through when picking. At the start of a new simulation run, all pickers are generated (upper left corner). In this particular part of the model, a token (green circle) most often represents one picker. Next, when a new day arrives, more tokens are created in the process in the upper right corner. These do not represent a picker but simply trigger the previously created tokens to start the next activity: “Acquire: Picker”. This is where the process flow and 3D model first connect: the token acquires another token on a list of pickers which is connected to an object “Worker” in the 3D model. The next steps in the model direct both the token in the process flow and the acquired worker in the 3D model.

In the right we have a so-called “sub flow” which triggers objects in the 3D model to execute tasks. The green tokens wait for these tasks to be finished in the 3D model before they continue to the next step .

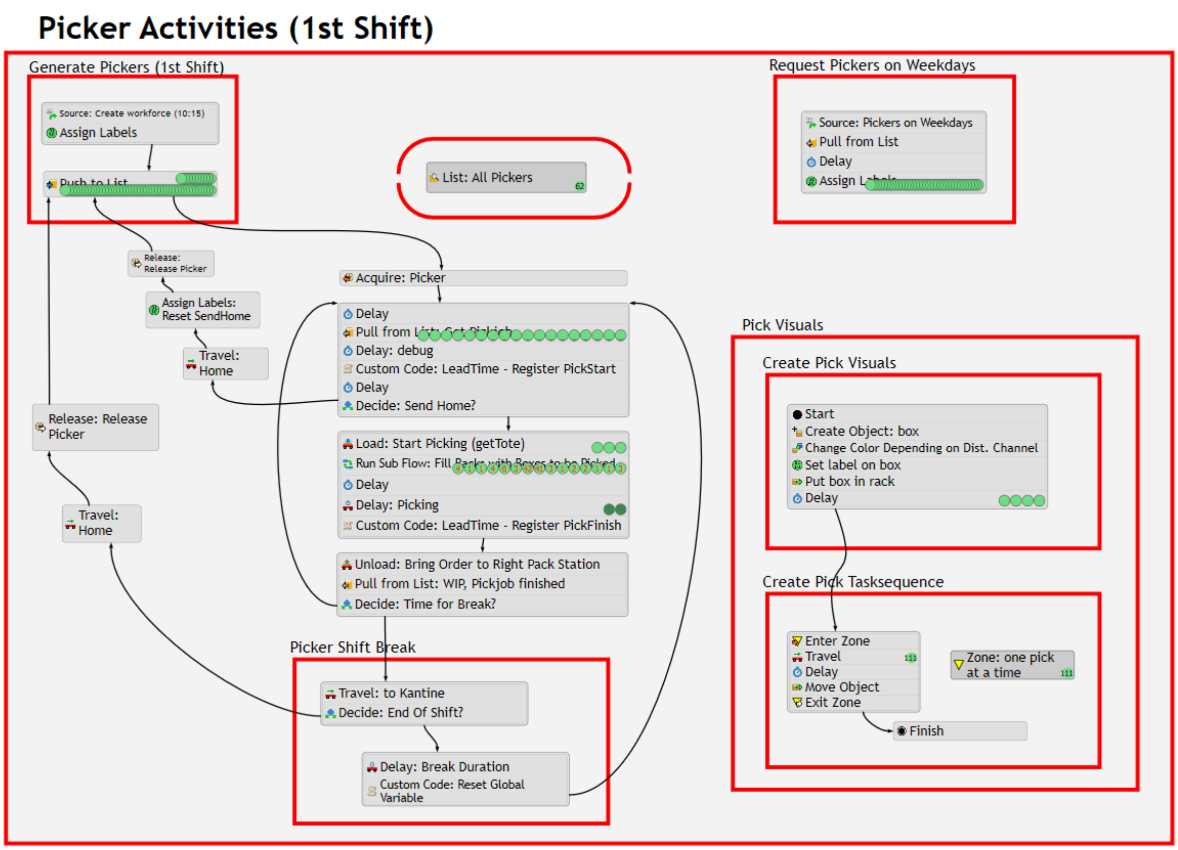


FIGURE 34 THE PICK PROCESS MODELED WITH PROCESS FLOW

7.3.2 | MODEL FUNCTIONALITIES

In the previous Chapter we discussed the three core processes that are modelled. In this section we present the supporting functionalities that were installed in the model to make it more realistic and variable.

Both pickers and packers take breaks. When a break is due, the worker travels to the canteen and takes a 15- or 30 minute break. Workers always first finish their current order before going on a break. In a similar fashion, workers are also sent home when their shift is over.

We also added a third, optional shift of pickers. A while ago, Schenker used to have three shifts, the third one existing of temporary workers and starting at 12:15. Since this was not done during the time over which we analyzed the data, we only use the two picker and packer shifts starting at 10:15 and 11:15 respectively, but the third-shift option may be interesting for experimentations purposes. Start times of all three shifts can be varied as well.

Since the model is not built to scale, we decided to not visually model the pick process. Although it looks impressive and is easily to implement in FlexSim, it would also imply that we need to analyze storage locations of different types of goods and how many times they are likely to be ordered. This would increase the complexity of modelling and therefore we decided to simplify the process in the 3D model to the picker standing still for an amount of time between the racks (process time).

For packers, we built in features where the user can assign skills (IMC/STO/regular packing) and priorities (carriers) to packers. Most packers only have one clear priority, in these cases we installed the carrier with the earliest cut-off as their second- and third priority. This is according to the real situation where packers always first pick at their “home” station before continuing to work for the carrier with earliest cut-off. If no work is available for the earliest cut off carriers, packers are assigned to a carrier with highest WIP or to picking. If a packer does not have a skill he cannot pack for certain carriers. The default configuration of packer skills and priorities can be found in Appendix H.

Finally, we built in a future that overrules a (variable) number of packers to go picking when an order drop is taking place. In the next section, we explain how we chose the initial model settings for the purpose of experimentation.

7.3.3 | Initial Conditions

The initial conditions of the model define from which point in time we start collecting data, how long we run the simulation and how many replications we run for a scenario. The first one is called the warm-up period. If a model starts in an empty state, the first collected data may not be reliable. That’s when we use a warm-up period. Our simulation model also starts off on a Monday in empty state. When the first workday is coming to an end, orders are scheduled for the next day Tuesday. So basically we can argue that a one day warm up period suffices since from here the system does not start in empty state anymore. Nevertheless we applied Welch's graphical procedure as described by Law (2015), which can be found in Appendix I. Welch's procedure has confirmed our expected warm-up period of one day and thus we set the warm-up period to one day accordingly.

We go on to determine the run length: how long should the model run in order to get reliable results? Robinson (1995) states that the best option is to both take a sufficiently long run length, and subsequently running multiple replications. To calculate the necessary run length, Robinson describes a method that assumes the cumulative mean of three replications would converge after running the simulation for a long time. We take the lead time (LT) as our variable and calculate the convergence given by Equation 2:

$$C_i = \frac{Max(\bar{Y}_{i1}, \bar{Y}_{i2}, \bar{Y}_{i3}) - Min(\bar{Y}_{i1}, \bar{Y}_{i2}, \bar{Y}_{i3})}{Min(\bar{Y}_{i1}, \bar{Y}_{i2}, \bar{Y}_{i3})}$$

EQUATION 2 CALCULATION OF CONVERGENCE OF SIMULATION OUTPUT VARIABLES

Where:

$$C_i = convergence\ at\ period\ i$$
$$Y_{ij} = cumulative\ mean\ of\ output\ data\ at\ period\ i\ for\ replication\ j$$

The methods states that when C_i drops and stays below 0.05, sufficient reliability has been attained. We performed this method on our simulation. We ran three replications of 100 days, which should be sufficient according to the rule of thumb of at least ten times the warm-up period. The results are attached in Appendix C. Unfortunately, in our case we did not find our convergence to drop below 5% and remain stable; a stable 10% seems to be the best we can get and this equilibrium shows op after about the 64th day.

The cause of this problem is that the output of the model we analyze (batch lead time) is rather unstable. We observe that the lead time often shows large outliers, especially on Tuesdays. We checked the model for deadlocks, if processing times were correctly calculated and assigned and if the amount of orders created was reasonable of over the days. Despite these efforts we are unable to tell the root cause of these outliers. We do not consider this to be an urgent matter because the output of the model overall is reasonable (we explain this further in the validation section 7.4), but these outliers and high variation in lead time output influence the application of Robinson's method, resulting in a limited stabilization of output.

We add the one day warm up period to the 64 days of stabilization and thus, we derive a total run length of 65 workdays, which corresponds with 91 days in total.

The last thing we need to do before we can properly start the simulation study is to determine how many replications are needed to get reliable results. We did this by applying the replication / deletion approach as described in Law (2015). This approach states that as many replications should be run until the error becomes smaller than the relative error (γ) which is at most $\frac{\gamma}{1+\gamma}$. The next formula describes this mathematically:

$$\boldsymbol{n}^{*} = \mathbf{min}\left\{\boldsymbol{i} \geq \boldsymbol{n}: \frac{\boldsymbol{t}_{\boldsymbol{i}-\mathbf{1},\mathbf{1}-\frac{\boldsymbol{\alpha}}{\mathbf{2}}}\sqrt{\boldsymbol{S}_{\boldsymbol{n}}^{\mathbf{2}}/\boldsymbol{i}}}{|\overline{\boldsymbol{X}_{\boldsymbol{n}}}|} \leq \boldsymbol{\gamma}'\right\}$$

EQUATION 3 CALCULATION OF ERROR COMPARED TO RELATIVE ERROR FOR REPLICATION NUMBER I

Here, n* is the smallest number of replications for which the formula applies. This approach was applied to our simulation model. We ran 80 replications (Appendix D), assuming that that would be more than enough, and checked whether our error dropped below the relative error. This did not happen. Similar to the problem we occurred in determining the run length, we had to conclude that the output does not reach the level of 5% reliability. Considering the time it costs to run additional replications (80 replications already take two and a half hours to run) and the limited additional decrease in the error that extra replications would establish (t still decreases with every additional replication, but at this number of replications S_n^2 and $\overline{X_n}$ behave very stable), we decide that running more than 80 replications is not a feasible option.

Taking a closer look, we again found that there are many outliers in the output (see figure in Appendix D). These outliers also result from the high variety that we find in lead times. Therefore we decided to remove these outliers and run the model with the 24 replications that result from applying replications/deletion approach to the remaining observations.

7.4 | Verification and Validation

Verification is the process of ensuring that the model design (conceptual model) has been transformed into a computer model with sufficient accuracy (Davis, 1992). Thus, to verify our model, we first need to check whether our conceptual model holds up. We decided to do this by conceptual model validation and data validation.

Conceptual Model Validation is defined by Robinson (2004) as determining that the content, assumptions and simplifications of the proposed model are sufficiently accurate for the purpose at hand. We have presented all the flowcharts discussed in section 7.1 to the operational management of DEPTG-out and a few senior- and support employees. After we have explained the flowcharts we asked relevant employees what their thoughts were on it and to judge the accuracy of modelling the process this way. In all cases, they agreed to the proposed modeling approach.

After improving the model based on the feedback we got, we continued with the validation of our computer model. This means that we compare the output of the computer model with data that would be expected form the actual (proposed) system. In the next sections we discuss different topics of validation namely the order arrival process, order batching and handling process and we compare the resulting performance indicators.

As input settings for personnel, we took the average number of personnel used per day over the time span of the analyzed data (2018 – Q3&Q4). This looks as follows:

	Average of hours spent picking	Average of hours spent packing	Number of workers (avg hours/40) Pick	Number of workers (avg hours/40) Pack
Monday	307	215	38	26
Tuesday	259	199	32	24
Wednesday	242	207	30	25
Thursday	243	188	30	23
Friday	226	182	28	22
Saturday	0	0	0	0
Sunday	40	4	5	0

TABLE 6 AVERAGE HOURS USED FOR PICKING / PACKING AND INITIAL WORKFORCE SETTINGS DERIVED FOR SIMULATION

We take a wave interval of 45 minutes as indicated by wave planners and made production runs. We call this combination of settings the baseline scenario. So, we first examine how our baseline simulation behaves compared to the real system. When this is done, we can experiment with the model to see what impact several decisions may have on the real system.

7.4.1 | ORDER ARRIVALS

It is very important that the arrival of orders is modelled accurately, because we expect it to have a strong impact on the workforce requirements. For the same reason, we also considered it to be a hard requirement to distinguish between the amount of order arrivals on different weekdays and from different distribution channels. This left us with (7 weekdays x 5 distribution channels) 35 combinations to examine.

Distinguishing between weekdays left us with only 26 data points per weekday that describe the amount of orders that dropped during that day Although hard, we were in most cases able to find fitting distributions. On all groups, we applied a normal, uniform and Poisson distribution and tested their fit with a chi-square test. For all tests, we required the p-value to be higher than 5%, meaning that the considered distribution does not significantly differ from our theorized distribution with at least 5% certainty. We select the distribution with the best fit to model order quantity for the concerned weekday and channel. In the cases where all these three distributions did not provide a sufficient fit, we applied an empirical distribution. Exact information on the applied distributions and their fits can be found in Appendix E.

Furthermore, we considered it essential to model the variable intensity of order arrivals during the day. We decided to use empirical distributions to schedule orders in an hourly arrival interval.

Now that we have explained the details of our modelling approach, we discuss the results of the validation. We started with validating the amount of orders to be handled each weekday and ran the simulation with the previously determined settings. We found the following statistics for order arrivals:

	AASP		**B2C**		**InterCompany**		**Retail**		**TELCO**			
	Sim	Real	Sim	Real	Sim	Real	Sim	Real	Sim	Real	**SUM SIM**	**SUM REAL**
Monday	3390	3345	1235	1198	69	93	360	358	449	454	5503	5448
Tuesday	5060	5300	957	950	27	35	471	411	692	690	7207	7386
Wednesday	4707	5334	980	947	30	37	413	383	605	638	6735	7339
Thursday	4885	4864	977	913	13	17	411	381	611	591	6897	6766
Friday	4913	4703	849	839	13	14	425	383	622	584	6822	6523
Saturday	1883	1851	40	42	0	1	12	11	119	137	2054	2042
Sunday	298	273	320	297	30	36	241	223	8	6	897	835
										SUM	36115	36339

Table 7 Validation of Order Arrivals

In most cases we see that the generated average lies close to the average retrieved from real data. We draw the conclusion that the order creation has been modelled with sufficient accuracy to be validated.

Now, we continue with the second part of the validation of order arrivals: the arrival pattern. The moment an order arrives is modelled by an empirical distribution that determines in which hourly interval the order arrives. The exact arrival moment in minutes and seconds is subsequently determined randomly with an uniform distribution.

	INTERVAL (Arrival Hour)																							
DAY	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Monday (Sim)		0,2					7,0	0,5		5,7	1,8	2,3	2,0	28,0	9,0	15,7	11,3	12,5	1,9	1,1	0,6			
Monday (Real)		0,2					7,2	0,8		4,1	2,5	1,9	2,4	30,0	2,4	22,2	2,6	20,7	1,4	1,1	0,7			
Tuesday (Sim)							3,9	0,3	1,3	23,3	1,3	2,3	1,4	24,9	7,2	10,7	9,3	10,6	1,7	0,9	0,5	0,1		0,2
Tuesday (Real)							3,9		1,4	23,0	1,4	2,4	1,2	27,9	0,9	13,1	4,6	17,5	1,5	0,8	0,4	0,2		
Wednesday (Sim)							3,8	1,0	0,3	24,5	2,0	2,4	1,5	24,4	6,0	11,9	10,1	9,0	1,5	0,9	0,4		0,1	
Wednesday (Real)							3,8	0,8	0,5	24,3	1,4	2,4	1,5	25,8	2,1	16,4	2,5	15,2	1,8	0,8	0,5			
Thursday (Sim)							3,6	0,2	0,5	22,8	1,5	2,4	1,4	25,7	8,3	12,0	9,2	9,6	1,4	0,8	0,4			
Thursday (Real)							4,1		0,4	21,6	1,5	2,9	1,7	28,6	1,8	16,1	4,1	14,8	1,2	0,8	0,3	0,1		
Friday (Sim)							4,2	0,3	0,3	23,3	1,6	2,5	1,6	25,3	7,6	11,8	10,2	9,1	1,3	0,6	0,5			
Friday (Real)							4,1		0,4	22,3	1,4	3,0	1,5	29,3	1,1	18,4	2,0	14,2	1,0	0,9	0,4	0,1		
Saturday (Sim)	0,4							2,5	0,1	57,5	0,5	0,2		26,3	1,7	2,7	3,4	4,6				0,1		0,1
Saturday (Real)								6,3	0,1	43,8	0,6	0,2		36,6	0,2	4,8	3,0	4,1				0,1		
Sunday (Sim)	34,5						20,9			25,5	2,4	1,2	0,7	3,1	3,3	3,2	1,6	3,1	0,2	0,2		0,1		
Sunday (Real)							69,1			15,5		5,1		0,6	0,2	3,6	1,5	3,3					0,6	0,5
	% orders arriving in interval																							

TABLE 8 VALIDATION OF ARRIVAL MOMENTS, MODELLED WITH EMPIRICAL DISTRIBUTION

As can be expected from an empirical distribution, the resemblance with the real data is high. However, we do see some remarkable results. In the 15th interval, we structurally underestimate the amount of arriving orders, whereas at the 16th interval we overestimate. In the 17th interval we underestimate again. Mistakes in specifically these intervals can be critical for the simulation success, since in these intervals often the decision falls if the order cut-off is today (same day, enough time left) or tomorrow. The difference might be due to the two months we took to deduce real data from: August and September. Our empirical distribution is based on data on the Q3Q4 last year, while the "real data for comparison" only covers two months. It might have happened that in these months the arrival pattern was more spiked than usually. Figure 35 shows the plot of the arrival pattern on Thursday. We clearly see that our modelled order drop is less intense then probably the case in reality.

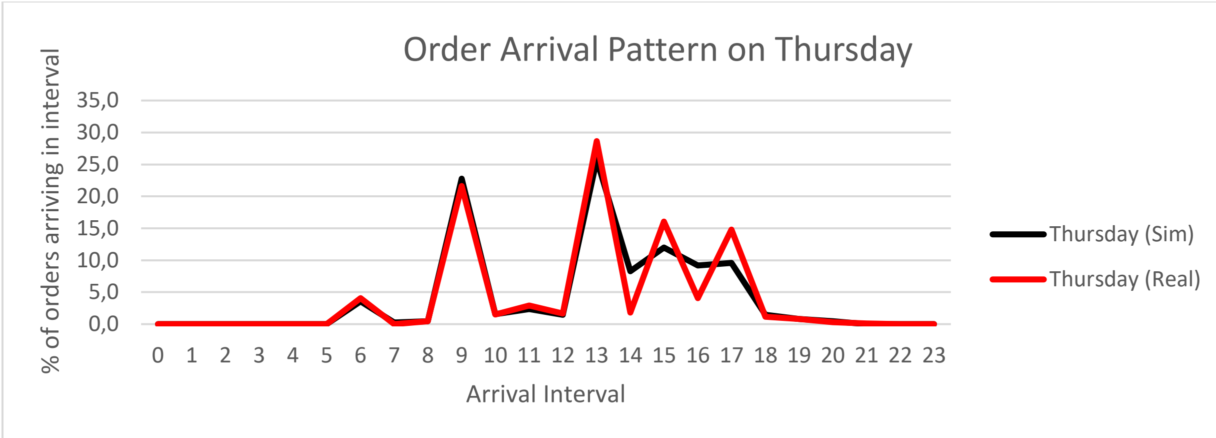


Figure 35 Example of Order Arrivals Created by Simulation and Observed in Real System

7.4.2 | Lead Times and Batching

In this section we assess whether the production process has been modelled with sufficient accuracy. The production process consists of the pick- and pack process. The pick process can only start when a job (consisting of single- or multiple orders) is released after the batch process. We first check whether the output of the batch process is in accordance with the actual system after which we will continue to inspect if the production process in our model resembles the real system in terms of lead- and processing times.

Batching

For validating the batching process, we examine two aspects that result from it: the average orders in a batch (occupancy rate) and the percentage of jobs processed in an OUT. Both strongly correlate with the time it will take to process the job, so we need the batching process to be modelled accurately to get reliable results. We found the following:

Table 9 Validation of Batch Fill Rate

	Avg. Number of Orders in Batch	
	Real	Simulation
OUT1	1,0	1,0
OUT2	3,0	2,2
OUT3	11,2	11,6
OUT4	25,9	27,3

Table 10 Validation of Batching into OUTs

	% Jobs in OUT	
	Real	Simulation
OUT1	18,6	11,8
OUT2	10,2	11,5
OUT3	35,4	36,1
OUT4	35,9	40,6

Although this data looks good, we can make the general observation that we tend to overestimate the jobs processed in the larger OUTs (3 & 4) on the cost of OUT1. OUT1 Batches have the highest processing time per order, so this observation may result in a possible underestimation of the average lead time.

Lead Time

Before we present the numbers on lead time validity, we first discuss the data analysis that was done to find the right input distributions. For picking, we determined the distributions as shown in Appendix B. Again, all distributions were tested on the 5% level with the chi-square goodness-of-fit test. Visual representations of the distribution fitted over the actual data can also be found in Appendix B.

For a pick process time, it does not matter for which carrier the picker picks. This property does not hold for packing. Individually assessing distributions for all carriers and OUTs would take too much time: this would result in 60 combinations to examine. After a quick inspection, we found that the mean of pack processing times was quite similar if we distinguished between OUTs and required pack skill. This was a founded assumption considering the nature of the orders packed with different skill types. Nevertheless, when visually examining the data we found that the underlying distributions could NOT be assumed to be equal. The shape of the histograms differs greatly between different carriers, despite being grouped in the same packing skill.

So we had to come up with a different approach. We looked into literature for distributions that have proven to be useful for modelling process times. Law (2015) describes the Gamma distribution to be a good choice for modeling time to complete some task. Other found candidates were Weibull, Lognormal, Beta, Pearson type V an Log-logistic. We chose Gamma because its parameters (α and β) can be easily derived form μ and σ which in turn are easily to calculate in Excel.

From here, our course of action was to just assume Gamma to be a good distribution for all 60 combinations and find its input parameters. A summary of the input parameters for packing can be found in Appendix F.

The first verification step we took was to check whether the lead times retrieved form the model were realistic and did not contain any bugs. We define lead time to be the job lead time, the lead time of a batch. As soon as batch picking is started, we start measuring the lead time. We chose not to include the waiting time of a batch before starting the pick process because this data is not stored in Schenker's ERP system and thus unknown. The waiting time between the pick and pack process is included. We stop measuring the lead time as soon as the last order in the batch is packed. Figure 36 presents a histogram plot of the processing times (lead times) in days. We see that most jobs have a lead time of less than half a day, these are the jobs that are processed the same day. As expected, this is the vast majority of jobs. We see that some orders take longer, these are the jobs where picking has been done to work in advance for the next day or where no packers were available before the end of the day and the job is processed late the next day. We see another very small bump around 2.7. These are the orders where picking started Friday or Saturday, while packing finished on Monday. We consider the results of the histogram to be explainable and as expected, and thus valid.

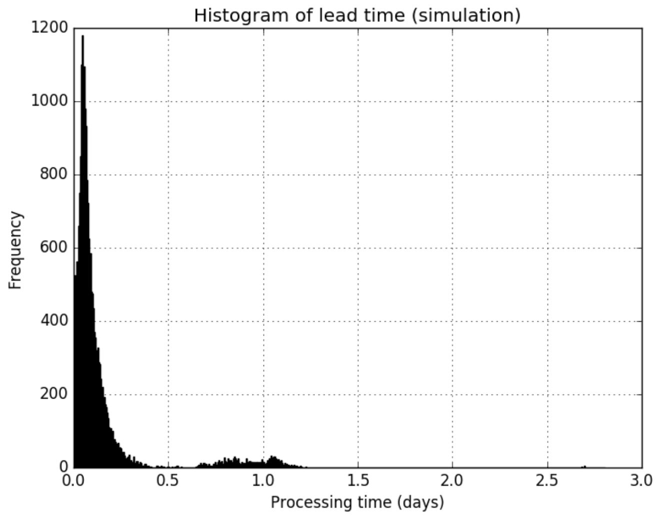


FIGURE 36 HISTOGRAM OF LEAD TIMES FOUND IN SIMULATION RUNS

But now we are going to zoom in on the validity of lead times per OUT. If we only take into account orders that have been processed the same day, we retrieve the following numbers:

	Average Lead Time	
	Reality	Simulation
OUT1	02:35:56	02:20:41
OUT2	02:38:11	01:56:01
OUT3	02:29:01	01:48:48
OUT4	01:33:20	01:40:04

FIGURE 37 VALIDATION OF JOB LEAD TIME PER OUT

Unfortunately, the difference between the actual system and the model is large. Especially in OUT2 and OUT3. To examine the cause of this difference, we further break down the average processing times for pick and pack, and the waiting time between the two to check if we chose the right distributions:

	Avg. Processing Time per JOB		Avg. Processing Time per ORDER	
	Picking		Packing	
	Reality	Simulation	Reality	Simulation
OUT1	01:22:22	00:31:15	00:42:37	00:29:42
OUT2	01:11:02	00:26:30	00:13:02	00:14:33
OUT3	01:15:15	00:23:28	00:02:24	00:03:27
OUT4	00:12:41	00:09:43	00:01:14	00:01:18
Waiting Time between Picking and Packing	Reality	01:03:07		
	Simulation	01:01:13		

Figure 38 Validation of Processing Times (in HH:MM:SS)

We conclude that, when taking this data for comparison, there is a big difference between the average processing time for picking between the real system and the simulation. However, seeing this data on the real system we doubt its reliability. We ran the found average pick processing times in our simulation and found that the system explodes in the long run. Therefore we turned to SMEs to validate our results. They accepted our outcomes and remarked that to them, our found processing times did not seem too unrealistic. Therefore, we decide to continue with this system despite not being able to validate it.

7.4.2 | Performance Indicator - SLA

The last property inspect for validation are the performance indicators. How many late orders occur?

Table 11 displays the SLA that we found in our simulation given the initial setting. As can obviously be concluded, the attained SLAs are lower than in reality.

WeekDay	Average of SLA (sim)	Average of SLA (real)
Monday	0,997	0,9959
Tuesday	0,971	0,9999
Wednesday	0,956	1
Thursday	0,980	1
Friday	0,988	1
average	*0,98*	*1*

TABLE 11 VALIDATION OF SLAS PER WEEKDAY IN BASELINE SCENARIO

We must note that our SLA isn't fully reliable. When testing the simulation, we discovered that, no matter how many packers and pickers we use, we will always have a small percentage of orders arriving late somewhere in each run. Although we have accurately modelled the rule that orders arriving less than two hours before their cut-off time are allowed to be processed the next day, we still find orders that are processed late.

7.5 | MODELLING ERRORS

In the previous sections we have encountered issues that obstruct us from fully the validating the model. In this section we reassess the modelling assumptions we made in section 6.2.2. The modelling assumptions we made have an impact on the outcomes of the model. We determine whether they may have caused the validity issues discussed previously.

The second assumptions we made was "Capacity remains unchanged during the day". This assumption may explain the lower attained SLAs in the simulation compared to the real system. Additional occasional capacity from support staff (e.g. shift leaders, seniors) positively affects SLA.

The third assumption, "Packers work with fixed priorities", is also likely to influence the output variable SLA. The mix of orders arriving differs significantly over weekdays. E.g. on Tuesdays, more Retail orders arrive than on other days. Not prioritizing on these related carriers may result in more missed orders. Furthermore, in reality the senior employees always make a trade off between carriers with highest WIP and earliest cut-off. The fact that we have modelled packers to work with priorities and WIP rather than earliest cut-off may also have resulted in more missed orders than the real system would have done.

The assumption “Workers do not work overtime” probably has the largest impact on SLA output. In the real systems, shift leaders can signal the probability of missing a cut-off and can, as a response, ask workers to work overtime. In the model, we measure how many orders miss their cut-off, but we do not model nor allow overtime. Therefore, the output of our model in SLA can be expected to be lower than that of the real system.

Other explanations for the lower SLA may be that the order drop is too large (which is unlikely as explained in section 7.4.1) or simply a misfortunate event (large orders dropping very late). We accept this defect in our model and in the next chapter, and take the average SLA over all weekdays of 98% as our baseline for comparison.

Finally, we want to make some remarks on the data used for determining processing times. During the process of determining adequate distributions for picking, we frequently encountered outliers. These were deleted one-by-one from the data set until a fitting distribution was found. Since these outliers were often the longer process times, it is likely that the removal of these outliers has caused the average processing times of our data to be lower than those retrieved from data on the real system. Moreover, the distributions fitted for packing were not tested with the chi-square test on being appropriate. This may also have caused the packing times to be unsimilar to the data retrieved form the real system. Nevertheless, the result of both picking and packing results in rather realistic job lead times, as we have seen in Figure 37 (page 79). Therefore we conclude the model to be sufficiently valid for its purpose of finding optimal resource levels and shift times.

7.6 | Conclusion

In this chapter we have presented a conceptual model. This model was approved by SMEs and modelled accordingly in FlexSim. We have briefly discussed how modelling in FlexSim goes in ProcessFlow and in the 3D model. We have discussed how the initial settings were determined for a baseline scenario and afterwards discussed how, with these settings, the model behaves in comparison to the real system. Unfortunately we could not fully validate the simulation. Though the batching approach and order creation resembles reality well, we find rather large differences between the average lead time, processing times and SLAs of the real system and those produced in simulation runs. We spent much time on debugging, but could not find mistakes in programming. Therefore we suggest that explanations for these inconstancies should be sought in unreliable data, initial settings or modelling assumptions. Despite the limited validation, we continue with the model in agreement of SMEs.

Chapter 8 | Experimental Design and Results

In section 6.1 we stated the problem that the simulation model should give insight into, but before we can compare the effects of interventions we first need to state a baseline scenario. In this section, we summarize what we understand when speaking about the baseline (8.1), and what alternatives to it (scenarios) will be examined in experiments (8.2). Finally, we discuss the results of these experiments (8.3) and end the chapter with a conclusion.

8.1 | Baseline Scenario

In the baseline scenario we assume resources are divided over weekdays as described in Table 6 (page 72). This includes an additional picker shift on Sunday to work ahead for Monday. For this scenario we have checked the resulting average service level. In all other experiments that we will conduct, we compare this baseline service level to the newly generated average service level in the experiment (Table 13). Besides the service level, we track the lead time in baseline and experiments for more information and validation. In the results section (8.3) we will compare service level and lead time of the baseline scenario to those retrieved in experiments.

8.2 | Running Experiments

The input settings for the number of pickers, number of packers, and the workload level form the basis to our scenario's. We can endlessly vary the number of resources, but for convenience we vary the number of workers always with at least 1 of each type from the baseline scenario. We call this input type the resource level.

We will vary the workload, respectively with +5% and +10%, of Q3Q4 respectively. We choose these numbers since Schenker is most interested in how to handle when workload is larger than expected. Due to numerous fixed contracts, possibilities to adjust the workforce when workload is lower than anticipated are limited. Furthermore a 5%- and 10% increase falls within the average forecast error of 15%. The baseline is thus a variation of 0%. We assume that the arrival pattern of orders does not change with the increased workload.

Literature describes many strategies for conducting experiments. This is called Design of Experiments (DOE). An easy and common strategy for experimenting is are so called *full factorial* experimental designs. When applying full factorial, we differ the variables one at a time (OFAT) to test its individual effect at all levels. When there are many variables, this method takes a lot of time. In our case, we have a limited set of variables: resource level, workload and shift start. A more efficient approach than OFAT is the 2k factorial design, this measures the effects of variables at a high/low level. In our research, we already have a clear idea of how high and low levels of resources and workload will interact with the output (SLA). We are more interested in the magnitude of their effect on SLA: we are basically looking for a break-even point between costs and service level restrictions. Therefore OFAT is the most suitable approach for our experiments.

If we vary pickers- and packers at the same rate, we only have two variables to vary: workload and resource level. On management request, we also decided to research the effect of the additional Sunday shift as currently is applied. So, we have three scenarios for workload: 0%, +5%, +10%. For the resource level, we initially assume a range between -2 and +6. Including the baseline, we thus have 9 different resource levels. Running a full factorial design, this results in 3*9 = 27 experiments. We additionally run an experiment without the Sunday shift, which sums up to 36 experiments. Using the FlexSim experimenter, each experiment takes about one hour to run. In the next section, we discuss the results of these experiments.

We also want to conduct experiments with our third factor, the shift start. We again decide to vary both the picker- and packer shift start simultaneously. We take intervals of 15 minutes to define experiments from the baseline (picker shift start at 10:15). Results are discussed in the next section.

8.3 | Results

In this section, we present the results of the experiments described previously. We start with the workforce experiments. When experimenting, we had the opportunity to run a few more experiments, and decided to also test the effects of shift start on the SLA.

8.3.1 | Workforce Requirements

Table 12 summarizes the results of the experiments with workforce and workload. We see that in the baseline scenario, the Sunday shift has a minor effect on the average SLA of 0,01%. When the resource level is scaled up with one, this effect diminishes and for both scenarios the break-even point lies at a scale-up of two workers. Additional deployment would not further improve the service level. When the workload is expected to be 5% higher than the baseline scenario, we recommend Schenker to hire three additional employees. For a 10% increase Schenker should hire 5 extra employees.

	Current situation incl. Sunday shift		excl. Sunday shift		+5% workload		+10% workload	
Resource Level	Avg SLA	st. Dev	Avg SLA	st. Dev	Avg SLA	st. Dev	Avg SLA	st. Dev
-2	0,51	0,33						
-1	0,93	0,12						
0	0,98	0,05	0,97	0,06	0,90	0,15	0,45	0,32
1	0,99	0,02	0,99	0,02	0,97	0,07	0,89	0,16
2	1,00	0,01	1,00	0,01	0,99	0,04	0,97	0,07
3	1,00	0,01	1,00	0,01	1,00	0,03	0,99	0,04
4	1,00	0,01	1,00	0,01	1,00	0,03	0,99	0,03
5	1,00	0,00	1,00	0,00	1,00	0,03	1,00	0,03
6	1,00	0,00	1,00	0,00	1,00	0,03	1,00	0,03

TABLE 12 RESULTS OF WORKFORCE EXPERIMENTS

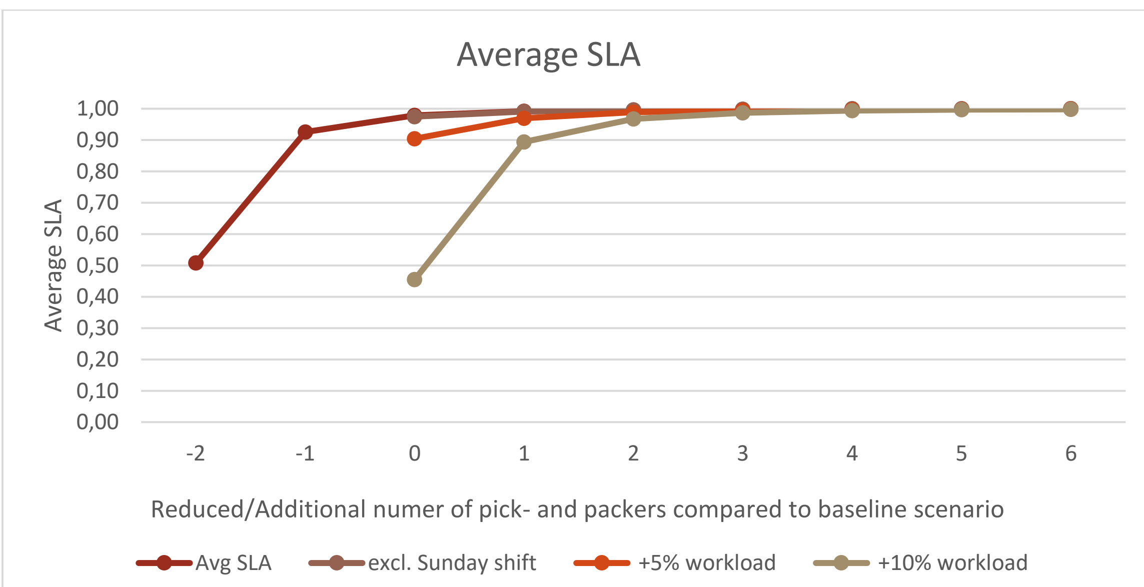


FIGURE 39 GRAPHICAL REPRESENTATION OF RESULTS WORKFORCE/WORKLOAD EXPERIMENTS

8.3.2 | Shift Starts

A second batch of experiments that we conducted was focussed on the start time of shifts. We varied the shift start for each experiment with 15 minutes for each shift, and looked at the effects on lead time and SLA. Table 13 summarizes our findings.

Shift Start		Avg LeadTime	stDev LeadTime	Avg SLA	stDev SLA
Pick	Pack				
09:45	10:45	6582	3243	0,980	0,047
10:00	11:00	7143	3795	0,978	0,046
10:15	11:15	7711	4227	0,978	0,048
10:30	11:30	8813	5382	0,981	0,052
10:45	11:45	9166	5325	0,980	0,052
11:00	12:00	10025	6086	0,976	0,064
11:15	12:15	10127	5695	0,969	0,066

Table 13 Results of Shift Start Experiments

We see that the lead time increases as we move the shift start to a later moment in time. This makes sense, since the a later shift start allows for a higher fill rate of trolleys but therefore also a longer lead time. The SLA behaves differently: here we see that an optimum occurs around 10:30/10:45 as start of the pick shift. Figure 40 graphically presents the course of SLA under various shift start times. We see that effects on the SLA are marginal for shift starts between 09:45 and 10:45, but that the SLA performance strongly deteriorates after 10:45.

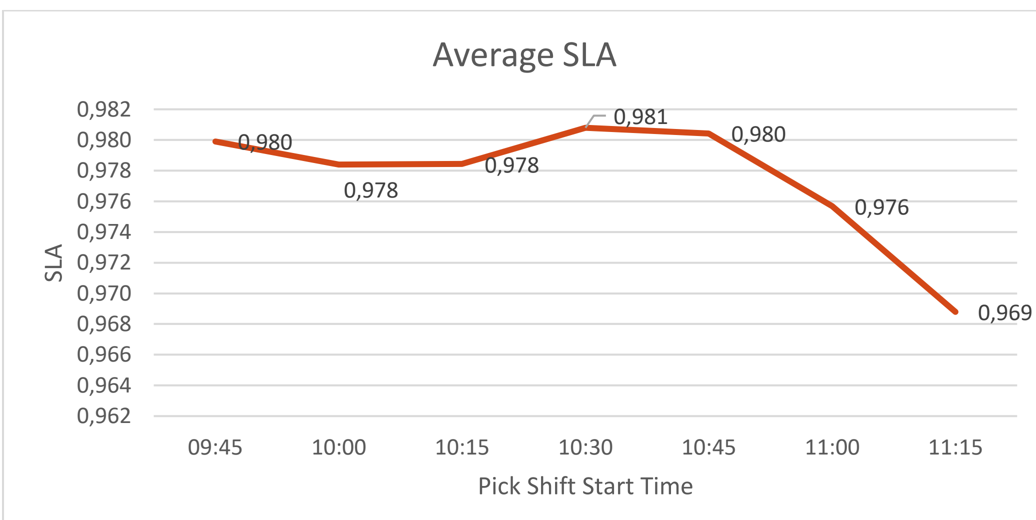


Figure 40 Effect of Shift Start on SLA Performance

8.4 | Conclusion

In this chapter, we have conducted experiments with the variables workload, resource level and shift start conform the OFAT method. Having defined the resource level interval at one picker and one packer, the results of the experiments conclude that in the current situation Schenker Breda lacks two pickers and two packers in order to attain a 100% SLA. With the current extra shift on Sunday, a 100% SLA cannot be guaranteed, which was also observed in the real system. Overtime hours in this extra shift only induce a 1% increase in SLA. If Schenker decides to hire additional full time employees, this effect diminishes.

If the workload level would increase with 5%, the results indicate that Schenker should hire six extra employees. If a 10% increase is expected or registered, Schenker needs ten additional employees to maintain a 100% service level with no overtime.

It is, however, important to remark that the method of experimentation strongly influences the recommendations. We chose to level up the workforce with 2 employees per experiment over all weekdays, corresponding to 2 fte. Due to the workload differences per weekday, these recommendations are very likely to be an overestimation of the real gap in workforce.

The best performing time for the pick shift start is between 10:30 and 10:45. However, differences with earlier shift starts are marginal. Shift starts later than 10:45 clearly deteriorate the SLA performance.

Chapter 9 | Implementation

In this chapter we answer the last research question "How can Schenker Breda implement the proposed solution?". The FlexSim simulation provides a tool for planning resources. Since this research was the first time FlexSim was used at DB Schenker to study operational improvements, we start with providing an implementation plan of the FlexSim software in section 9.1. We continue to discuss how we think the FlexSim simulation made for this research can be implemented as a tool for the planning department (section 9.2). Finally, we give recommendations on the implementation of the outcomes of our experiments in the operational context of DEPTG-out (9.3).

9.1 | Implementation of FlexSim

We have briefly introduced the motivation of Schenker to purchase simulation software in section 1.2. This research has resulted in a first product made with the FlexSim software, but Schenker wishes to continue using FlexSim to optimize operational processes. We recommend two focus points that are important for successful implementation of the software in DB Schenker's business in Breda: employees that are skilled in working with FlexSim and acceptance of the operational management and employees.

9.1.1 | Training

If Schenker wants to produce reliable simulations, it is necessary that employees working with FlexSim are sufficiently skilled and familiar with the program. Most employees at LS have never carried out a simulation study before, none of them have in FlexSim. Employees that know the program well and have experience with the different steps of carrying out a simulation study will produce more reliable results. For successful implementation, Logistics Support should train its employees to work with FlexSim and teach them the structure of a simulation study. Considering the fact that Schenker does not have this knowledge within the (global) company, we recommend to provide employees with external training, for example from TALUMIS B.V., the official distributor of FlexSim in The Netherlands from which Schenker also purchased the software.

9.1.2 | Engagement of SMEs

The success of a simulation study is not only dependent on its quality, but just as much on of the implementation of the retrieved results.

A requirement for a successful simulation study is acceptance of the results by the operational department that the research has been conducted for. Many literature sources (Law, 2015) (Robinson, 2004) as well as the lean methodology (Theisens, 2015) stress the engagement of subject matter experts (SMEs) and shop floor employees when conducting research on operational processes. High engagement of SMEs raises the chance of acceptance of the research outcomes and thus successful implementation. Moreover, the lean methodology stresses that most operational knowledge is stored at the shop floor which in turn, could provide valuable input for the modelling process.

9.2 | Simulation Deliverable

The simulation that we have built for this research provides a tool for the planning department. To enable the planners to use the simulation in their activities we have provided an user guide in Appendix K. However, as we have seen section 3.2 , the root cause of “the mismatch problem” is twofold: an inaccurate forecast and circumstances that make it hard to find resource requirements matching the forecast. Since it is unlikely that the client will make changes to the current unit forecast, we recommend Schenker to extend the administration with its own shadow forecast. Simple methods such as simple exponential smoothing can be used to create an own forecast. Simple exponential smoothing can be applied easily in Excel and does not require advanced knowledge of forecasting techniques. In Appendix J we explain the details of exponential smoothing and show an example in which we have applied exponential smoothing and compare it to the results of the current forecast. Considering the total absolute error in units, exponential smoothing performs better than the current forecast. The data of realized orders (deliveries) per week is already available in the weekly “shipclean report”. With some minor preparations, this data can be used to create a forecast from. Once the forecast is adjusted to orders, planners can convert the forecast into resource requirements using the following conversion table:

Table 14 Resource Action Plan Regarding Demand Increase

Workload Level	0	+5%	+10%
Expected Number of Weekly Orders	35669	37656	39346
Recommended Resource Level Compared to Baseline	+ 4 fte.	+ 6 fte.	+ 10 fte.

9.3 | Operational Implementation

The conclusion in section 8.4 summarized the outcomes of the experiments. For the operational department of DEPTG-out this resulted in two clear recommendations: given the current workload, hire 4 additional employees (1) and optimal shift start occurs around 10:30 (2).

Although recommendation (1) is rather easy to implement in practical sense, the current labor market makes it very hard to find new employees. Moreover, the current raise in workload may also be temporary. Therefore we recommend Schenker to expand the workforce with 4 temporary employees. To attract these employees, we suggest Schenker to consider financial compensation for the temporary workforce to be more competitive to other employers. Currently, Schenker already applies a bonus structure to increase for current employees: if they recommend to work for Schenker and this person stays for at least four consecutive days, the employee receives a gift card of bol.com for the amount of €50. This measure did not prove to be sufficient to overcome the current labor gap.

The second recommendation (2) may be more complex to implement in operational context. Since the current shift times are agreed in labor contracts, operators have to agree to the change of time. Although the change we propose is minor (15 to 30 minutes later), it may become a long process to implement this change if there is no support. We suggest to create support for this idea by explaining operators the need for this study and how it has been conducted. The 3D simulation in FlexSim can be used to increase the understanding.

9.4 | Conclusion

In this chapter we discussed the implementation of FlexSim, the simulation, and the experiment outcomes and therewith gave answer to our last research question: *How can Schenker Breda implement the proposed solution?* For successful implementation of FlexSim, Schenker Breda needs to have employees that know how to work with the software and acceptance of operational management and employees of this research method. The simulation itself can be used to examine what resource level fits the expected workload in orders, provided that the forecast is also measured in orders. Schenker Breda can implement the results of the experiments operationally by hiring 4 additional employees and changing the shift start to 10:30.

Chapter 10 | Conclusion and Recommendations

In this final chapter we will provide an answer to the main research question of this thesis, namely: *'How can simulation in FlexSim help to better match workload and resources at DEPTG-out?'.* In section 10.1, we present the key findings of this research. Section 10.2 provides a critical review of FlexSim as simulation software and its suitability for this research. We end the chapter with recommendations for further improvement and future research.

10.1 | Conclusions

In this section we summarize the most important findings of this research.

- Overtime is due to poor workload control and productivity losses.

We started the research with assembling a problem cluster to gain insight into what factors contribute to the problem of the workforce not being able to finish work in time. All problems that we found could roughly be divided into two categories: problems with controlling the workload and productivity losses due to suboptimal work methods. Proper operational workload control is hard due to the fact that many orders arrive in batches. On a tactical level most problems occur in forecasting and planning of resources.

Productivity losses undermine an efficient way of working. However, most causes of productivity losses are hard to avoid. These problems follow from carrier-based working, which is necessary to get the right products to the right dock. We examined the extent that idle time contributes to overtime, but high levels of idle time do not occur on weekdays where overtime is high. Idle time and overtime even seem to have a negative relation and therefore idle time may not be considered as the core of the of the overtime problem. We thus conclude that the root cause of the overtime problem lies in resource planning.

- Units are not a good indicator for workload.

Although the current forecast is provided in units, many irregularities exist that make a one-to-one translation to workforce requirements inaccurate. STO orders can be picked in pallets, whereas in other orders, due to their different composition, usually only a handful of items will be picked simultaneously, and only if required. Also at packing we see irregularities in unit processing speed: the high quantity of STOs makes them harder to pack, resulting in higher unit processing speed. The same holds for units in IMC orders: the complex pack requirements of these orders induce a longer processing time. Not taking these differences between order types into account results in a wrong estimation of workload and thus resource assignment. We confirmed this theory by finding a lack of correlation between overtime and unit workload.

- The current workforce lacks <u>at most</u> 4 fte. to function at a 100% service level.

Simulation experiments disclosed a lack of 4 fte. to function at a 100% service level with the current workload. Yet, this number is a product of our experimental design, the real gap between workload and resources is expected to be smaller. In Figure 24 (page 45) we saw that in the past months the hours worked in overtime were on average 250 per month. Dividing this number over 4 weeks per month it does not correspond with 4 fte. but rather 1.5 fte.

Hiring 4 additional employees will certainly diminish the risk of not meeting the service level, but also make the extra shift on Sunday redundant. Yet, we recommend Schenker to experiment with levelling up the workforce on days where overtime occurs most first, in order to save costs.

- The current shift start is not a bad option, but operations could be slightly improved if the shifts would start 15 to 30 minutes later.

The results of the simulation experiments indicate that Schenker could win 3% in SLA if it would let start the worker shifts at DEPTG-out at least 15 minutes later than they do now. The later start will allow for more order consolidation and higher trolley fill rates, which will enable the workforce to work more efficiently. Shift starts should be no later than 11:00: after 11:00 the positive effect of consolidation diminishes and the service level deteriorates strongly.

10.2 | FlexSim Review

We had the requirement to conduct this research study in Flexsim, and therefore FlexSim has played an integral part in this research. In this section we will discuss our experiences with FlexSim by means of a SWOT analysis. The analysis is presented in Table 15 In the next paragraphs, we elaborate on its content. We make comparisons between FlexSim to Plant Simulation, a package we also have experience with.

	Helpful	Harmful
Internal	- Advanced 3D graphics	- Steep learning curve
	- Modelling in 3D is easy	- Limited tutorials
	- Low code option: ProcessFlow	- Complexity
	- Active online community	- Many different language types
	- Queries	- Heavy to run
	- Dedicated support from a local supplier	- Building to scale
	- Clear and elaborate user guide	- Many interfaces
External	- Educational institutions	- High price
	- Training	- Limited flexibility & priced extensions

TABLE 15 SWOT ANALYSIS FLEXSIM

FIGURE 41 WORKER ANIMATION IN FLEXSIM

Strengths – Advanced 3D graphics

FlexSim absolutely stands out in 3D graphics. We have also searched pictures of other simulation software 3D graphics, but none of them provide the level of detail in animations that FlexSim does. A nice example of the animation quality are the workers in Figure 41.

Strengths – Modelling in 3D is easy

As opposed to many other simulation software packages, FlexSim allows to model directly in 3D, whereas other in other packages such as Plant Simulation modelling is initially done in 2D. Later on, the user can choose to convert the model into a 3D animation. This requires quite some time and does not always look as you would expect, but no changes can be made in the 3D: in Plant Simulation, the user would need to make changes in the 2D model and convert again. In FlexSim, 3D modelling is made just as easy 2D modelling in other packages.

Strengths – Low code option: ProcessFlow

ProcessFlow enables users that do not have programming experience to create models with a very low amount of programming. Modelling logic in

ProcessFlow is less abstract and does not require much knowledge of programming and syntax.

Strengths – Active Online community

FlexSim has an active online community that is concentrated in an online forum. Members help each other out with problems and also official FlexSim consultants are active on the forum to answer questions.

Strengths – Queries

Users of FlexSim can define queries to order lists, install priorities, or request an entry on a list fulfilling a certain condition. Use of queries can save a lot of time compared to programming a selection procedure oneself.

Strengths – Dedicated support from a local supplier

Companies buy FlexSim from a local supplier. FlexSim has many local suppliers in all the world's continents. They represent FlexSim in one or more countries and provide consultancy services and support. FlexSim's local supplier in The Netherlands is TALUMIS b.v. During the process of building this simulation, we have frequently used the support of TALUMIS b.v. We are very positive about the quality of their support and their response time and experienced a high degree of dedication to DB Schenker as a new customer.

Strengths – Clear and elaborate user guide

Information about objects and code commands is well organized and clearly documented in the FlexSim user guide.

Weaknesses – Steep learning curve

Learning how to work with FlexSim is not straightforward. Due to its many options and interfaces, users can get lost easily. Trainings are provided by local suppliers, but against an extra price.

Weaknesses – Limited tutorials

The steep learning curve combined with the absence of in depth tutorials make most users reliant on external training.

Weaknesses – Complexity

Users can decide to create a model in 3D directly, or to create a model in ProcessFlow, or a combination of the two. Tutorials discuss the latter option, to make the user familiar with both. Most objects in 3D modelling have a similar twin in ProcessFlow, for instance: the “processor” in 3D can be resembled by a “delay” object in ProcessFlow. For this reason, new users will also have to learn twice as much object characteristics than software packages that only deploy either of the two options.

Weaknesses – Many different language types

We briefly mentioned that FlexSim enables the use of queries. Besides queries, logic can be programmed in ProcessFlow and in FlexScript. Objects that are a task executer (e.g. workers, AGV’s), require a different style than the rest of FlexScript. It is easier to program task executers in ProccesFlow, but on the other hand, a change of object color depending on some manual rule must be done in FlexScript. Therefore, users that make advanced models will always end up between a mixture of the two, which makes models messy and unclear.

Weaknesses – Heavy to run

Advanced graphics and interconnectedness between ProcessFlow and 3D models make FlexSim heavy to run. Large advanced models with many animations are likely to become slow.

Weaknesses – Building to scale

According to their website, FlexSim believes that any model that doesn’t take spatial relations into account is not going to tell the whole story. We experienced that using the combination of ProcessFlow and 3D requires you to build a model to scale: ProcessFlow waits for an activity to be completed in the 3D model, say, walking to the pack area. This is the easiest way to implement the activity “walk to pack area”. Letting a worker “jump” to this destination within a prespecified amount of time is harder to implement, especially in 3D. Although this can also be a considered a positive aspect, it also requires more time and effort to build the 3D model.

Weaknesses – Many interfaces

Users that are very skilled in using ProcessFlow will definitely save time in modelling. Yet, for unskilled users, ProcessFlow objects contain many different options and checkboxes, of which the purpose or application use often is not clear at first sight. A nice example is the object “List”, an object that can hold other objects when requested. This object has 5 different checkboxes, “All or Nothing”, “Leave Entries On List”, “Use Max Wait Timer”, "Use Max Idle Timer" and "Keep Back Order On Early Release" on top of seven entry fields.

Opportunities – Educational Institutions

There are many parties that offer commercial object oriented discrete event simulation software. FlexSim could increase its market share by offering its software for free to educational institutions. Students that learn to work with FlexSim, can introduce the software in institutions where simulation is not yet applied. According to TALUMIS' website, FlexSim already collaborates with Breda University of Applied Sciences, University of Antwerp, Eindhoven University of Technology and Delft University of Technology.

Opportunities – Training

Like Schenker, some companies only buy a software license. It may happen that forget about the software or simply don't find the time to learn with it. We think would be a good idea if FlexSim would offer packages to new customers with training outside office hours together with a license.

Threads – High price

Most prices of discrete event simulation software providers are not publicly available. Yet, we can safely state that FlexSim is one of the more expensive packages. This was experienced by DB Schenker when they started looking for a simulation software provider. FlexSim charges about double the price that PlantSim does.

Threads – Limited Flexibility

Many FlexSim functionalities such as the experimenter are preprogrammed and can be found in the object library. The current experimenter has many downsides: there no easy way to define 2k experiment design and storing information at the end of a replication already requires advanced programming in the developers environment. It is very hard to create an own experimenter-like method. In PlantSim, this is easy but in FlexSim (almost) impossible. It would require developer level knowledge of the software to implement an own search algorithm or making an own experimenter. FlexSim rather offers these services for an extra price, also preprogrammed. For these reasons, we consider FlexSim to be less suitable for advanced users of simulation software.

In conclusion, we can say that FlexSim is a good simulation package for modelling simple systems. Its graphics make it an attractive and fun package for beginning modelers that are up for a training. For more intermediate users FlexSim does not provide the same flexibility as for example PlantSim does. The high price, limited options, and fast decreasing run speed does not make FlexSim a good option for extensive simulation studies like the one performed in this research.

Since in the case of DB Schenker no advanced knowledge of simulation is present in the company yet and the high price is not much of an issue, we conclude FlexSim to be a decent start into optimization through simulation. Yet, we stress that when the knowledge of simulation advances, DB Schenker could both save costs and save time with the use of other packages.

10.3 | Recommendations and Future Research

In this section, we discuss the limitations of this research, followed by recommendations. We end the section by giving ideas for future research.

10.3.1 | Research Limitations

The data analysis we conducted to determine processing times, does not take into account any idle time, despite our observations in section 4.4.1. in which we concluded idle time certainly plays a role of at least 14% in the daily operations of staff members. The model does not take this into account.

The reliability of the simulation in general and the conclusions drawn from its experiments is questionable. We saw in section 7.4 that the model is only moderately validated. It contains significant deviations from the existing system, especially in pick processing times. We tried running the model with average pick times retrieved from the real system, but this resulted in exploding queues.

The latter issue is likely to be related to the quality of the analyzed data. Many data sources for processing times exist within SAP, that provide inconsistent averages on processing speed. Moreover, when asking about these differences, none of our experts were able to give a clear answer.

In the process, the simulation gradually became more complex. It now contains many functions that are fun for experimentation, but are also the cause of the high variation that we came across. A more simple model would have made it easier to detect the cause(s) of the high variation and unreliability.

10.3.2 | Recommendations

During the process of this thesis, we quickly noted that Schenker maintains a 100% service level, even though only 99,5% is contractually agreed. Schenker could thus also reduce the cost of overtime or increase revenue by re-evaluating the service level with the client.

In the previous section we wrote about inconsistencies in data. To avoid basing decisions on unreliable data, we recommend Schenker to thoroughly examine and document how data is created and where it is stored, before using it for analysis.

Finally, we recommend the use of lines as productivity measure rather than units. Similar to units, the lines productivity is available in most productivity reports, but unlike units, lines provide a better productivity indication in case of pallet picking: one visited pick location is equals one line. This way, large (STO) orders will induce less variation in productivity measures and will be more reliable.

10.3.3 | Future Research

With the functionalities of the simulation built for this research more interesting experiments can be conducted than we have assessed in this thesis. We have implemented packer priorities: playing with these variables are interesting to find an optimal prioritization carriers. Similarly, one could also experiment with worker skills: what benefit can be obtained if we train the whole workforce for both picking and packing?

Also in resource planning experimentation can be elaborated. With the simulation, Schenker can also examine the benefits of using parttime personnel. In this thesis, we chose to expand the workforce with at least 2 fte. for each experiment, but it is also interesting to experiment with a larger workforce on only one of 5 workdays, for instance, the day at which most overtime occurs.

Finally, we saw in the problem cluster that DEPTG-out struggles with narrow pick aisles and crowding in the A-aisles. Using pickzones may provide a solution to this problem. With pickzones, pickers are assigned to fixed zones and only pick the items assigned to their zone. Moreover, pickers that know the storage locations in their pickzone well, are likely to work faster and more efficient.

Finally, we found an interesting improvement opportunity in workload levelling STO and IMC orders. These often large orders also have more flexibility in their cut-off than other orders, but are treated the same way as regular orders i.e. cut-off at the same day or day after. It is likely that the workforce can be relieved on busy days by spreading the workload of these orders over multiple days or postponing them.

References

Bagatourova, O., & Mallya, S. K. (2004, December). Coupled heuristic and simulation scheduling in a highly variable environment. In *Simulation Conference, 2004. Proceedings of the 2004 Winter* (Vol. 2, pp. 1856-1860). IEEE.

Hans, E. W., Herroelen, W., Leus, R., & Wullink, G. (2007). A hierarchical approach to multi-project planning under uncertainty. *Omega*, *35*(5), 563-577.

Heerkens, J. M., & van Winden, A. (2012). *Geen probleem, een aanpak voor alle bedrijfskundige vragen en mysteries*. Business School Nederland.

Law, A. M., Kelton, W. D., & Kelton, W. D. (1991). *Simulation modeling and analysis* (Vol. 2). New York: McGraw-Hill.

Mabert, V. A. (1979). A case study of encoder shift scheduling under uncertainty. *Management Science*, *25*(7), 623-631.

Robinson, S. (1995). A heuristic technique for selecting the run-length of non-terminating steady-state simulations. *Simulation*, *65*(3), 170-179.

Robinson, S. (2004). *Simulation: the practice of model development and use* (p. 336). Chichester: Wiley.

Sawicki, S., Frantz, R. Z., Fernandes, V. M. B., Roos-Frantz, F., Yevseyeva, I., & Corchuelo, R. (2016). Characterising enterprise application integration solutions as discrete-event systems. In *Handbook of Research on Computational Simulation and Modeling in Engineering* (pp. 261-288). IGI Global.

Theisens, H. C. (2015). *Climbing the Mountain: Mindset, Skill Set and Toolset for Lean Six Sigma Green & and Black Belts*.

Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., & De Boeck, L. (2013). Personnel scheduling: A literature review. *European journal of operational research*, *226*(3), 367-385.

Winston, W. L., & Goldberg, J. B. (2004). *Operations research: applications and algorithms* (Vol. 3). Belmont: Thomson Brooks/Cole.

Appendices

Appendix A: Detailed Rules for Order Batching

To understand this logic we should first distinguish six different material groups: MP3 Players, Phones, Tablets, Computer(parts) and Earphones, Smart Watches and Others.

Based on what materials are ordered together in one order, the SAP logic determines the corresponding "Delivery OUT" (OUT). It can be seen as a picking method for orders (batches). Batches are picked either on a pallet, trailer or trolley. Four different trolley sizes are available, differing in layout so they can handle different order volumes for orders within the same batch. So, for example, trolley OUT 3 is divided in 20 different cells (orders) that can each handle a volume of 30 dm^3 per order. Other trolleys or pallets have a different or no layout and are thus optimal for other order volumes. Based on the design of the trolleys, the following business rules were determined to decide to which OUT an order should be assigned.

Rule 1. Order consists of one unit (MP3 Player, Phone, Tablet or Smart Watch)

→ OUT 4

Rule 2. Order consists of up to three units Computer(parts) or Others

→ OUT 4

Rule 3. Order consists of one unit MP3, Phone, Tablet or Watch together with up to two units Computer(parts) or Others

→ OUT 4

Rule 4. Order consists of multiple items of any material group except Others and volume is less than 30 dm^3

→ OUT 3

Rule 5. Order consists of multiple items of any material group and total volume is less than 70 dm^3

→ OUT 2

Rule 6. Everything else

→ OUT 1

After the orders are grouped on a OUT, the wave planner starts creating a pick wave. This is the third step. He or she does so by entering the following criteria:

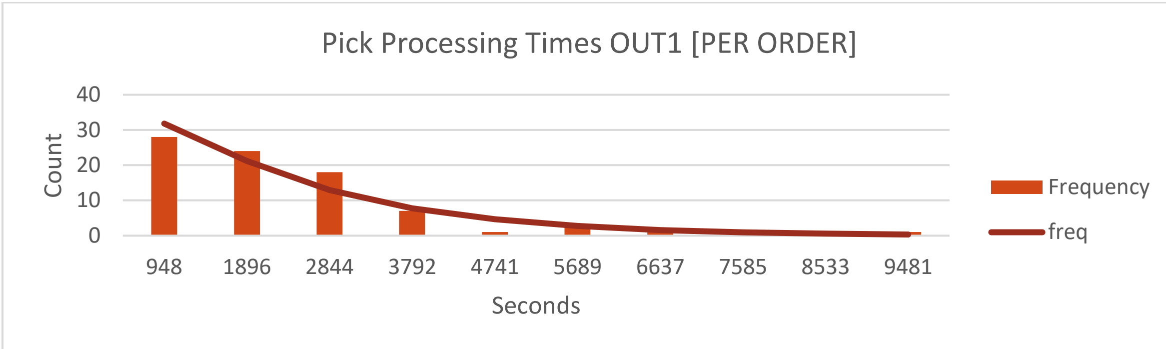
1) Cut-off date
2) Cut-off time
3) Carrier
4) OUT (optional)

After running, the SAP system shows the order batches based on the input and OUTs, so order batches are created based on cut-off date, time, carrier, material and volume (OUT). All criteria have to be identical or similar to be batched in the same group. Furthermore, the wave planner has some manual options that he/she can select to optimize the grouping process and operations. For instance: a minimum number of orders that is assigned to a OUT to avoid empty spaces and a checkbox 'Group D03 deliveries as D02' for when operation is out of OUT 3 Trolleys.

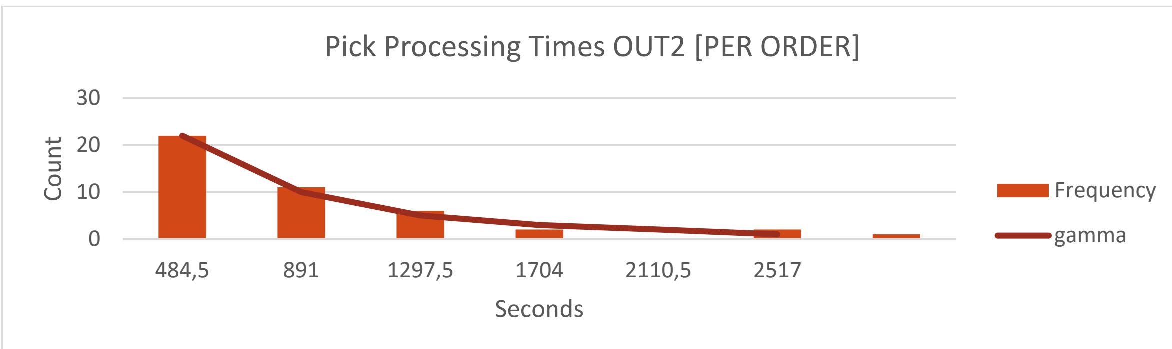
Besides normal pick orders, there are Transfer Orders (TOs) to be picked. TOs are inventory transfers. They need to be waved separately to update the current inventory position of the warehouse. Regular orders and TOs are after acceptance of the wave planner released to one of the queues OUT1, OUT2, OUT3 or OUT4, depending on their OUT.

Finally, the wave planner can decide to give the order batch priority (PRIO). The order batch is then assigned to a different queue: PRIO1, PRIO2, PRIO3 or PRIO4, corresponding with the four different OUTs. Wave planners usually decide to do this when the cut-off time of a certain carrier needs priority over the rest or when order batches need special attention. Another wave planner then notes that there are orders in the PRIO queue and hands them out to the pickers before continuing with the regular queues.

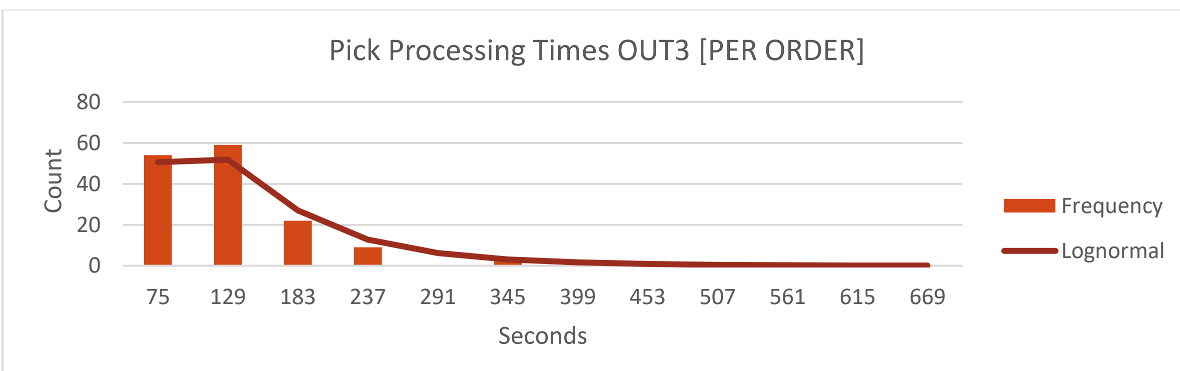
Appendix B: Distributions Fit on Pick Processing Times



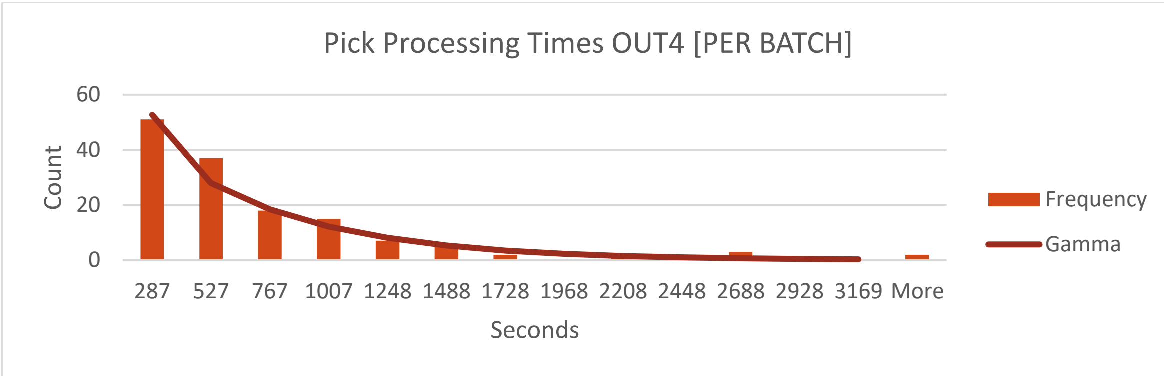
APPENDIX Figure 1 Distribution Fit (Gamma alpha = 1.1, beta = 1748) for Picking OUT1 Orders



APPENDIX Figure 2 Distribution Fit (Gamma alpha = 0.9, beta = 787) for Picking OUT2 Orders



APPENDIX Figure 3: Distribution Fit (Lognormal mu = 4.6, variance = 0.63) for Picking OUT3 Orders

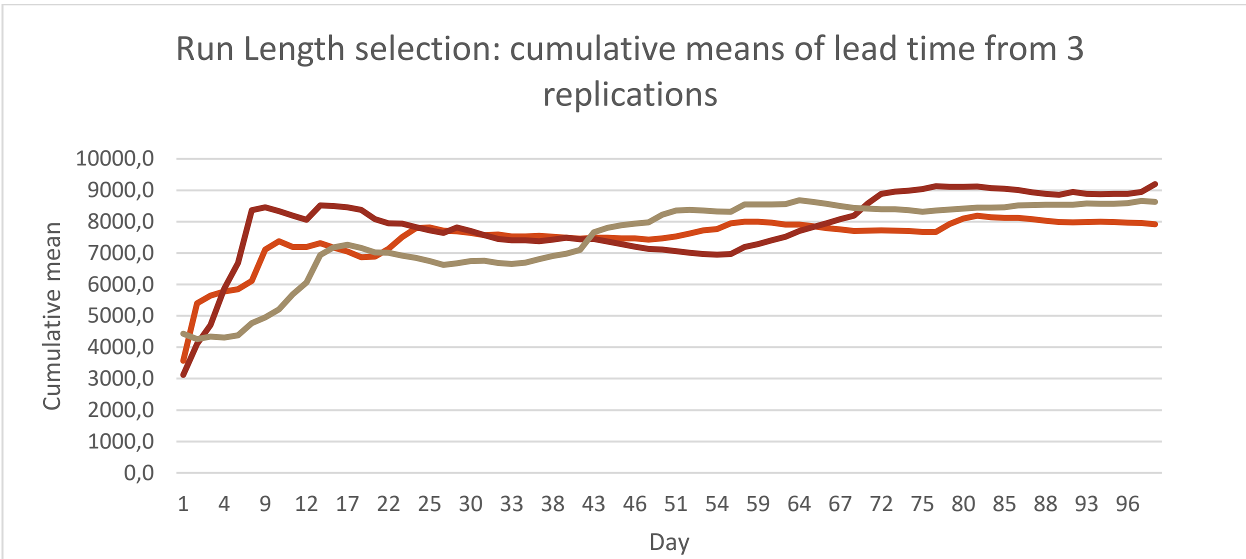


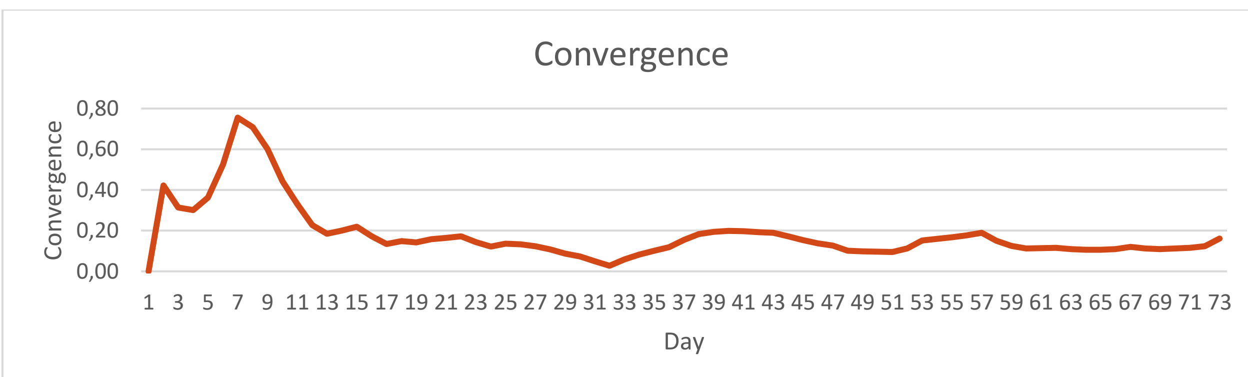
APPENDIX DISTRIBUTION FIT FIGURE 4 (GAMMA ALPHA = 1, BETA = 576) FOR PICKING OUT4 BATCHES

Appendix C: Determining Runlength with Robinson's method

	replication 1		replication 2		replication 3		
Day	lead time [sec]	cum mean	lead time [sec]	cum mean	lead time [sec]	cum mean	convergence
1	3568,74	3568,7	3118,96	3118,96	4434,5	4434,50	0,42
2	7227,4	5398,1	5094,44	4106,70	4084,19	4259,35	0,31
3	6132,81	5643,0	5914,96	4709,45	4485,45	4334,71	0,30
4	6180,14	5777,3	9353,39	5870,44	4238,05	4310,55	0,36
5	6127,61	5847,3	9912,17	6678,78	4658,68	4380,17	0,52
8	7441,74	6113,1	16772,78	8361,12	6677,65	4763,09	0,76
9	13139,15	7116,8	8999,4	8452,30	6061,82	4948,62	0,71
10	9218,03	7379,5	7549,53	8339,45	7011,37	5206,46	0,60
11	5691,3	7191,9	7036,7	8194,70	9472,52	5680,47	0,44
12	7168,48	7189,5	6883,68	8063,60	9462,94	6058,72	0,33
15	8584,84	7316,4	13063,36	8518,12	15721,78	6937,18	0,23
16	5601,63	7173,5	8243,07	8495,20	9893,71	7183,56	0,18
17	5580	7050,9	8040,93	8460,26	8268,4	7267,00	0,20
18	4524,35	6870,4	7286,04	8376,39	5829,7	7164,34	0,22
19	7151,97	6889,2	3905,35	8078,32	5022,21	7021,53	0,17
22	10798,52	7133,5	6052,67	7951,71	6872,71	7012,23	0,13
23	13484,34	7507,1	7719,4	7938,05	5353,49	6914,66	0,15
24	12697,41	7795,5	5954,41	7827,85	5744,12	6849,63	0,14
25	8075,02	7810,2	5803,37	7721,30	4844,33	6744,09	0,16
26	5900,83	7714,7	6173,41	7643,90	4292,03	6621,48	0,17
29	7354,44	7697,6	11339,87	7819,90	7749,6	6675,20	0,17
30	6552,61	7645,5	5324,3	7706,46	8102,82	6740,09	0,14
31	5855,22	7567,7	4618,09	7572,19	6988,06	6750,88	0,12
32	8052,48	7587,9	4679,99	7451,68	5094,55	6681,86	0,14
33	6247,31	7534,3	6299,93	7405,61	5890,58	6650,21	0,13
36	7340,17	7526,8	7571,25	7411,98	7904,15	6698,44	0,12
37	8039,13	7545,8	6501,64	7378,26	9654,42	6807,92	0,11
38	6668,42	7514,4	8889,41	7432,23	9559,45	6906,19	0,09
39	6710,05	7486,7	9057,58	7488,28	9074,46	6980,96	0,07
40	6572,93	7456,2	6014,37	7439,15	10690,87	7104,62	0,05
43	8426,24	7487,5	7732,6	7448,61	24232,32	7657,13	0,03
44	7496,04	7487,8	4895,35	7368,83	12434,75	7806,43	0,06
45	6900,09	7470,0	4748,75	7289,43	10477,65	7887,37	0,08

46	7365,4	7466,9	4435,07	7205,48	9683,77	7940,21	0,10
47	6047,39	7426,3	4576,9	7130,37	9239,39	7977,33	0,12
50	9073,36	7472,1	6623,98	7116,31	16815,61	8222,84	0,16
51	9556,22	7528,4	5124,96	7062,49	13129,29	8355,44	0,18
52	11062,59	7621,4	4969,68	7007,41	9059,5	8373,97	0,20
53	11678,4	7725,5	5710,29	6974,15	7783,65	8358,83	0,20
54	9350,72	7766,1	5917,66	6947,74	6929,66	8323,11	0,20
57	15308,81	7950,1	7986,14	6973,07	7960,05	8314,25	0,19
58	9997,19	7998,8	16135,4	7191,22	18222,55	8550,16	0,19
59	8103,49	8001,2	11377,57	7288,58	8372,66	8546,03	0,17
60	6726,15	7972,3	12599,83	7409,29	8451,46	8543,88	0,15
61	5084,81	7908,1	12510,91	7522,66	9031,35	8554,72	0,14
64	7907,43	7908,1	15791,08	7702,40	14408,13	8681,97	0,13
65	5667,1	7860,4	13601,39	7827,92	6147,52	8628,04	0,10
66	4888,46	7798,5	13711,21	7950,48	5726,68	8567,60	0,10
67	5527,03	7752,1	14120,28	8076,40	5074,64	8496,31	0,10
68	5153,69	7700,2	13666,6	8188,20	5551,15	8437,41	0,10
71	8446,62	7714,8	28019,51	8577,05	7243,45	8414,00	0,11
72	8098,79	7722,2	24836,59	8889,73	7589,7	8398,15	0,15
73	7505,12	7718,1	12186,09	8951,93	8209,33	8394,58	0,16
74	6879,37	7702,5	11007,37	8989,99	7085,27	8370,34	0,17
75	6217,15	7675,5	11524,44	9036,07	5494,59	8318,05	0,18
78	7463,29	7671,8	14001,41	9124,74	10132,29	8350,45	0,19
79	22032,79	7923,7	8206,94	9108,64	10507,66	8388,29	0,15
80	18096,48	8099,1	9239,62	9110,90	10299,43	8421,24	0,12
81	13386,39	8188,7	9406,36	9115,91	9696,68	8442,86	0,11
82	5385,86	8142,0	6515,14	9072,56	8565,84	8444,91	0,11
85	6576,27	8116,3	7778,86	9051,35	9417,96	8460,86	0,12
86	8442,07	8121,6	6095,46	9003,68	12006,25	8518,05	0,11
87	5381,13	8078,1	4961,46	8939,51	8892,25	8523,99	0,11
88	5164,87	8032,6	5349,62	8883,42	9425,48	8538,07	0,11
89	5017,7	7986,2	7299,6	8859,05	8878,89	8543,31	0,11
92	7716,88	7982,1	14310,32	8941,65	8552,32	8543,45	0,12
93	8157,74	7984,7	5152,62	8885,10	10876,43	8578,27	0,11
94	8597,13	7993,7	8057,69	8872,93	7794,66	8566,75	0,11
95	7382,79	7984,9	9471,88	8881,61	8797,42	8570,09	0,11
96	6612,34	7965,3	9362,2	8888,48	9744,23	8586,86	0,12
99	7705,34	7961,6	12974,82	8946,03	13908,52	8661,82	0,12
100	4594,3	7914,8	26965,35	9196,30	6391,91	8630,29	0,16

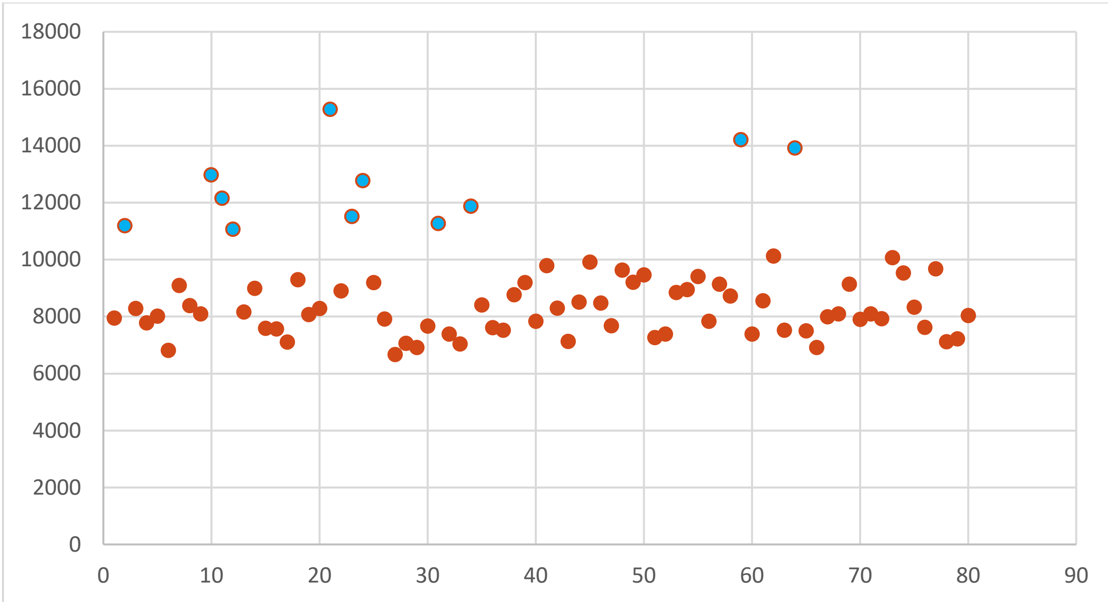

Run Length selection: cumulative means of lead time from 3 replications
Cumulative mean
10000,0
9000,0
8000,0
7000,0
6000,0
5000,0
4000,0
3000,0
2000,0
1000,0
0,0
1 4 9 12 17 22 25 30 33 38 43 46 51 54 59 64 67 72 75 80 85 88 93 96
Day


Convergence
Convergence
0,80
0,60
0,40
0,20
0,00
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51 53 55 57 59 61 63 65 67 69 71 73
Day

Appendix D: Replication / Deletion Approach

	Gamma	0,05	Gamma'	0,047619			
i		LT	X(n')	S^2(n')	T	Err	Test
1	Run1	7947,851					
2	Run2	8280,582	8114,217	235,2761	25,4517	0,521835	NOT OK
3	Run3	11182,3	9136,911	1779,155	6,205347	0,697621	NOT OK
4	Run4	7774,805	8796,385	1604,399	4,176535	0,380885	NOT OK
5	Run5	8017,003	8640,508	1432,501	3,495406	0,25916	NOT OK
6	Run6	6813,288	8335,972	1482,6	3,163381	0,229691	NOT OK
7	Run7	9091,369	8443,885	1383,21	2,968687	0,183807	NOT OK
8	Run8	8386,943	8436,768	1280,762	2,841244	0,152495	NOT OK
9	Run9	8090,746	8398,321	1203,582	2,751524	0,131442	NOT OK
10	Run10	12969,27	8855,415	1837,664	2,685011	0,176199	NOT OK
11	Run11	12153,69	9155,259	2007,056	2,633767	0,174088	NOT OK
12	Run12	11067,5	9314,612	1991,68	2,593093	0,16006	NOT OK
13	Run13	8166,3	9226,281	1933,302	2,560033	0,148781	NOT OK
14	Run14	8988,367	9209,287	1858,545	2,532638	0,136602	NOT OK
15	Run15	7594,831	9101,657	1838,811	2,509569	0,130909	NOT OK
16	Run16	7568,979	9005,864	1817,314	2,48988	0,12561	NOT OK
17	Run17	7103,444	8893,957	1819,096	2,472878	0,12267	NOT OK
18	Run18	9299,402	8916,482	1767,368	2,458051	0,114839	NOT OK
19	Run19	8075,898	8872,241	1728,364	2,445006	0,109271	NOT OK
20	Run20	8289,624	8843,11	1687,303	2,43344	0,103823	NOT OK
21	Run21	15275,9	9149,433	2162,211	2,423117	0,124959	NOT OK
22	Run22	8899,767	9138,085	2110,773	2,413845	0,118873	NOT OK
23	Run23	11513,79	9241,376	2120,905	2,405473	0,115112	NOT OK
24	Run24	12770,7	9388,431	2195,829	2,397875	0,114479	NOT OK
25	Run25	9196,903	9380,77	2149,938	2,390949	0,109594	NOT OK
26	Run26	7909,317	9324,176	2126,174	2,38461	0,10664	NOT OK
27	Run27	6668,697	9225,825	2146,606	2,378786	0,106517	NOT OK
28	Run28	7066,83	9148,718	2145,63	2,373417	0,105194	NOT OK
29	Run29	6916,79	9071,755	2147,344	2,368452	0,104106	NOT OK
30	Run30	7668,879	9024,992	2125,484	2,363846	0,101641	NOT OK
31	Run31	11262,03	9097,155	2128,033	2,359562	0,099134	NOT OK
32	Run32	7382,456	9043,571	2115,26	2,355568	0,097397	NOT OK
33	Run33	7036,595	8982,753	2111,057	2,351835	0,096214	NOT OK
34	Run34	11867,92	9067,611	2136,9	2,348338	0,09491	NOT OK
35	Run35	8403,656	9048,641	2108,23	2,345056	0,092354	NOT OK
36	Run36	7611,689	9008,725	2091,65	2,341969	0,090627	NOT OK
37	Run37	7521,448	8968,529	2076,838	2,339061	0,089048	NOT OK
38	Run38	8765,402	8963,183	2048,845	2,336316	0,086634	NOT OK

39	Run39	9193,039	8969,077	2022,042	2,333721	0,084248	NOT OK
40	Run40	7837,668	8940,792	2003,951	2,331264	0,082618	NOT OK
41	Run41	9789,12	8961,483	1983,173	2,328935	0,080491	NOT OK
42	Run42	8298,151	8945,689	1961,511	2,326723	0,078722	NOT OK
43	Run43	7132,967	8903,533	1957,635	2,32462	0,077945	NOT OK
44	Run44	8507,922	8894,542	1935,657	2,322618	0,0762	NOT OK
45	Run45	9917,918	8917,283	1919,606	2,320711	0,074472	NOT OK
46	Run46	8474,083	8907,649	1899,282	2,318891	0,0729	NOT OK
47	Run47	7684,63	8881,627	1886,976	2,317152	0,071809	NOT OK
48	Run48	9633,156	8897,284	1869,943	2,31549	0,070241	NOT OK
49	Run49	9206,645	8903,597	1850,889	2,313899	0,068717	NOT OK
50	Run50	9459,171	8914,709	1833,589	2,312375	0,067262	NOT OK
51	Run51	7261,839	8882,299	1829,857	2,310914	0,066664	NOT OK
52	Run52	7391,751	8853,635	1823,581	2,309512	0,065966	NOT OK
53	Run53	8849,041	8853,548	1805,962	2,308165	0,064673	NOT OK
54	Run54	8950,472	8855,343	1788,892	2,30687	0,063417	NOT OK
55	Run55	9403,997	8865,319	1773,794	2,305625	0,062204	NOT OK
56	Run56	7831,302	8846,854	1763,018	2,304426	0,061367	NOT OK
57	Run57	9134,967	8851,909	1747,622	2,303271	0,060231	NOT OK
58	Run58	8720,564	8849,644	1732,31	2,302158	0,059173	NOT OK
59	Run59	14212,65	8940,543	1853,82	2,301084	0,062117	NOT OK
60	Run60	7391,152	8914,72	1848,894	2,300047	0,061584	NOT OK
61	Run61	8552,072	8908,774	1834,01	2,299046	0,060599	NOT OK
62	Run62	10122,01	8928,343	1825,43	2,298078	0,059671	NOT OK
63	Run63	7520,84	8906,002	1819,311	2,297142	0,059121	NOT OK
64	Run64	13919,14	8984,332	1910,507	2,296237	0,061036	NOT OK
65	Run65	7504,369	8961,563	1904,39	2,29536	0,060502	NOT OK
66	Run66	6915,529	8930,563	1906,393	2,294512	0,060291	NOT OK
67	Run67	7995,857	8916,612	1895,339	2,293689	0,059564	NOT OK
68	Run68	8099,937	8904,602	1883,746	2,292891	0,058822	NOT OK
69	Run69	9138,374	8907,99	1870,056	2,292118	0,057928	NOT OK
70	Run70	7905,846	8893,674	1860,315	2,291367	0,057286	NOT OK
71	Run71	8091,769	8882,379	1849,43	2,290639	0,056603	NOT OK
72	Run72	7930,704	8869,161	1839,781	2,289931	0,055981	NOT OK
73	Run73	10066,65	8885,565	1832,328	2,289243	0,055252	NOT OK
74	Run74	9527,458	8894,24	1821,264	2,288575	0,054477	NOT OK
75	Run75	8335,772	8886,793	1810,065	2,287925	0,05381	NOT OK
76	Run76	7620,339	8870,13	1803,817	2,287292	0,053355	NOT OK
77	Run77	9672,226	8880,546	1794,241	2,286677	0,05265	NOT OK
78	Run78	7115,31	8857,915	1793,722	2,286078	0,052416	NOT OK
79	Run79	7218,491	8837,163	1791,707	2,285494	0,052134	NOT OK
80	Run80	8034,896	8827,135	1782,589	2,284926	0,051589	NOT OK


18000
16000
14000
12000
10000
8000
6000
4000
2000
0
0
10
20
30
40
50
60
70
80
90

Appendix E: Distributions for Day Order Quantity

	CHANNEL		AASP				
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Distribution	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal
Parameters	μ= 3345.5, σ= 475.1	μ= 5119.3, σ= 1055	μ= 5066.7, σ= 1159.3	μ= 4864.3, σ= 802.8	μ= 4702.5, σ= 655.3	μ= 1851.3, σ= 269	μ= 273.2, σ= 127.7
Chance Zero Orders						0,00	0,00

	CHANNEL		B2C				
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Distribution	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal	Uniform	Truncated Normal
Parameters	μ= 1198.1, σ= 140.1	μ= 964.2, σ= 95.6	μ= 947.0, σ= 111.24	μ= 928.9, σ= 126.2	μ= 839.4, σ= 106.5	min = 18, max = 63	μ= 297.0, σ= 75.5
Chance Zero Orders						0,00	0,08

	CHANNEL		RETAIL				
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Distribution	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal	Truncated Normal	Uniform	Truncated Normal
Parameters	μ= 358.1, σ= 77.7	μ= 394.6, σ= 91.6	μ= 382.6, σ= 90.0	μ= 380.6, σ= 77.3	μ= 383.1, σ= 77.2	Min = 1, Max = 18	μ= 228.1, σ= 29.7
Chance Zero Orders						0,38	0,15

	CHANNEL		STO				
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Distribution	Uniform	Uniform	Uniform	Uniform	Poisson	Uniform	Uniform
Parameters	min = 22, max = 125	min = 20, max = 53	min = 16, max = 42	min = 4, max = 45	μ= 14	min = 1, max = 1	min = 23, max = 45
Chance Zero Orders						0,92	0,65

	CHANNEL		TELCO				
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Distribution	Empirical	Truncated Normal	Empirical	Empirical	Empirical	Truncated Normal	Truncated Normal
Parameters		μ= 689.9, σ= 110.5				μ= 134.1, σ= 30.24	μ= 4.318, σ= 2.607
Chance Zero Orders						0,00	0,04

APPENDIX F: GAMMA DISTRIBUTIONS FOR PACK PROCESSING TIME

	OUT1		OUT2		OUT3		OUT4	
	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta
COL	0,65	2260,94	0,2	2721,96	0,04	1735,24	1,44	41,21
DOM	0,56	821,51	0,18	1109,59	0,05	1215,98	1,44	41,21
EHVTNT	3,57	445,27	4,62	32,76	0,04	1849,41	1,44	41,21
EHVUPS	0,92	848,58	1,11	221,61	0,2	281,31	1,44	41,21
KNAC	0,42	5352,49	0,14	6695,98	0,04	9125,82	1,44	41,21
LGG	1,55	924,08	0,63	868,89	0,41	403,67	1,44	41,21
OWNAC	1,96	935,21	1,3	402,05	0,18	1209,23	1,44	41,21
SAB	1,12	895,39	0,51	958,93	0,05	1356,4	1,44	41,21
SCHAC	0,96	6609,48	0,46	2369,59	12,41	23,28	1,44	41,21
SCHAIR	0,43	9477,47	0,1	6111,92	0,1	4473,11	1,44	41,21
SCHCORE	0,17	5847,86	0,52	412,25	0,24	860,04	1,44	41,21
TDI	0,41	1609,7	0,37	1132,63	0,02	2585,15	1,44	41,21
TDIWPX	1,4	1082,59	0,27	1695,97	0,07	825,79	1,44	41,21
TIL	2,46	47,32	1,77	49,79	0,08	906,47	1,44	41,21
WILAMS	0,36	6263,84	0,12	4521,81	0,32	1115,4	1,44	41,21

Appendix G: InterCompany Cut-Off Flexibility

Since Schenker had no clear insight in the cut-off requirements of orders coming from the channel InterCompany, we have conducted a data analysis. This analysis describes the number of working days an order from a carrier has. It should be interpreted as follows: KNAC and WILAMS orders always have at their cut-off date at least 3 days after their drop date.

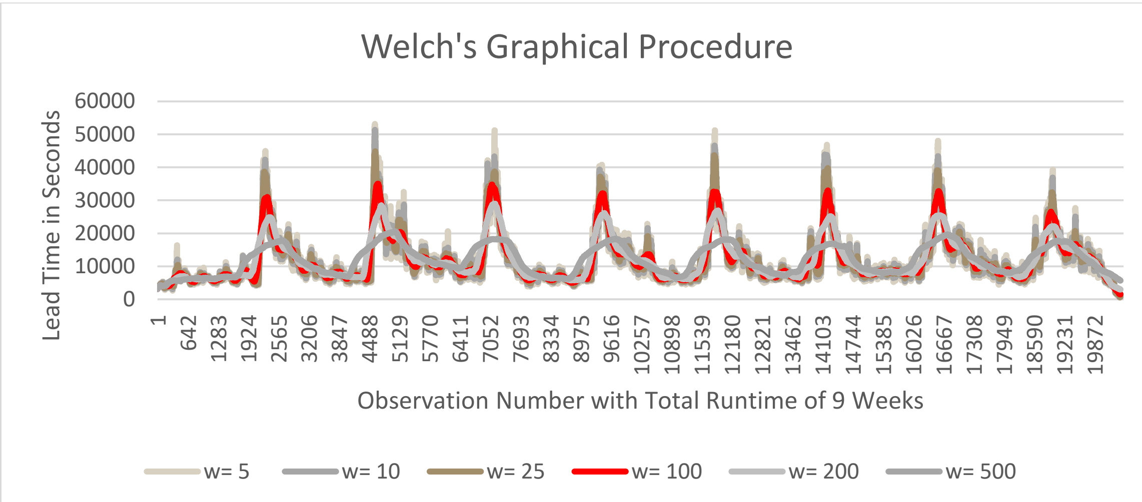
		Carriers						
		COL	KNAC	OWNAC	SAB	SCHAC	SCHAIR	WILAMS
Workdays before cut-off date	0	18%	0%	100%	20%	36%	33%	0%
	1	29%	0%	0%	13%	16%	54%	0%
	2	45%	0%	0%	60%	46%	11%	0%
	3	8%	43%	0%	6%	1%	2%	63%
	4	1%	45%	0%	1%	1%	0%	34%
	5	0%	9%	0%	0%	0%	0%	3%
	6	0%	1%	0%	0%	0%	0%	1%
	7	0%	0%	0%	0%	0%	0%	0%
	8	0%	0%	0%	0%	0%	0%	0%

Appendix H: Inserted Packer Priorities

	1st Priority	2nd Priority	3rd Priority	1st Priority	2nd Priority	3rd Priority
Packer1	DHL	picken		DHL	6	7
Packer2	DHL	picken		DHL	6	7
Packer3	DHL	picken		DHL	6	7
Packer4	DHL			DHL	6	7
Packer5	DHL			DHL	6	7
Packer6	STO	SAB/Crossdock	DHL	STO	SAB/Crossdock	DHL
Packer7	STO	SAB/Crossdock	DHL	STO	SAB/Crossdock	DHL
Packer8	TNT			TNT	6	7
Packer9	TNT	picking		TNT	6	7
Packer10	TNT			TNT	6	7
Packer11	SAB			SAB	6	7
Packer12	SAB			SAB	6	7
Packer13	SAB			SAB	6	7
Packer14	SAB			SAB	6	7
Packer15	OWNAC			OWNAC	6	7
Packer16	OWNAC			OWNAC	6	7
Packer17	OWNAC			OWNAC	6	7
Packer18	IMC	picking		IMC	6	7
Packer19	IMC			IMC	6	7
Packer20	IMC			IMC	6	7
Packer21	*n/a*	*n/a*	*n/a*	6	7	4
Packer22	*n/a*	*n/a*	*n/a*	6	7	4
Packer23	*n/a*	*n/a*	*n/a*	6	7	4
Packer24	*n/a*	*n/a*	*n/a*	6	7	4
Packer25	*n/a*	*n/a*	*n/a*	6	7	4
Packer26	*n/a*	*n/a*	*n/a*	6	7	4
Packer27	*n/a*	*n/a*	*n/a*	6	7	4
Packer28	*n/a*	*n/a*	*n/a*	6	7	4
Packer29	*n/a*	*n/a*	*n/a*	6	7	4
Packer30	*n/a*	*n/a*	*n/a*	6	7	4
Packer31	*n/a*	*n/a*	*n/a*	6	7	4
Packer32	*n/a*	*n/a*	*n/a*	6	7	4
Packer33	*n/a*	*n/a*	*n/a*	6	7	4
Packer34	*n/a*	*n/a*	*n/a*	6	7	4
Packer35	*n/a*	*n/a*	*n/a*	6	7	4

Appendix I: Welch's Approach for Determining Warm-Up Period

The batch lead time was taken as a measure to perform the analysis on, since it is a good indicator of the warm-up period. The result is presented in Figure 27.



We verify that the first Monday, lead time stays rather low, whereas at the second Monday (around observation 2565) we see that the lead time is rather high. In the second Monday, orders that dropped in the previous Friday late afternoon, Saturday or Sunday are included. It thus makes sense that there is a longer lead time on Monday since the later orders are often already picked in the weekend shift. Similarly, late orders on Mondays have a shifted due date to Tuesday, which is often also their handling day. In conclusion, we take 1 day as warm-up which in our case will be a Monday.

Appendix J: Comparing Exponential Smoothing to Current Forecast

ACTUAL Total	FORECAST Total	Absolulte Error Curr. Forecast	FORECAST Exp. Smoothing	initialization and abs error exp smoothing	
186553	150009,051			**93514,68815**	**Alpha**
145740	159946,03		152062,2077	39879,79228	0,15490671
191942	157759,559		184785	3,71589E-06	
184785	147047,394		185893,6674	6912,667353	
178981	147514,841		179880,0786	278,9214315	
180159	148304,197		179976,5199	5479,519891	
174497	199553,123		175374,0818	13147,08182	
162227	193522,225		164127,7054	27816,70538	
136311	176561,062	40250	140325,5624	3643	
143969	170780	26811	142782,7244	814	
141969	146548	4579	142278,8134	5085	
147364	144318	3046	146528,2783	18199	
128329	141184	12855	131277,6493	9624	
121654	138703	17049	122688,0023	20587	
143275	128980	14295	139925,7619	12308	
127618	123178	4440	130043,3744	5881	
124162	116827,2	7335	124697,3576	10265	
134962	128590,35	6372	133289,0075	7366	
125923	110609,59	15313	127323,2018	17620	
144943	126159	18784	141996,6743	10331	
152328	112541,4	39787	151184,0139	14210	
165394	135126	30268	163369,9889	17648	
145722	139687	6035	148769,3249	7466	
156235	143155	13080	154606,4657	2081	
156687	140141	16546	156616,9822	1282	
155335	140587	14748	155544,4339	15338	
170882	142237	28645	168473,6653	22432	
146042	154936	8894	149889,8828	10474	
139416	155752	16336	140442,4119	7272	
147714	155953	8239	146428,5841	492	
146921	156402	9481	147043,841	14441	
161485	156373	5112	159228,9386	10032	
169261	152415	16846	168056,4454	5238	
162818	152666	10152	163816,064	22971	
140845	152741	11896	144248,7652	23322	
167571	152404		163430,9632		
	Total error	**407193,5219**	**Total error**	**296421,4332**	

Appendix K: User Guide

In this appendix we discuss how a user can run experiments in the provided simulation.

Simulation logic

Simulation logic is stored in process flow: “Global Process Flow” which can be accessed by clicking “Process Flow” in the upper menu > : “Global Process Flow”. Here changes can be made to the model’s logic and input variable processing time: “D01/D02/D03/D04 pickspeed” and “Assign Labels: Set Pack Time”.

Running Experiments

For all experimental variables we have made shortcuts in the folder “— CONTROLS –”. The Tables in this folder “WorkerSettings” and “Shift Times” allow the user to play with resource levels and shift starts. After changing these tables an experiment can be run using the “Experimenter”.