MASTER

Development of a decision support tool for short-term labour capacity planning at CEVA Eindhoven (Sandvik-Outbound)

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Development of a decision support tool for short-term labour capacity planning at CEVA Eindhoven (Sandvik – Outbound)

By

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Abstract
This report presents a labour capacity setting method for a single process, make-to-order system with a fixed set of multiple due dates in the planning horizon. The method is developed as a decision support tool to match available capacity with required capacity when the amount of required capacity per due date is highly uncertain. The values of three parameters are free to choose by the user of the method. In a case study the impact of several parameter values are compared with respect to the trade-off between overcapacity and undercapacity. The results can help the users of the method to make efficient use of their capacity. The case study results revealed that CEVA could reduce the costs for undercapacity and overcapacity together with at least 8%.
Preface

This report is conducted as the final thesis of the master Operations Management & Logistics, under supervision of the Department Industrial Engineering & Innovation Sciences at the Eindhoven University of Technology. The project was executed at the Sandvik – Outbound department of CEVA Logistics located at Eindhoven from September 2014 to May 2015. In performing the project I had to take help and guidance of a number of people who deserve my gratitude.

I would like to thank my university supervisor Henny van Ooijen for the many feedback sessions we had. During a project like this it is pleasant to have someone available who takes the time to completely understand the problem. Also a word of thanks goes to my second supervisor Rob Broekmeulen for his attention to errors and flaws. His critical feedback and advice during the project really improved the level of the thesis.

I would like to thank my both supervisors from CEVA. I would like to thank Annelies Verheijen and Gertjan Stout for their time, guidance and support during the project. The discussions we had were very useful to get experienced with the practical relevance of the research problem. Next to this, I really appreciate the extra time they gave me to make the project a success in both theoretical and practical perspective. I also want to acknowledge the effort and time from all other people from CEVA who directly or indirectly helped me during the project.

I would like to express my special appreciation and thanks to my parents. I am very grateful for the opportunities and support they gave me during my years of college. Finally, thanks to my brother and friends for the enjoyable time I had during college.

Joep Janssen,
Eindhoven, the Netherlands
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Management summary
This report concerns the labour capacity planning process in the warehouse of CEVA Eindhoven. CEVA Eindhoven provides warehouse services for their main customer Sandvik and several smaller customers. This study only takes into account activities concerned with the outbound logistics of the customer Sandvik. Sandvik uses the warehouse of CEVA Eindhoven as a global consolidation hub for their spare parts.

Problem introduction
The research is initiated because CEVA faces difficulties in their operational, short-term labour capacity planning process. Labour capacity planning is defined as the determination of the right capacity levels at the right time. The planners of CEVA currently have a lack of support in the process of short-term labour capacity planning. This causes that planners make inefficient and inconsistent decisions. As an effect this results in poor KPI performance and poor employee utilization. A poor KPI performance generally results in penalty costs; additionally, capacity is generally expensive and should therefore be utilized efficiently. Cutting these costs by having a proper capacity planning method could therefore be very beneficial (Van den Bergh, Beliën, De Bruecker, Demeulemeester & De Boeck, 2013).

Apparently, CEVA does not have a robust method for their process of short-term capacity planning. The work environment CEVA operates in is known as a make-to-order (MTO) environment; this means that orders cannot be processed in advance. Next to this, there are several fixed due dates in the planning horizon. The capacity that is required for each due date is highly uncertain. Consequently it is hard to determine the right amount of available capacity levels to satisfy the required capacity. The available literature revealed that short-term capacity planning for logistic providers is still limited. Available research showed that there is room for research in short-term capacity problems in a make-to-order environment with highly uncertain required capacity for multiple due dates in the planning horizon. This project mainly focused on providing insights in the problem of matching the available capacity with the required capacity. The research assignment is defined as:

“Develop a decision support tool which provides insights for a short-term labour capacity planning problem in a make-to-order environment with multiple due dates in the planning horizon.”

Research approach
In order to fulfil the research assignment. The research is divided into three phases:

- Analysis phase
- Development phase
- Case study phase

In the analysis phase, an extensive data analysis is conducted to get a deeper understanding of the uncertainty characteristics of required capacity. Unstructured interviews also gave us the opportunity to figure out all constraints and possibilities in the short-term capacity planning problem. The conclusions made during the analysis phase are:

- There is a lack of information available in supporting the decisions during the capacity planning process; therefore, current capacity plan decisions are not made consistently.
- Total required capacity per day is uncertain which makes the determination of the total size of planned capacity challenging.
- The amount of required capacity across the due dates is uncertain which makes the timing of planned capacity throughout the day challenging.
- The percentages of required capacity per day across the competencies are reasonably constant which makes the amount of available capacity per competency less challenging.
The rate of forwarded order lines throughout the day is uncertain which makes the timing of planned capacity throughout the day challenging. A challenging part of the capacity planning problem is the size of total available capacity. Apparently, the most challenging part of the capacity planning problem is the timing of available capacity throughout the planning horizon.

In the development phase, the conceptual design discusses and defines the structure, constraints and objectives of the method we developed. Thereafter, the detailed design is constructed in such a way it is applicable in other industries with equal characteristics. The method in this report is developed as a decision support tool for a situation where the number of employees for each shift in a given day should be determined. One single cost-optimization model turned out to be computationally impractical in terms of decision support due to the many uncertainties of required capacity. Therefore, an alternative method was developed which decomposed the problem in three distinct subproblems:

- The first subproblem considers a target level for total available capacity.
- The second subproblem considers multiple target levels of available capacity throughout the planning horizon.
- The third subproblem considers a capacity plan which most closely satisfies the target levels from subproblem 1 and subproblem 2.

The developed method left three parameters open for determination. These are the control knobs of the method. The first parameter, $a$, affects the target level of total available capacity in subproblem 1. In other words, it affects the total safety margin that is used for the capacity plans. The second parameter, $cc$, affects the target levels of available capacity throughout the planning horizon in subproblem 2. In other words, it affects the way how available capacity is spread during the day. There could be a focus on having relatively more capacity available early or late in the planning horizon, or there could be a focus on spreading the available capacity more equally throughout the planning horizon. The third parameter, $\beta$, is a risk parameter which also affects the target levels of available capacity throughout the planning horizon. Because each work environment is different from each other, each work environment requires its own ‘best’ set of parameter values. In order to consciously choose the values for these parameters a case study is conducted applied to CEVA.

The case study phase examines and discusses how the developed method can be applied in practice for CEVA. Moreover, in total 36 scenarios of capacity planning were compared to a reference scenario. We defined a scenario as a combination of values for the three parameters which a user of the method is free to choose the values for. We evaluated the following averages values for each scenario denoted by:

- The average size of overcapacity in one planning horizon.
- The average size of undercapacity in one planning horizon.

These two averages makes it able to visualize the controversial trade-off existent in the capacity planning problem. At a high level the relevant trade-off exists between the KPI performance and employee utilization. Capacity is generally expensive and should therefore be utilized efficiently; overcapacity should therefore be minimized. A poor KPI performance generally result in penalty costs in the short term; moreover, it could harm the relationship with the customers in the long term. Undercapacity should therefore also be minimized. From a practical point of view, the results of each scenario affect the trade-off of corrective actions that has to be made to correct for unanticipated disruptions. Upscaling available capacity should be done to correct for undercapacity, while downscaling available capacity should be done to correct for overcapacity. Considering multiple scenarios helped us exploring the parameter settings, it gained insights into the consequences and visualized the risks in the planning process. Anticipating several parameter settings helps CEVA to adapt and implement a capacity plan that most closely resembles their needs.
Results

For CEVA, the developed method is implemented as a decision support tool in MS Excel. The practical usefulness of the developed decisions support tool lies in the consistent way in which the planners are now able to make a capacity plan; instead of making capacity decisions on an intuitive sense. The managers of CEVA have the possibility to adjust three parameters in this tool ($\alpha, \gamma$, & $\beta$). The results from the case study gained useful insights in the consequences and risks for the different parameter values. This makes it able to consciously change parameters in the decision support tool in order to choose a position between the trade-off between overcapacity and undercapacity. Apparently, CEVA currently runs the risk of ignoring significant cost savings to base its capacity decisions on an intuitive sense. This is quantified by the results of the case study performed in this research. The best balanced scenario from our case study (scenario 30), when counting with equal weights in the trade-off, makes it able to reduce the average size of overcapacity from 36,80 to 9,09 man-hours; however, this also means that the average size of undercapacity increases from 2,48 to 8,80 man-hours. It has to be mentioned that this scenario requires another flexibility from CEVA. Moreover, managers should not ignore qualitative factors such as practical usefulness. For example, changing the abilities of upscaling could generally not be achieved in the short-run and therefore requires long-term strategic capacity decisions. The practical usefulness of a scenario therefore partially depends on the results for undercapacity. However, without significantly increasing the average size of undercapacity, from 2,48 to 3,17, the average size of overcapacity could be reduced from 36,80 to 26,80. Depending on CEVA’s cost ratio between overcapacity and undercapacity this could cause an expected **minimum cost saving of 8%** and an expected **maximum cost saving of 31%** without having to significantly change the abilities of upscaling.

This research contributes to current literature by proposing a decomposition method to produce capacity plans which takes into account three aspects of uncertainty; uncertainty of total required capacity, uncertainty of required capacity at several fixed time points in the planning horizon, and uncertainty of useful capacity levels at different time points in the planning horizon.
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1. Introduction

This report concerns the labour capacity planning process in the warehouse of CEVA Eindhoven. Capacity planning can be defined as the determination of the right number of capacity levels at the right time (Thompson & Goodale, 2006). This research is initiated because CEVA faces difficulties in their short-term labour capacity planning process. CEVA Eindhoven just signed a new contract with their largest customer Sandvik which drives CEVA to cut their costs and simultaneously improve their service. In many warehousing environments labour costs are one of the major direct costs; cutting these costs by having a proper planning method could therefore be very beneficial (Van den Bergh, Beliën, De Bruecker, Demeulemeester & De Boeck, 2013). CEVA is looking for new insights in how they could cut their costs and improve their supply chain performance in the field of labour capacity planning. Therefore, the major concern of this research is analyzing the current capacity planning method and presenting insights in how this method could be improved. This first chapter aims to introduce the reader. Section 1.1 describes the company in scope. Then, the problem is introduced in section 1.2 and the problem context is discussed in section 1.3. The introductory chapter ends with the remainder structure of this report.

1.1. CEVA Logistics

CEVA Logistics is a third-party logistics provider (3LP) with an end-to-end service portfolio. In August 2007 the company was formed as a result of a merger between TNT logistics and EGL Eagle Global Logistics. Nowadays CEVA employs more than 44,000 people in facilities operating in more than 170 countries. The services offered by CEVA are found in manufacturing support, inbound logistics, warehousing, distribution centers, outbound logistics, aftermarket services and final mile solutions. Services are provided for clients in the sectors of automotive, technology, retail, industrial, energy, aerospace and healthcare (www.cevalogistics.com).

CEVA Eindhoven is the site considered in this study. CEVA Eindhoven provides warehouse services for their main client Sandvik and several smaller clients. The processes executed in the warehouse differ from client to client and are managed independently from each other. The client Sandvik takes more than 70% of all space, activities and budget at CEVA Eindhoven. The warehouse activities for Sandvik are split into an inbound department and an outbound department. This study only takes into account activities concerned with the outbound department of Sandvik. The processes for the outbound department of Sandvik encompass differences from the other departments present in Eindhoven. The outbound department of Sandvik is selected because this department is larger; therefore, an improvement in capacity planning decisions for processes related to the outbound department of Sandvik will result in the largest gains. The process flow concerned with the outbound logistics of Sandvik could be summarized in three main processes which are carried out consecutively for each order: picking, packing and marshalling.

The company Sandvik is active in the mining and construction area. The warehouse of CEVA Eindhoven is used as a global consolidation hub for spare parts of Sandvik; seven other consolidation hubs of Sandvik are located in Singapore, Australia, South Africa and the USA. The spare parts service provided by Sandvik to their customers falls in the area of after sale services. The more than 60,000 different spare parts in stock vary in a wide range of volume and weight; parts can vary from a 5 grams screw of 6 centimeters to a 20 meters long tube or to a 10,000 kilograms iron part of, for example, an excavator. Sandvik stores these parts at CEVA’s warehouse in Eindhoven. The process flow for the outbound logistics at CEVA starts when Sandvik forwards an order to CEVA. Orders of Sandvik could be forwarded directly from the other consolidation hubs, known as replenishment orders, or could be forwarded directly from the customers of Sandvik, known as customer orders.
1.2. Problem introduction

Sandvik forwards their orders throughout the day and these should usually be processed the same day. The orders forwarded by Sandvik fluctuate in many characteristics. One can think of characteristics such as the number of forwarded orders, the time at which an order is forwarded and the required workload per order. Basically, each order is a collection of multiple spare parts that should be collected in the picking process. Thereafter, all picked items should be packed together. Subsequently, the order should be marshalled, at this moment the order is ready to ship. The work environment CEVA operates in is known as a make-to-order (MTO) environment; this means that CEVA cannot process orders in advance. The capacity that is required to process the orders needs to be planned in advance, while orders are forwarded during the same day as it should be processed. As a consequence, CEVA faces difficulties in matching the available capacity with the required capacity in such a way that they are able to cope with current levels of fluctuations. The fluctuations cause situations of undercapacity and overcapacity. Undercapacity harms the service level agreed between Sandvik and CEVA; overcapacity harms the employee utilization performance. Both situations lead to extra costs. In order to reduce these costs and improve supply chain performance, CEVA looks for a way in which the decisions taken in labour capacity planning could be improved.

1.3. Problem context

This section encompasses the description of the processes related to CEVA’s outbound logistics. As mentioned in section 1.1, operational processes executed in the warehouse are split into three main processes: picking, packing and marshalling, see Figure 1 which shows and delineates the processes in scope of this project. Orders forwarded by Sandvik (i.e. orders entering the system) always require these three main processes. Picking is the process of retrieving items from stock and deliver them to a packing station. Picking is split into three different competencies: picking shelving, picking HOPT and picking reach. The picking competency an item requires depends on its weight, volume and quantity. Packing is the process of checking, wrapping and confirming the picked items of one order. Packing is split into two different competencies: packing plywood and packing parcel. The packing competency an order requires depends on the weight and volume of the order. Marshalling is the process of moving a packed order to the right location on dock such that the order is ready for shipment. Appendix A presents a map of the warehouse indicating the physical execution area of each process and competency within the warehouse.

Each order includes one or multiple order lines. An order line includes one or multiple quantities of one specific stock keeping unit (SKU). Each order line requires one of the three picking competencies, one of the two packing competencies and the marshalling competency. The structure between order, order line and SKU is graphically presented in Appendix B.

![Figure 1: The process flow of CEVA](image)

Each order forwarded by Sandvik belongs to a specific due date group (DD group). The DD group an order belongs to mostly depends on its destination, but also on its priority, order type and carrier. At this moment there exist too many exceptions to present a clear view for the set of rules which determines the DD group an order belongs to. The DD groups mainly exist because the orders
will be shipped globally, this means that CEVA needs to take into account the time zone for the destination of an order. A DD group is characterized by its own combination of pick by time, pack by time, marshal by time and cut-off time; see Appendix C for the exact times per group. According to the service level agreement (SLA) with Sandvik, each order should be marshalled before its marshal by time. Consequently, in order to meet this requirement, each order should completely be picked before its pick by time and should be packed before its pack by time. The cut-off time is the last possible point of time on a day until an order could be forwarded by Sandvik such that it will have a marshal by time at the same day it is forwarded. Logically, when an order is forwarded after its cut-off time it will have a marshal by time on a date later than its forwarded date. For more detail, Appendix D provides an example order to explain how an order should be processed to meet the SLA.

The service level agreement between CEVA and Sandvik is based on a key performance indicator (KPI). This KPI is measured for the stock-to-dock time performance and is literally defined as follows: “The percentage of outbound order lines that has to be available for shipment before the marshal by date/time according to the agreed cut-off time.” This is calculated by dividing the total number of order lines that are marshalled before its marshal by time by the number of order lines that should be marshalled before its marshal by time in the reporting period. An order can only be in time when it is picked before its pick by time, packed before its pack by time and marshalled before its marshal by time; otherwise the order is not in time. The KPI target both Sandvik and CEVA agreed on was 98% and is raised to 98.5% in the new contract.

On average, 485 orders are received per day with on average 6,5 order lines per order, which makes it on average 3.150 order lines per day and 15.750 lines per week. CEVA currently has a labour pool with 89 employees to process its demand; 35 permanent employees and 54 contingent employees. Permanent employees have a fixed contract at CEVA and contingent employees are hired from an external labour supply agency (ELSA). Working days are from Mondays to Fridays which all start at 06:00 and end at 24:00. Employees are usually planned to work a morning shift (from 06:00 to 15:00), a day shift (from 10:00 to 19:00) or an evening shift (from 15:00 to 24:00).

1.4. Report structure
The structure of this report is as follows: Chapter 2 describes the problem of CEVA’s short-term capacity planning. A literature review elaborates the problem and presents future research directions by discussing the gaps in literature regarding this subject. A research assignment and research design complete chapter 2. Then, the problem is analyzed extensively in chapter 3 and a new method is developed according to the analysis in chapter 4. Subsequently, chapter 5 performs a case study in which simulation is used to compare the performance of several planning scenarios. The results of the simulation analysis are presented and discussed in chapter 5 as well. In chapter 6 a description is given on how the method, implemented in MS Excel, should be used. The report finalizes in chapter 7 in which the conclusions, limitations and further research directions are described.
2. Problem definition and research assignment

This chapter first focuses on understanding the problem and problem context; then the aim of this report is described in a research assignment. Section 2.1 discusses the issues for short-term capacity planning at CEVA. The literature about the subjects from Section 2.1 is explored and interesting gaps in the literature are presented in section 2.2. Subsequently, the research assignment of this report is outlined in section 2.3 and the research design is presented in section 2.4.

2.1. Short-term capacity planning

Literature uses different synonyms and definitions for capacity planning. Capacity planning decisions can be taken at three levels: strategic, tactical and operational. Strategic planning is supposed to deal with the long term (several years); assets and human resources are the object of decisions (Martínez-Costa, Mas-Machuca, Benedito & Corominas, 2014; Huang, Lee, Song & Eck, 2009). Tactical planning, which is related to medium term decisions (monthly, quarterly, yearly), is concerned with the size of the staff; usually, production management and assets are given (Martínez-Costa et al., 2014; Huang et al., 2009). Operational planning deals with last-minute adjustments and short term decisions in order to assign workers to cover demand. Depending on the planning horizon, decisions are made in days or weeks (Martínez-Costa et al., 2014; Huang et al., 2009). Due to the fluctuating demand from day to day CEVA faces difficulties in matching the available capacity with the required capacity on a daily basis. Therefore, this study is concerned with operational capacity planning, i.e. short-term capacity planning.

The remainder of this section is structured as follows: Section 2.1.1 presents how CEVA describes their problem on short-term capacity planning. In section 2.1.2 the environment characteristics of the situation in scope are outlined.

2.1.1. Problem statement by CEVA

CEVA, the initiator of this research, indicates having problems in their process of short-term capacity planning due to uncertainties. First of all, the only thing a short-term capacity plan is currently based on is one aggregated forecast value; which is remarkable given the complexity of the processes a planning should be made for. CEVA indicates that the lack of support in the process of short-term capacity planning causes that available capacity does not match required capacity, both in quantity and timing. This causes significant reductions in both KPI performance and employee utilization. At this point of the research data for the five most recent months, from April to August 2014, is made available by CEVA to quantify these issues. The figures for the forecast performance, the safety margin, the KPI performance and employee utilization performance are presented and discussed in this section respectively:

2.1.1.1. Forecast error

CEVA forecasts the total forwarded order lines for each day. The performance of a forecast is calculated with a forecast error. CEVA determines for each day the forecast error (FE) by calculating: \( FE = \frac{d_n - FC_n}{FC_n} \) where \( d_n \) is the realization of forwarded order lines at day \( n \) and \( FC_n \) is the forecast for day \( n \). Figure 2 shows the forecast error for the days from April to August 2014. The forecast error reflects a volatile pattern and the figures show that the forecast error fluctuated between -42% and 42%. From these figures we can infer that a perfect match between available capacity and required capacity for each day is infeasible.

We have to mention that the forecast (FC) determines a range with a minimum and maximum number of order lines CEVA should be able to process each day. For each day, the minimum of this range is equal to \( FC * 0.85 \) and the maximum is equal to \( FC * 1.15 \). All costs accounted to the fact that the total forwarded order lines in a day are outside this range can be charged to Sandvik.
2.1.1.2. Safety margin

To cope with the volatile forecast errors, planners of CEVA state that they add a certain safety margin to the total size of planned capacity. Apparently, the safety margin is determined on an intuitive sense for each capacity plan individually. A fleeting glance at capacity plans from historical data let us know that the safety margin is not applied consistently. For example, ten days were found in which the total number of order lines was forecasted between 3700 and 3800; this data is shown in Appendix E. For those ten days, the total planned capacity ranged between 376 and 514 man-hours. From this we can infer that the safety margin is not applied consistently. Actually, this is not surprisingly since there are no safety margin guidelines offered to the planners of CEVA.

2.1.1.3. KPI performance

In Figure 3 it can be seen that the KPI target is not met from April to August 2014. CEVA indicates that the major part of all order lines not finished in time are caused by planning and forecast issues. To quantify this they presented a detailed KPI report in which reason codes are presented for the order lines which were not finished in time. A reason code can be CEVA uncontrollable and CEVA controllable. As the name suggests, order lines not finished in time with a CEVA uncontrollable reason code are caused beyond the control of CEVA, for example caused by Sandvik or an external carrier. Order lines not finished in time with a CEVA controllable reason code are caused by CEVA itself. When calculating CEVA's KPI performance, only order lines not finished in time which are CEVA controllable are taken into account. A concise version of the detailed KPI report is presented in Appendix F and shows that each month around 45% of all order lines not finished in time are allocated to reason code 3.4. This code refers to order lines that are not in time due to planning and forecast issues. The daily KPI figures for the month August 2014 are shown in Appendix F and are shown to give a detailed view on the KPI performance. Remarkably, almost every day order lines are not on time due to reason code 3.4. These figures let us suggest that planning and forecast issues substantially cause a lower KPI performance.
2.1.1.4. Employee utilization

Employee utilization represents how the installed labour capacity is being utilized. Employee utilization is quantified by CEVA by calculating a productivity value. CEVA calculates productivity by dividing the total number of finished order lines by the total number of man-hours installed for finishing these order lines. A lower productivity means that relatively more capacity is installed to finish the order lines. Figure 4 shows the overall productivity values from April to August 2014. The figure shows that the target productivity level is only met in May; and thus, for the other months, relatively more capacity is installed then targeted. Figure 5 shows for August 2014 the daily productivities for the processes picking, packing, marshalling and an overall outbound productivity value. These figures show that productivity targets are not met in most of the days. CEVA indicates that the main cause of lower productivities is caused by a mismatch between available capacity and required capacity. This is verified in the literature, according to research employees spend up to 36% of their working time unproductively caused by a lack of planning and control (Günther and Nissen, 2010). Due to excess available capacity employees are ‘waiting’ for forwarded orders to process; when employees are waiting for work it means that productivity will decrease. Instead, higher productivities are reached when the available capacity is insufficient because in this case employees are not waiting for work. Another statement that one could make is that the target productivities are set to high. However, the fact that the target productivities are met in several occasions means that the target values are not unattainable.

![Graphs showing productivity values](image)

Figure 5 Daily productivity performance for August 2014.

2.1.1.5. Problem enumeration

This section enumerates CEVA’s problems on short-term capacity planning:

- The only value a short-term capacity plan is currently based on is one aggregated value for the forecaster number of forwarded order lines.
- From the volatile pattern of the forecast error we can infer that a perfect match between the total available capacity and the total required capacity for each day is infeasible.
- A safety margin is applied to cope with forecast errors; however there is no consistency of applying the safety margin.
- The KPI performance is under target; the figures show that when orders are not finished in time this is mainly caused by planning and forecast issues.
- The performance of employee utilization is under target.
2.1.2. Environment characteristics
The environmental characteristics considered in this report are outlined in this section. These characteristics are:

- In each week, demand for each day of the following week is forecasted.
  - There is no difference in available information between making this forecast either 3 day or 7 days in advance
- Make-to-order (MTO) environment.
- Demand is split into multiple, so called, DD groups. All groups having their own cut-off time, pick by time, pack by time, marshal by time, see section 1.3 for explanation.
- Sandvik forwards their orders to CEVA throughout the day. An order could be forwarded at any point in time, there is no one fixed time point at which orders are forwarded.
- Orders forwarded before their cut-off time should be processed the same day and are taken into account for the KPI calculations.
- Orders forwarded after their cut-off time may, but not need to, be processed the same day and are not taken into account for the KPI calculations.
- Each order line requires one of the three picking competencies, one of the two packing competencies and the marshalling competency, in this sequence respectively.
- The required capacity is uncertain:
  - The quantity of forwarded order lines per DD group per day is uncertain.
  - The point in time at which order lines are forwarded by Sandvik is uncertain.
  - The required workload of an order line is uncertain.
  - The competencies each order line requires are uncertain.
- For each individual day employees are planned to work during one shift of a predefined set of shifts. The shift for which an employee should work could differ from day to day.

2.2. Literature review
The literature review discusses existent research related to the subjects in scope of section 2.1. This section makes use of what has been presented in the literature review (Janssen, 2014) executed as preparation for this project. The purpose of this literature study is to delineate the research area of the thesis project and to identify new lines of inquiry. This section contains four subsections which discuss the business environment, capacity planning and forecasting respectively. The last subsection suggests future research directions related to the focus of this project.

2.2.1. Business environment
The master thesis project is executed at a warehouse handling spare parts for the mining industry, therefore literature about mining and spare parts is discussed first to have a clear view of the business environment. In each operational process of mining equipment is being exposed to the possibility of failures and/or breakdowns. For mining operations, downtime of equipment can be extremely expensive due to penalties, lower availability, and increased operational risks (Louit, Pascual, Banjevic & Jardine, 2011). Also standpoints of safety, quality, health, and environment can be compromised when equipment is down (Kumral, 2005). In cases when parts cannot be repaired immediately, spare parts need to be used to minimize the downtime of equipment. Therefore, reliable and fast availability of spare parts is a necessity in industries such as mining.

Usually, spare parts are not sold to a customer such as an intermediate or final product (Kennedy, Patterson & Fredendall, 2002) but are used as high quality after-service in order to respond to high competitive markets (Kutanoglu & Lohiya, 2008; Frazzon, Israel, Albrecht, Pereira & Hellingrath, 2014). As a result, spare parts supply chain operations need to reach high fulfillment rates and reliability (Cohen, Agrawal & Agrawal, 2006). A spare parts supply chain is characterized by its intermittent demand and high service levels (Frazzon et al., 2014), therefore it differs from other materials supply chains. According to the literature, spare parts supply chains are characterized by the following aspects in general:
The number of identical spare parts is large.
Demand is highly variable.
Spare parts inventory is expensive.
The costs of being out of a spare part are relatively high.
Spare parts demand is triggered by maintenance policies.
The risk of obsolescence inventory of spare parts is high.

2.2.2. Capacity planning
A good capacity planning is important because unused capacity is generally expensive. According to research, employees spend up to 36% of their working time unproductively caused by a lack of planning and controlling (Günther and Nissen, 2010). Literature uses different synonyms for capacity planning; workforce planning, personnel scheduling, shift scheduling, workforce scheduling and workforce planning are used interchangeable. Several definitions are given in literature. In the review of Ernst, Jiang, Krishnamoorthy and Sier (2004) workforce planning is defined by the determination of the staff levels required by an organization wishing to achieve its goals. Differences in the definitions are usually found in the level in which decisions are made; capacity planning is done in three levels; operational, tactical and strategic. The scheduling review by Aytug, Lawley, McKay, Mohan and Uzsoy (2005) presents a number of purposes which can be applied to all three decision levels of capacity planning: it provides the possibility of a capacity check, it provides visibility for future plans, it provides degrees of freedom for reactive scheduling, it enables to evaluate performance, and it should avoid future problems. According to Thompson (1995), a proper scheduling model contains the following four phases: (1) forecast demand, (2) translate forecast of demand into requirements for capacity, (3) develop best capacity schedule that satisfy the requirements, and (4) control the real-time execution.

Capacity planning is applied in different industries, according to the literature reviews by Ernst et al. (2004) and Van den Bergh, De Bruecker, Demeulemeester and De Boeck (2013), popular application areas for scheduling problems are for example service providers like hospitality/nursing, transportation industries like railway, airline and bus companies, call centers, and also retail and manufacturing industries. All of them have characteristics in common; but more importantly, each of them has their own characteristics specific to their field. Different application areas require different approaches because each situation has different characteristics that could be critical. Literature on capacity planning problems in logistics, and especially for logistics providers, is still very limited. The industries whose capacity planning problem is the closest to logistics providers are found in industries such as call centers and hospitality/nursing.

In the papers from Lagodimos and Leopoulos (2000), Lagodimos and Mhiiotis (2006) and Lagodimos and Mhiiotis (2010) the production load per machine in a given time period is determined by a master production schedule. They do not take into account uncertainty of demand and an important assumption in these papers is that manpower is employed for one and the same shift for each day of the entire planning horizon. This indicates that these models are not applicable for capacity planning models in a highly uncertain environment such as CEVA is operating in. The approach of Castillo, Joro and Li (2009) only takes into account the variability of demand per day and is able to cope with multiple objectives in a call center environment. It does not take into account forecasted demand and real-time control; two important steps in labour scheduling according to Thompson (1995) and two important phases in CEVA’s short-term capacity planning. Also the multiple due dates and specific process flow in the environment of CEVA is not included in the method of Castillo, Joro and Li (2009). Although literature provides interesting findings in short term scheduling and uncertainty (Janak, Lin & Floudas, 2004 & 2007; Kopanos & Pistikopoulos 2014; Bonfill, Espuna & Puigjaner, 2008), they are all focused on production scheduling rather than workforce scheduling. Instead of finding the optimal capacity plan, they try to find the optimal sequence of tasks taking place in each unit to minimize for example the makespan or maximize overall profit. In other papers uncertainty is included in variables which are not relevant to our case.
The approach of Sabar, Montreuill and Frayret (2011) takes into account the master production schedule where uncertainty is found in personnel absenteeism. Savino, Brun and Mazza (2014) presented a multi-agent system re-scheduling approach where uncertainty is found in machine failure and operator missing. Ladier, Alpan and Penz (2014) present a decision support tool for a logistics company in which they divide the planning problem into three sub-problems: workforce dimensioning, task allocation for a week, and a detailed rostering for a day. Their approach allows making adjustments to the initial planned shifts when there are differences between the forecasted and actual workload during the day. However, also in this paper the characteristics of CEVA’s capacity problem are not applicable, for example the make-to-order environment does not match with the characteristics of the environment used in the paper of Ladier et al. (2014). The capacity setting method for a make-to-order environment developed by Hübl, Altorfer and Jodlbauer (2014) does not take into account forecast values and shift allocation.

2.2.3. Forecasting
When a forecast is used in a capacity planning model, the quality of that model will depend on the quality of the forecast. Due to different business conditions, one technique can be more appropriate than another. Therefore, one should make clear exactly what he/she is trying to forecast in terms of all relevant characteristics (Zotteri, Kalchschmidt & Caniato, 2005). Danese and Kalschmidt (2011) emphasized that the development of the forecasting method should be connected with the final goal of this forecasting method.

Zotteri and Kalchschmidt (2007) show that the choice of aggregation level depends on the nature of demand. Research already found evidence that there is no ‘one best way’ in defining the right aggregation level (Zotteri et al., 2005). Moon, Hicks and Simpson (2012 & 2013) has revealed that at individual item level combinatorial forecasting is superior to top down forecasting and direct forecasting. Zotteri and Kalchschmidt (2007) emphasizes that the level of aggregation of the forecasting method should depend on the final goal of this forecasting method. They only discuss demand to be stationary and therefore they propose further research directions in for example spare parts demand, for further development of the model. Widiarta, Viswanathan & Piplani (2009) and Sbrana and Silvestrini (2013) both state that for hierarchical aggregation the top-down or bottom up approach does not outperform one another. Also no significant difference in performance was found between informal, formal and randomized hierarchical forecasting (Fliedner & Lawrence, 1995). In all cases time series forecasting was used. The belief of Dekker, Pinçe, Zuidwijk and Jalil (2013) is that spare parts control is not reliable when time series forecasting methods is used. This is due to a lack of demand data, intermittent demand, product life cycles, relatively long lead times and the need for short delivery times.

Regarding forecasting models, most of the literature based on forecasting spare parts demand is focused on a single-item and the long term. This is not surprisingly because the main issue for spare parts is availability of the items in stock. Minimizing inventory costs is often an objective taken in mind when forecasting spare parts demand. But if the objective lays in short-term capacity planning, single-item and long term forecasting does not make any sense. For a short-term capacity planning purpose, it should be worthwhile to study the performance of forecasts focusing on multi-items in the short term. To the best of our knowledge no scientific work is available that considers forecasting aggregate intermittent (spare parts) demand in the short term. In a warehouse environment with highly variable demand it could provide valuable information for making capacity decisions.

2.2.4. Further research directions
Research in short-term planning of capacity, taking into account uncertainty, is mainly focused to the production schedule rather than the workforce schedule. To the best of our knowledge, there exists no off-the-shelf solution approach that meets the characteristics as desired in the situation of CEVA. Especially when looking to the combination of CEVA’s process flow, multiple due dates, uncertainty in quantity of demand and uncertainty in demand arrivals.
Current literature on forecasting can be extended by considering a short-term situation of demand aggregation where demand for single items is highly uncertain. Considering the context of the project, a case study in a warehouse handling spare parts could give valuable information in the effectiveness of forecasting such a situation.

The literature review revealed that short-term capacity planning for logistic providers is still limited. Available research showed that there is room for research in short-term capacity problems in a make-to-order environment where total demand and demand arrivals are uncertain, with multiple due dates, and where planned workforce strongly determines the capacity. To the best of our knowledge, there exists no off-the-shelf solution approach that meets the characteristics as desired in the situation of CEVA.

2.3. Research assignment

As presented in section 2.1, planners of CEVA make inefficient and inconsistent decisions. As an effect, this results in poor KPI performance and poor employee utilization. Clearly, CEVA does not have a robust method for their process of short-term capacity planning. The main purpose of this research is to find out how the process for this specific short-term capacity planning problem should be supported at its best. The results of this report should support CEVA in making conscious capacity planning decisions in the short term. To the best of our knowledge, there exists no off-the-shelf solution approach that meets the characteristics as desired in our specific situation. This let us formulate the research assignment as follows:

“Develop a decision support tool which provides insights for a short-term labour capacity planning problem in a make-to-order environment with multiple due dates in the planning horizon.”

2.3.1. Research questions

One main research question will be answered to fulfill the research assignment. The research question is in line with the research assignment and is stated as follows:

How should short-term labour capacity decisions in a make-to-order environment with multiple due dates in the planning horizon be supported and made respectively?

The main research question is associated with several sub-questions. These sub-questions are split and answered in an analysis phase, development phase and case study phase respectively:

- **Analysis phase:**
  - For the short term capacity planning perspective of CEVA, what are the current constraints and possibilities of CEVA’s capacity planning?
  - For the short term capacity planning perspective, which types of uncertainty are problematic for the capacity planning problem?

- **Development phase:**
  - How can a method support decisions for the short-term capacity planning problem in a make-to-order environment with multiple due dates in the planning horizon?

- **Case study phase:**
  - What are the consequences of short-term capacity decisions a user can make in the developed method?
  - How should the developed method be translated into a decision support tool?

2.4. Research design

This section presents the way of working which is used to find an answer to the research questions and to fulfill the research assignment. The research is divided into three phases:

- **Analysis phase**
- **Development phase**
- **Case study phase**
The analysis phase continues on the observations presented in section 2.1. To examine the short-term capacity planning problem a detailed analysis is performed on multiple perspectives. Unstructured interviews are held with key stakeholders and are chosen to let employees explain the processes, give their view of current methods and let them suggest points of improvements. Key stakeholders are employees who determine how the department’s goals are measured, employees who execute the daily process and employees who are managing the execution of the daily processes. An extensive data analysis is chosen to get a deeper understanding of concepts that require to be quantified. Analyzed concepts are for example the uncertainty characteristics of required capacity. The interviews and data analysis should also give us the opportunity to figure out all constraints and possibilities in short-term capacity planning. The analysis phase enables to sketch a detailed view of the short-term capacity planning problem considered in this report.

The development phase involves a redesign of current method for short-term capacity planning. This phase describes how to tackle the problem and is split into two parts: a conceptual design and a detailed design. These two parts are both devoted to the research assignment. The conceptual design discusses and defines the structure, constraints and objectives of the method we developed. The second part translates the conceptual design into a detailed design. The detailed design is constructed in such a way it is applicable in other industries with equal characteristics.

The case study phase examines and discusses how the developed method can be used in practice for CEVA. Multiple planning scenarios are compared within this method. This is done by implementing the method into Excel, the simulations are executed by using Visual Basic for Applications (VBA). To compare the performance multiple runs are executed for each individual scenario. The method, implemented in MS Excel, is refined to CEVA’s requirements in a way the planners of CEVA are able to use it as a decision support tool. An implementation plan which describes how the tool should be used is given subsequently. The results of the case study should provide valuable insights in CEVA’s problem of short-term capacity planning. Finally, conclusions are drawn, recommendations are given, limitations are discussed and future research directions are presented.

2.4.1. Project scope

This section describes which aspects falls in or outside the scope of the project. Due to the fluctuating demand CEVA faces difficulties in matching the available capacity with the required capacity on a daily basis. Therefore, this study only concerns with short-term capacity planning. The client Sandvik takes more than 70% of all space, activities and budget at CEVA Eindhoven. The warehouse activities for Sandvik are split into an inbound department and an outbound department. Managers of CEVA indicate that their capacity planning is more problematic in the outbound section. This is likely to assume since the inbound department does not have the different due date groups as present in the outbound department. Moreover, the required capacity is smaller and is less uncertain for the inbound department. The departments present at CEVA Eindhoven require tailored designs because their processes differ significantly from each other. The outbound department of Sandvik is selected because an improvement in capacity planning decisions for these processes will result in the largest gains. The operational processes in scope of the research are shown and delineated in Figure 1 of section 1.3. The due date groups as discussed in section 1.3 are taken for granted because the determination of these groups are in control of Sandvik. Often, it is practically impossible to deal with all relevant elements required to generate an optimal roster computationally (Ernst et. al., 2004), think about individual preferences such as holidays, days off, preferred duration or start times etc. Besides, individual staff allocation is performed manually in many applications or it is partially outsourced, for example when employees are hired from an ELSA, which is the case for CEVA. Therefore, final individual staff assignment is not considered in this report. The method that is developed in this project should support in short-term capacity setting. A method should be developed in general such that it is applicable in other environments with the same characteristics.
3. Analysis

The analysis in this chapter examines the work environment illustrative for a situation like CEVA in more detail. The results from the analyses are essential in defining the conceptual model in chapter 4 and are used in the case study in chapter 5 as well. First, in section 3.1 the capacity planning process is analyzed and the possibilities and constraints for capacity planning are examined. Subsequently, several types of uncertainty relevant for the researched environment are examined and discussed in section 3.2. Finally, section 3.3 summarizes the detailed analysis performed in this chapter.

3.1. Capacity planning

Section 3.1.1 first explains the current method of short-term capacity planning. Then, section 3.1.2 examines capacity plans which were made in the past with current method. Subsequently, section 3.1.3 presents the possibilities a planner of CEVA has to correct the capacity plan for unanticipated disruptions. Section 3.1.4 discusses how the process flow influences the challenges of the capacity planning problem. Section 3.1.5 summarizes and discusses the analyses from section 3.1.

3.1.1. Current process of short-term capacity planning

CEVA’s process of short-term capacity planning can be distinguished into three main steps: (1) forecast demand, (2) translate the forecast into a capacity plan, (3) adjustment and control. The methods used in these three steps are discussed respectively:

Step 1: For each working day a data-driven forecast is made for the total number of order lines forwarded by Sandvik that day. CEVA’s method is based on time-related factors. During the year 2014 CEVA expected an upward trend in the average number of order lines per day. CEVA expected a seasonality pattern on a monthly basis and on a weekly basis. Where for each month demand at the beginning of the month is relatively higher and sloping downwards during the month, the same principles applies for each week. These three factors are combined to generate a forecasted value for the total number of order lines per day. See Appendix G for a detailed description of current forecast method. The forecasts of the model are discussed between CEVA and Sandvik on a weekly basis to agree on one final forecast for each day.

Step 2: For each working day in the coming week a capacity plan is made which is based on the forecasted number of order lines determined in step 1. The forecast value is divided by one overall productivity value to determine the total required capacity. A certain safety margin is added to determine a target value of total capacity one should use in its capacity plan. A planner is free in the level of the safety margin, in how capacity is planned during the day and how capacity is planned over the competencies mentioned in section 1.3. There already have been multiple attempts to develop a method which improves the method in step 2. However, according to the employees of CEVA, no method has been proven to be of added value, causing that planners currently make the capacity plan on an intuitive sense.

Step 3: Adjustments to the initial capacity planning determined in step 2 are made according to real-time data. During the day a planner could adjust its capacity plan by upscaling or downscaling its initial available capacity, also known as corrective recourse actions. Logically, contingent employees are far more flexible in their capacity adjustments than permanent employees. Also in this phase of short-term capacity planning no guidelines are offered to the planners of CEVA. As a result, decisions are made on an intuitive sense.

3.1.2. Quantified capacity plans

This section examines the capacity that was planned based on a data set from week 27 to week 50 of 2014. From the available data we obtained the number of shifts planned per competency per day. During the analysis in this section the following is assumed: each shift is planned for eight hours (excluding breaks); the productivity per employee per competency is set equal to the figures shown
in Appendix H; the percentage of order lines per competency per day are set equal to the percentages shown in Appendix H.

According to our assumptions, one should plan 49% of capacity for the picking competencies, 44% of capacity for the packing competencies and 7% for the marshal competency. See Appendix H for the calculation. From Figure 6 it can be seen that in general more safety is planned for the picking competencies compared to the packing competencies. The planners of CEVA explain this by the fact that employees who master one of the picking competencies automatically master both packing competencies; instead, employees who master a packing competency do not automatically master all picking competencies. This is why more safety is planned for the picking competencies.

According to our assumptions, the capacity planned for the competency picking shelving is systematically lower than required, while capacity planned for the competencies picking reach and picking HOPT are systematically higher than required. This is confirmed by the planners of CEVA and explained by the fact that all employees who master the picking competency reach or HOPT also master the competency picking shelving; instead, not all employees who master the competency picking shelving master the competency picking reach or HOPT. This is why less safety is planned for the picking shelving competency.

In section 2.1 was already shown that the safety margin for each day is applied inconsistently. The safety margin for a certain day is defined as follows:

\[
\text{Safety Margin} = \frac{(\text{Planned capacity} - \text{minimum required capacity})}{\text{minimum required capacity}}
\]

The safety margin for all days in the dataset fluctuated between -12% and 104%. The average safety margin is found to be 7%. The purpose of a safety margin is explained by CEVA as a way to cope with the fluctuations in required capacity. The fact that this safety margin is not applied consistently reveals the lack of support and lack of control during the short-term capacity planning process.

The total capacity planned per competency is found to be rather consistent. For example, in total eight days were found in which the total capacity was planned between 385 and 395 hours. For these days the capacity planned for each competency independently fluctuated within a range of eight hours. Although current capacity planning method does not provide support at this point, this consistent way of planned capacity over the competencies is not surprisingly because section 3.2.4 will show that the percentage of order lines per competency is consistent as well.

### 3.1.3. Corrective recourse actions

The capacity decisions taken in section 3.1.2 are decisions taken prior to the start of a working day. These decisions are made when no real demand information is available. Other capacity decisions can be taken at a later stage (during the day) when more information becomes available; these capacity decisions are called corrective recourse actions. Corrective recourse actions are actions modifying the original capacity plan to correct for unanticipated disruptions. There are several opportunities to re-plan the original capacity plan. Possible corrective recourse actions that can be taken by CEVA are summarized as follows:

![Figure 6 Percentage of capacity planned per process over time (from week 27 to week 50).](image)
- One can...
  - Cancel a complete shift which was originally planned.
  - Plan an extra shift.
  - Change the competency a shift was originally planned for (in part or in its entirety)
  - Adjust the length of a shift which was originally planned:
    - by adjusting the original start time of a shift.
    - by adjusting the original end time of a shift.

The planner should decide for a corrective action at least 2 hours before this action will have its effect. The mentioned corrective recourse actions are only applicable for contingent employees. Permanent employees usually have a fixed start and end time of their working times at each day of the working week. Unfortunately, no historical data is available which shows how often each of the corrective actions are taken in the past.

### 3.1.4. Process flow

The process flow CEVA currently operates in affects the way of capacity planning. Orders first need to be picked before they can be packed. The input of orders for the packing process is therefore dependent on the output of orders from the picking process. Therefore it does not make sense to have much more capacity available for the packing process than capacity available for the picking process. On the other hand, when the capacity available for picking can process much more orders than the number of orders that capacity available for packing can process, there arises a buffer of orders between these two processes. This buffer cannot be too large because there simply is a limited amount of space for this buffer. The same logic applies between packing and marshalling because orders first need to be packed before they can be marshalled. The issue just described is an extra challenge one could take into account in the capacity planning problem.

### 3.1.5. Capacity planning conclusions

There are several conclusions we could make from the analyses in section 3.1. First of all, the information made available for a planner is solely based on total quantities. For each day there is one forecast value, which is divided by one general productivity number from which follows one target value of capacity to be planned. We can put this aside the environment characteristics outlined in section 2.1.2: multiple DD groups, multiple processes and competencies and uncertainty of required capacity in several ways. We can state that there is a lack of information available in supporting the decisions during the capacity planning process. The environment characteristics show that CEVA should think about considering more than just one target capacity value in their capacity planning method. Secondly, from our observations, we state that capacity plans are far from consistent. This is a logical cause when looking to the little support current capacity planning method provides and the fact that most decisions are made on an intuitive sense. Thirdly, these decisions are barely evaluated afterwards because there is no method available on how current short-term capacity method should be adjusted and controlled. Clearly, CEVA does not have a robust method for their process of short-term capacity planning.

### 3.2. Uncertainty of required capacity

This section examines the uncertain characteristics of required capacity. Uncertainty is first analyzed at high level (per day), after which the uncertainty of required capacity is analyzed in more detail.

#### 3.2.1. Total forwarded order lines per day.

The forecast model, as described in Appendix G is based on three time-related factors. This section examines the forecasts according to these three time-related factors. For this analysis a data set from week 1 to week 52 of 2014 is used.

The first time-related factor assumes the average forwarded order lines per day to be different and increasing over the four quarters of 2014. The forecasted averages and realized averages per quarter of 2014 are presented in Appendix J.1. A growing trend was forecasted over
the year, the figures do not show similar results. A one-way ANOVA is used to test the following hypothesis:

- **The average of forwarded order lines per day differs across the four quarters of the year.**

Results of the test are shown in Appendix J.1. The P-value of the F-test is greater than 0.05 which tells us that there is no statistically significant difference found between the average from one quarter to another at the 95% confidence level. One can therefore state that it was not correct to treat the quarters of the year differently.

**The second time-related factor** assumes the average forwarded order lines per day to be different and decreasing over the different week numbers of a month. Again a one-way ANOVA test is performed; the following hypothesis is posed:

- **The average of forwarded order lines per day differs across the week numbers of the month.**

The results of the test are shown in Appendix J.2. The P-value of the F-test is less than 0.05 which tells us that there is a statistically significant difference between the average of forwarded order lines from one week number of the month to another at the 95% confidence level. Therefore, a multiple range test is used to determine which weeks significantly differ from one another. The output of the test tells us that the average forwarded order lines in week number one is significant higher than at all other week numbers of the month. No statistical significant difference is found between week number two, three, four and five at the 95% confidence level. One can therefore state that, instead of all weeks of the month, only week one of each month should be treated differently.

**The third time-related factor** assumes average forwarded order lines per day to be different and decreasing over the different days of the week. Again a one-way ANOVA test is performed; the following hypothesis is posed:

- **The average of forwarded order lines per day differs across the days of the week.**

The results of the test are shown in Appendix J.3. The P-value of the F-test is less than 0.05 which tells us that there is a statistically significant difference between the average of forwarded order lines from one day of the week to another at the 95% confidence level. Also in this case a multiple range test is used to determine which averages significantly differ from one another. The output of the test tells us that the average forwarded demand at Friday is significantly different from Tuesday; no other significant differences were found between the other days of the week at the 95% confidence level. One can therefore not simply state that the days of the week should be treated differently.

The findings of the tests in this section were pointed during the unstructured interviews held with employees from both CEVA and Sandvik. The fact that no positive trend during the year is found could be explained by the disappointing sales of Sandvik which caused that less spare parts were demanded as expected. Apparently, the significant higher forwarded order lines at the beginning of each month are caused by replenishment orders. The re-order system of Sandvik, to replenish the other consolidation hubs across the world, runs at the beginning of each month which causes more replenishment orders in the first week of each month. Although the averages for each day of the week show somewhat similar figures as what was expected by CEVA and although this pattern is noticed by the operators of CEVA as well, from the analysis we cannot significantly justify treating a specific day differently from all the others.

The MAPE (Absolute Mean Percentage Error) is calculated by using the following formula: $MAPE = \frac{1}{n} \sum_{n=1}^{N} \left| \frac{d_n - FC_n}{FC_n} \right|$, where $d_n$ is the realization of forwarded order lines at day $n$, $FC_n$ is the forecast for day $n$, and $N$ is the number of days in the

3.2.2. Forecast error

This section examines the performance of the current forecast model. Literature presents multiple different measures for the forecast error. One of the most popular and recommended measure for the forecast error is the MAPE (Hanke and Reitsch, 2001; Bowerman, O'Connell and Koehler, 2005). As explained by Silver, Pyke and Peterson (1998), the MAPE (Absolute Mean Percentage Error) is calculated by using the following formula: $MAPE = \frac{1}{n} \sum_{n=1}^{N} \left| \frac{d_n - FC_n}{FC_n} \right|$, where $d_n$ is the realization of forwarded order lines at day $n$, $FC_n$ is the forecast for day $n$, and $N$ is the number of days in the
calculated period. The mean absolute percentage error of the forecasted forwarded order lines per day is calculated to be 16%.

To check for a relation between the forecast error and different time periods we hypothesize, based on the three time-related factors used in the forecast model, that:

- The forecast error differs across the quarters of the year.
- The forecast error differs across the week numbers of the month.
- The forecast error differs across the days of the week.

These three hypotheses are checked by using a one-way ANOVA in a similar fashion as the analyses performed in section 3.2.1. The results of all three tests, shown in Appendix J.4, reject all three hypotheses because no statistically significant differences between the different time periods are found at the 95% confidence level.

The Shapiro-Wilk test (Field, 2000) is used to test whether results of the forecast error can be adequately modeled by a normal distribution. The measured p-value is 0.0629 which is greater than 0.05 and means that we cannot reject the hypothesis that the forecast error comes from a normal distribution with 95% confidence.

Based on the analysis we can state that the forecast error in percentages $FE = \frac{d - FC}{FC}$ is distributed normally by $\mu^{FE} = -0.019$ and $\sigma^{FE} = 0.166$.

### 3.2.3. Forwarded order lines per day across the DD groups.

As mentioned in section 1.2, each DD group is characterized by a cut-off time, pick by time, pack by time and marshal by time. A DD group thus specifies at which time point during the day order lines should be finished at latest. It would be useful to know how the quantity of forwarded order lines per day is distributed across the DD groups. For the analysis we use a data set from week 1 of 2014 to week 52 of 2014 in which all 12 different DD groups are considered.

Figure 7 shows that DD group two and seven have the most impact on the total forwarded order lines together they represent almost 47% of the total. DD group three, four, five, six and eight together have a fractional impact on the total; together they represent almost 8% of total forwarded order lines. The other five DD groups each represent between 6% and 16% of total forwarded order lines. The descriptive statistics and Box-and-Whisker Plot presented in Appendix J.5 reveal that there is much variability in relation to the median of each DD group individually. Consequently, there is much uncertainty from day to day in the quantity and the timing that order lines should be finished throughout the day.

![Figure 7 Average forwarded order lines per DD group per day](image)

Some noteworthy issues came up during the unstructured interviews while discussing the variability of forwarded order lines per DD group, two about customer orders, one about replenishment orders:

**Customer orders:** (1) multiple customers postpone their orders and collect them such that shipping costs could be limited; causing customers forwarding their orders in an intermittent behavior. (2) There is no fixed set of customers for Sandvik; first, because new mines are found causing new customers; second, active mines are getting exhausted causing lost customers. As an example, data of forwarded order lines per day is shown for eight customers in Appendix J.5. The figures confirm
the two issues; however, we could imagine that other unknown customer-related factors exist and influence the amount of forwarded order lines per DD group per day.

**Replenishment orders**: The number of forwarded order lines per DD group mostly depend on the destination, also mentioned in section 1.3. This idea matches the figures shown in Appendix J.5, it shows the percentages of total demand for each DD group–region combination. We can see that, except for Europe, most of demand for each region belongs to one specific DD group. As we know from section 1.1, replenishment orders are only shipped to three regions; APAC, Africa + TR and North America. Besides, we also know about the re-order system of Sandvik: replenishing the consolidation hubs at the beginning of each month, see section 3.2.1. DD groups two, seven and twelve mainly includes the regions with replenishment orders which thus should have a peak of forwarded order lines at the beginning of each month. We therefore hypothesize:

- **Positive correlations should exist between DD groups two, seven and twelve in the number of forwarded order lines.**

A Spearman’s rank correlation analysis is executed to test the correlations between all DD groups, see Appendix J.5. It shows that we can accept the hypotheses that positive correlations exist between DD groups two, seven and twelve.

In conclusion, multiple customer-related factors influence the variability of forwarded order lines per DD group. A comprehensive study of the behavior for each of Sandvik’s customer should be executed in order to get a clear understanding of all relevant factors. This goes beyond the scope of this research because the required data lies in the hands of Sandvik and could not be retrieved by CEVA. Moreover, according to Dekker, Pinçe, Zuidwijk and Jalil (2013), it is not reliable when time series forecasting methods are used for spare parts due to a lack of demand data, intermittent demand and product life cycles. Therefore, the decision support tool developed in this report should be able to cope with the variability of forwarded order lines per DD group per day.

### 3.2.4. Forwarded order lines per day across the competencies.

This section analyses how forwarded demand is distributed across the three competencies within the picking process and across the two competencies within the packing process. Two visualized analysis are executed: one with respect to time and one with respect to the DD groups. For this analysis we use a data set from most recent weeks (week 40 of 2014 to week 50 of 2014); only limited data is available for this analysis because CEVA started from week 40 to store the information about which competency an order required.

Figure 8 shows the percentage of forwarded order lines per picking competency per day. Alongside some small variability from day to day, the percentages per picking competency are reasonably constant over time. Figure 9 shows the percentage of forwarded order lines per packing competency per day. Slightly larger variability is found for these competencies. This information makes the capacity planning decisions less complex.

Figure 10 shows the average percentage of forwarded order lines per DD group across the different picking competencies. DD group 4 has on average relatively more forwarded order lines for the picking reach competency and thus has relatively less order lines for the picking HOPT and shelving competency. From section 3.2.3 it is known that the amount of forwarded order lines for this DD group is practically negligible with respect to the total. Therefore, it is reasonable to assume equal percentages of forwarded order lines per DD groups across the picking competencies. Figure 11 shows the average percentage of forwarded order lines per DD group across the different packing competencies; it shows slightly more variability. The groups with relatively more forwarded order lines for the parcel competency are groups which represent only a small percentage of the total; however, for the packing competency it is not reasonable to assume similar percentages across all DD groups.
Neither the figures 9 and 10, nor the interviews, trigger us to check for significant time sequence dependencies. Although we cannot be sure, we assume no significant trends, cycles, or other time dependencies take place in the area of forwarded order lines per competency per DD group. The fact that the quantity of forwarded order lines for the packing competencies is variable across the different DD groups is confirmed by the planners from CEVA, it makes the capacity planning problem more complicated. To deal with this, the planners indicate that for the two packing competencies employees are relatively easy to interchange. Employees are relatively easy interchangeable from the picking competencies to the packing competencies as well.

### 3.2.5. Forwarded order lines throughout the day.

Simply, one cannot process more orders than the amount of orders forwarded cumulatively throughout the day; this makes the capacity planning process more challenging. Therefore, this section analyses the rate of forwarded order lines throughout the day. Due to the time consuming part of retrieving data from the warehouse management system (WMS) of CEVA we use a limited data set. In consultation with CEVA the period from July 2014 to October 2014 is selected as a representative dataset for the behavior of forwarded order lines throughout the day.

Figure 12 shows the average rate of forwarded order lines per hour. Order lines start to flow in from 4 am; on average 10% of the lines are forwarded before 8 am. Then, most of the lines flow in from 8 am to 12 am, close to 45% on average. Another 30% of the order lines arrive between 12 pm and 16 pm. At the end of the day the rate of forwarded order lines decreases; the last 15% of forwarded order lines arrive from 16 pm to 24 pm. These figures are average based, the box-end-whisker plots in Figure 13 visualizes the existent uncertainty in the amount of forwarded order lines for each hour independently. For example, between 9 am and 10 am, 25% of the days between 600 to 1100 order lines are forwarded, while another 25% of the days less than 250 order lines were forwarded by Sandvik.

As we know, each DD group is characterized by its cut-off time. There is a possibility for orders being forwarded after cut-off time, in this case the order does not have to be processed at
the date of forwarding. This means the size of forwarded order lines after cut-off time is equal to the difference between the size of forwarded order lines per day and the size of order lines that is required to be finished the same day. On average 7.1% of the orders are forwarded after cut-off time. These figures differ per DD group, shown in Appendix J.6. Logically the groups with a cut-off time early in the day have more order lines forwarded after cut-off time than groups with a cut-off time late in the day.

![Figure 12 The average rate of forwarded order lines per hour](image1)

![Figure 13 Box-end-whisker for the rate of forwarded order lines per hour.](image2)

Sandvik currently offers their spare parts service to over 300 customers. Instead of analyzing each customer independently, we try to draw conclusions on an aggregate level, see the cumulated numbers presented in Figure 14. We see that in 25% of the days less than 1000 order lines were forwarded from the start of the day to 10 pm. When one plans capacity which is able to process 1000 order lines from the start of the day to 10 pm, one plans capacity which causes overcapacity in 25% of the days if no corrective actions are taken.

![Figure 14 Box-end-whisker for the cumulated size of forwarded order lines per hour.](image3)

The data shows that, excluding some exceptions, total forwarded order lines per day fluctuates between 2000 and 5000. As a consequence the rate of forwarded order lines throughout the day fluctuates as well. According to the interviews, the uncertainty of the rate of forwarded order lines throughout the day is partly caused by the different time zones over the world. Customers forward their orders between working hours, orders come from different time zones and the quantity of orders per customer per day is uncertain; this causes that the rate of forwarded demand throughout the day is uncertain as well. Moreover, unknown factors affect the time between working hours when customers forward their demand.
3.2.6. Picking lead time per DD group

This section analyses when order lines are forwarded throughout the day with respect to their pick by time by distinguishing between the DD groups. The time between an order line is forwarded and the time an order line should be picked is called the picking lead time, see Figure 15.

On average the picking lead time is 4.9 hours. The average picking lead time per DD group is presented in Table 1. Logically, DD groups with a pick by time early in the day, like DD group 1, mainly have orders with a shorter picking lead time; DD groups with a pick by time later in the day, like DD group 12, mainly have orders with relatively large picking lead times.

<table>
<thead>
<tr>
<th>DD group</th>
<th>Average picking lead time (in hours)</th>
<th>DD group</th>
<th>Average picking lead time (in hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.2</td>
<td>8</td>
<td>4.3</td>
</tr>
<tr>
<td>2</td>
<td>4.5</td>
<td>9</td>
<td>4.3</td>
</tr>
<tr>
<td>3</td>
<td>4.0</td>
<td>10</td>
<td>4.6</td>
</tr>
<tr>
<td>4</td>
<td>3.5</td>
<td>11</td>
<td>4.8</td>
</tr>
<tr>
<td>5</td>
<td>5.6</td>
<td>12</td>
<td>7.2</td>
</tr>
<tr>
<td>6</td>
<td>4.4</td>
<td>Total</td>
<td>4.9</td>
</tr>
<tr>
<td>7</td>
<td>5.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1 Average picking lead time per DD group

Appendix J.8 shows the average percentage of order lines within each DD group with a certain range of picking lead times. Almost 80% of the orders have a picking lead time between 1 and 9 hours. Interesting is that the picking lead time of an order closely resembles a uniform distribution between 1 and 9 hours because for all one-hour intervals between 1 and 9 hours the picking lead time is approximately equally probable. The standard deviation for the percentage of order lines within each DD group and for each period of one hour is presented as well; in most of the cases the standard deviation is fairly close to the average which resembles high variations for the picking lead time of orders within the DD groups. In practice this means that for example at one day the majority of the orders for a certain DD group has a picking lead time between 0 and 3 hours, while at another day the majority of the orders for the same DD group has a picking lead time between 4 and 6 hours. This uncertainty exists for each DD group, making the capacity planning problem more complicated. The phenomenon just described is confirmed during the interviews and noticed as a challenging part of the labour capacity planning problem.

3.2.7. Cycle times

Each competency in the process flow requires competency specific handlings. For example, the picking shelving competency requires walking through aisles and retrieving items from stock by hand, while the picking reach competency requires driving through aisles with a reach-truck and retrieving items from stock with the reach-truck. With picking shelving one can process relatively more order lines per hour because items are smaller and one can retrieve more items in one picking route; i.e. the average cycle time per order line is much smaller for picking shelving than for picking reach. Table 2 shows the average cycle time per order line for each competency. The cycle time for picking one order line is measured by the time between two pick movements in the system. A pick movement in the system is the time when an employee scans an item and thus retrieves this item from stock. The time between two pick movements is therefore assumed to be equal to the cycle time of one order line. The same applies for pack movements; no data about marshal movements were available.
<table>
<thead>
<tr>
<th>Competency</th>
<th>Average cycle time per order line (in seconds)</th>
<th>Target productivity (in lines per hour)</th>
<th>% of total demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOPT picking</td>
<td>148</td>
<td>23</td>
<td>51%</td>
</tr>
<tr>
<td>Reach picking</td>
<td>324</td>
<td>10</td>
<td>12%</td>
</tr>
<tr>
<td>Shelving picking</td>
<td>121</td>
<td>30</td>
<td>37%</td>
</tr>
<tr>
<td>Parcel packing</td>
<td>83</td>
<td>22.5</td>
<td>78%</td>
</tr>
<tr>
<td>Plywood packing</td>
<td>103</td>
<td>30</td>
<td>22%</td>
</tr>
<tr>
<td>Marshalling</td>
<td>*</td>
<td>160</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 2 The average cycle time per order line for each competency

Appendix J.7 provides a concise analysis for the cycle time for the picking shelving competency. In consultation with CEVA three representative days are used for this analysis. For these three days the cycle times of the picking shelving competency are used to get a sense of what could affect the cycle time of an order. The following points summarize the findings of the analysis presented in Appendix J.7:

- The employee who processed the order line affects the cycle time of an order line.
- The quantity of items in an order line affects the cycle time of an order line.
- The row height of a SKU affects the cycle time of an order line.
- The DD group of an order line does not affect the cycle time of an order line.
- No data was available to test the effect of the weight and/or volume of an order line.

This shows that there are several causes affecting the cycle time of an order. Different average cycle times for different employees makes the capacity planning problem more challenging. The almost equal average cycle times per DD group is something that does not make the capacity planning problem more challenging. The other three issues are, in our opinion, too detailed for our capacity planning problem and therefore not relevant to take into account.

3.3. Conclusions detailed analysis

This section summarizes the conclusions made during the analysis phase:

- There is a lack of information available in supporting the capacity decisions.
- Current capacity plan decisions are not made consistently.
- Total amount of forwarded order lines is uncertain which makes the total size of planned capacity challenging. The forecasts which are made could be helpful.
- The amount of forwarded order lines per day across the DD groups is uncertain which makes the timing of planned capacity throughout the day challenging.
- The fraction of forwarded order lines per day across the competencies is reasonably constant which makes the size of planned capacity per competency less challenging.
- The rate of forwarded order lines throughout the day is uncertain which makes the timing of planned capacity throughout the day challenging.
- The picking lead time for order lines across the DD groups is uncertain which makes the timing of planned capacity throughout the day challenging.

Apparently, the most challenging part of the capacity planning problem is the timing of available capacity. Would it be better to plan more available capacity early in the day or later in the day? What provides the best trade-off between KPI performance and employee utilization? Moreover, a challenging part of the capacity planning problem is the size of total available capacity. Would it be better to plan a relatively large safety margin? In this case more attention is paid to the KPI performance and less attention is paid to employee utilization. Or would it be better to plan a relatively small safety margin? In this case more attention is paid to employee utilization rather than KPI performance. The answers to these questions are unknown at this moment but we should be able to answer these questions with the method developed in chapter 4.
4. Method development

This chapter describes the development of a method which can be used to generate capacity plans. The method in this report is developed as a decision support tool for a situation where the number of employees for each shift in a given day should be determined. The method should provide support to decide upon the total size and timing of available capacity. The method should provide insights in how the short-term capacity decisions should be taken for a make-to-order environment given a set of different due dates in the planning horizon.

Chapter 3 showed that decisions regarding a capacity plan are taken without knowing actual required capacity. Subsequently, corrective recourse actions are taken in the control part when required capacity is (partially) known and it does not match with the available capacity. In terms of hierarchical planning, this relationship seems to be similar to the interrelationship between the provision of capacity at the top-level and operational usage in the base-level as described by Schneeweiss (2003). In such a method both individual models, top-model and base-model, should first be described individually in a non-reactive anticipation situation. Subsequently, a reactive anticipated model could be developed which considers possible reaction of the base-level with respect to the top-level’s instructions, see Figure 16. In our case, both the top-model and base-model should be developed first since, to the best of our knowledge, no off-the-shelf solution models exist for the specific problem in this report. The first focus of this chapter lies on developing a top-model for the non-reactive anticipation at the top-level. Due to time constraints no method is developed including corrective recourse actions in the case of reactive anticipation. Thus, no specific corrective recourse actions are taken into account. However, corrective recourse actions have been included in the evaluation of the results in chapter 5.

![Figure 16 General structure of hierarchical planning](image_url)

Regularly, the objectives of capacity plans, especially in logistics, are a controversial trade-off between high utilization and high service levels (Jodlbauer, 2008); the same trade-off applies for CEVA between KPI performance and employee utilization. Unused capacity is generally expensive and should therefore be minimized. Violating service levels generally result in penalty costs in the short term; moreover, it could harm the relationship with the customers in the long term. An extensive understanding of the relationship between performance of utilization and service level is necessary to make conscious decisions in the capacity plan. This should be achieved with the method developed in this chapter. We first explain important parameters and variables in section 4.1. Subsequently, section 4.2 introduces the reader to the type of problem we develop a method for. Then, section 4.3 shows that, in terms of decision support, one single cost-optimization model is not computationally practical. Section 4.4 thereafter presents a design for the conceptual method of this report. Section 4.5 transforms the conceptual design into a detailed design.

4.1. Understanding of parameters and variables

At first, it is important to understand the definitions of parameters and variables used in the remainder of this report. These are explained in detail in this section.

The planning horizon is divided into multiple planning periods. The number of planning periods \( t \) in the planning horizon equals \( T \). For the sake of clarity, all variables regarding capacity are defined in terms of man-hours. A planner can decide upon the available capacity \( \omega(t) \) within each
period of the planning horizon by deciding upon the number of available employees $\varphi_s$ for each shift $s$. The number of shifts in the planning problem equals $S$. Each shift $s$ is characterized by $\{x_s(t)\}$ which defines for each period $t$ whether this period is included in shift $s$, yes ($x_s(t) = 1$) or no ($x_s(t) = 0$). Hence, the available capacity value for planning period $t$ is $\omega(t) = \sum_{s=1}^{S} \varphi_s \times x_s(t)$. This principle is made clear with an example in Table 3.

<table>
<thead>
<tr>
<th>$S = 3$</th>
<th>$T = 4$</th>
<th>$\varphi_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t = 1$</td>
<td>$s = 1$</td>
<td>$x_1(1) = 1$</td>
</tr>
<tr>
<td>$t = 2$</td>
<td>$s = 2$</td>
<td>$x_2(2) = 1$</td>
</tr>
<tr>
<td>$t = 3$</td>
<td>$s = 3$</td>
<td>$x_3(3) = 1$</td>
</tr>
<tr>
<td>$t = 4$</td>
<td>$s = 3$</td>
<td>$x_3(4) = 1$</td>
</tr>
</tbody>
</table>

- Explanation of example:
  - The number of planning periods $t$ in the planning horizon equals $T = 4$.
  - The number of shifts $s$ in the planning problem equals $S = 3$.
  - Shift $s = 1$ includes the planning periods $t = 1 \& t = 2$.
  - Shift $s = 2$ includes the planning periods $t = 2 \& t = 3$.
  - Shift $s = 3$ includes the planning periods $t = 3 \& t = 4$.
  - In this example the planner chooses 7 employees to be available in its capacity plan, $\sum_{s=1}^{S} \varphi_s = 7$:
    - 2 employees for shift $s = 1$ 
    - 3 employees for shift $s = 2$ 
    - 2 employees for shift $s = 3$ 
  - The available capacity in planning period $t = 1$ equals $\omega(1) = \sum_{s=1}^{S} \varphi_s \times x_s(1) = (2 \times 1) + (3 \times 0) + (2 \times 0) = 2$
  - The same logic applies for the planning periods $t = 2, 3 \& 4$.

Table 3 Example explaining the available capacity in a planning period.

The system assumes to have multiple due dates in the planning horizon, and thus different sizes of capacity are required in different periods of the planning horizon. The number of due dates $dd$ in the planning problem equals $DD$. Each due date $dd$ requires capacity in a certain planning period $t$; we aggregate the required capacity for all due dates within planning period $t$ and we state that this is equal to $D(t-1)$. Logically, when there are no due dates in planning period $t$, $D(t-1) = 0$. We define $D(t)$ as the minimum required capacity at the end of planning period $t$. See Figure 17 for more detail.

![Figure 17 Visualization of the minimum required capacity per period](image)

As we know from the analysis, the required capacity for each due date is uncertain and thus the minimum required capacity $D(t)$ for each period $t = \{1, \ldots, T\}$ is uncertain as well. In the remainder of this report we use the minimum required capacity per planning period instead of the required capacity per due date. In order to define the minimum required capacity at the end of period $t$ we cumulate the minimum required capacities $D(t)$. Therefore, we define the cumulated minimum required capacity $\bar{D}(t)$ at the end of period $t$ equal to the sum of all minimum required capacities from period 1 to $t$; hence, $\bar{D}(t) = \sum_{t=1}^{T} D(t)$. See Table 4 for more detail.

The system is assumed to work on a make-to-order basis. This means that an order cannot be processed until this order is forwarded and received by the system; see section 1.3 in which this issue is explained in detail. An order $i$ is forwarded in planning period $t$; we aggregate all forwarded orders within planning period $t$ and we state that this is equal to $A(t)$. Logically, when there are no
orders forwarded in a planning period, $A(t) = 0$. We define $A(t)$ as the size of \textbf{forwarded orders} at the end of planning period $t$. $A(t)$ is defined in terms of capacity required to finish these orders. See Figure 18 for more detail.

![Diagram](image)

**Figure 18 Visualization of the forwarded orders per period**

As we know from the analysis, the size of forwarded orders in each period is uncertain and thus the size of \textbf{forwarded orders} $A(t)$ for each period $t = \{1, ..., T\}$ is uncertain as well. Because we are in a MTO environment no more orders can be processed than the number of orders that are forwarded. In other words, no more capacity is ‘useful’ than the size of forwarded orders (in terms of capacity required to finish these orders). This means that there is a maximum size of ‘useful’ capacity, depending on the size of forwarded orders. In order to define the maximum useful capacity at the end of period $t$ we cumulate the size forwarded orders $A(t)$. Therefore, we define the \textbf{cumulated maximum useful capacity} $\bar{A}(t)$ at the end of period $t$ equal to the sum of all forwarded orders from period 1 to $t$; hence, $\bar{A}(t) = \sum_{t=1}^{t} A(t)$. See Table 4 for more detail.

<table>
<thead>
<tr>
<th>$T = 4$</th>
<th>$t = 1$</th>
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<tbody>
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<td>$\omega(3) = 5$</td>
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<tr>
<td>$\omega(3)$</td>
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<td>$\bar{\omega}(2) = 7$</td>
<td>$\bar{\omega}(3) = 12$</td>
<td>$\bar{\omega}(4) = 14$</td>
</tr>
<tr>
<td>$\bar{D}(3)$</td>
<td>$D(1) = 2$</td>
<td>$D(2) = 6$</td>
<td>$D(3) = 6$</td>
<td>$D(4) = 0$</td>
</tr>
<tr>
<td>$\bar{D}(3)$</td>
<td>$\bar{D}(1) = 2$</td>
<td>$\bar{D}(2) = 8$</td>
<td>$\bar{D}(3) = 14$</td>
<td>$\bar{D}(4) = 14$</td>
</tr>
<tr>
<td>$\bar{A}(3)$</td>
<td>$A(1) = 3$</td>
<td>$A(2) = 5$</td>
<td>$A(3) = 5$</td>
<td>$A(4) = 1$</td>
</tr>
<tr>
<td>$\bar{A}(3)$</td>
<td>$\bar{A}(1) = 3$</td>
<td>$\bar{A}(2) = 8$</td>
<td>$\bar{A}(3) = 13$</td>
<td>$\bar{A}(4) = 14$</td>
</tr>
</tbody>
</table>

- **Explanation of example:**
  - The number of planning periods $t$ in the planning horizon equals $T = 4$.
  - The available capacity $\omega(t)$ in planning periods 1, 2, 3 are respectively 2, 5 and 5. Therefore the cumulated available capacity $\bar{\omega}(t)$ at the end of period 3 is: $2 + 5 + 5 = 12$.
  - The minimum required capacity $D(t)$ in planning periods 1, 2, 3 are respectively 2, 6 and 6. Therefore the cumulated minimum required capacity $\bar{D}(t)$ at the end of period 3 is: $2 + 6 + 6 = 14$.
  - The size of forwarded orders $A(t)$ in planning periods 1, 2, 3 are respectively 3, 5 and 5. Therefore the cumulated maximum useful capacity $\bar{A}(t)$ at the end of period 3 is: $3 + 5 + 5 = 13$.

Table 4 Example explaining the variables of available capacity, minimum required capacity and the size of forwarded orders.
Table 5 presents the definitions of parameters and variables used in the remainder of this report.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(S)</td>
<td>Number of shifts considered.</td>
</tr>
<tr>
<td>(s)</td>
<td>Shift number, (s \in {1, \ldots, S}).</td>
</tr>
<tr>
<td>(T)</td>
<td>Number of planning periods in the planning horizon.</td>
</tr>
<tr>
<td>(t)</td>
<td>Planning period, (t \in {1, \ldots, T}).</td>
</tr>
<tr>
<td>(DD)</td>
<td>Number of due dates in the planning horizon.</td>
</tr>
<tr>
<td>(dd)</td>
<td>Due date number, (dd \in {1, \ldots, DD}).</td>
</tr>
<tr>
<td>(\varphi_s)</td>
<td>Number of available employees for shift (s).</td>
</tr>
<tr>
<td>({\varphi_s})</td>
<td>Vector representing the set of all components (\varphi_s); where ((\varphi_1, \varphi_2, \ldots, \varphi_{S-1}, \varphi_S)) are the components of ({\varphi_s}).</td>
</tr>
<tr>
<td>(x_s(t))</td>
<td>Variable indicating whether planning period (t) is included in shift (s). (x_s(t) = 1) if planning period (t) is included in shift (s); (x_s(t) = 0) if planning period (t) is not included in shift (s).</td>
</tr>
<tr>
<td>(\omega(t))</td>
<td>Available capacity value in planning period (t). (\omega(t) = \sum_{s=1}^{S} \varphi_s x_s(t)).</td>
</tr>
<tr>
<td>(\tilde{\omega}(t))</td>
<td>Cumulated available capacity at the end of planning period (t). (\tilde{\omega}(t) = \sum_{t'=1}^{t} \omega(t')).</td>
</tr>
<tr>
<td>({\tilde{\omega}(t)})</td>
<td>Vector representing the set of all components (\tilde{\omega}(t)); where ((\tilde{\omega}(1), \tilde{\omega}(2), \ldots, \tilde{\omega}(T - 1), \tilde{\omega}(T))) are the components of ({\tilde{\omega}(t)}).</td>
</tr>
<tr>
<td>(D(t))</td>
<td>Random variable of minimum required capacity at the end of planning period (t).</td>
</tr>
<tr>
<td>(\bar{D}(t))</td>
<td>Random variable of cumulated minimum required capacity at the end of planning period (t). (\bar{D}(t) = \sum_{t'=1}^{t} D(t')).</td>
</tr>
<tr>
<td>(\bar{\bar{D}}(t))</td>
<td>Random variable of cumulated minimum required capacity at the end of planning period (t) as a percentage of total minimum required capacity. (\bar{\bar{D}}(t) = \frac{\bar{D}(t)}{\bar{D}(T)}).</td>
</tr>
<tr>
<td>(A(t))</td>
<td>Random variable of forwarded orders at the end of planning period (t) (in terms of required capacity to process these orders).</td>
</tr>
<tr>
<td>(\tilde{A}(t))</td>
<td>Random variable of cumulated maximum useful capacity at the end of planning period (t). (\tilde{A}(t) = \sum_{t'=0}^{t} A(t')).</td>
</tr>
<tr>
<td>(\bar{\tilde{A}}(t))</td>
<td>Random variable of cumulated maximum useful capacity at the end of planning period (t) as a percentage of maximum useful capacity. (\bar{\tilde{A}}(t) = \frac{\tilde{A}(t)}{\tilde{A}(T)}).</td>
</tr>
<tr>
<td>(c(t))</td>
<td>Target capacity value for planning period (t).</td>
</tr>
<tr>
<td>(\tilde{c}(t))</td>
<td>Cumulated target capacity level at the end of planning period (t). (\tilde{c}(t) = \sum_{t'=1}^{t} c(t')).</td>
</tr>
<tr>
<td>(\bar{\tilde{c}}(t))</td>
<td>Cumulated target capacity level at the end of planning period (t) as a percentage of total cumulated target capacity level. (\bar{\tilde{c}}(t) = \frac{\tilde{c}(t)}{\tilde{c}(T)}).</td>
</tr>
<tr>
<td>(q^o)</td>
<td>Penalty costs for each unit when cumulated available capacity exceeds cumulated maximum useful capacity.</td>
</tr>
<tr>
<td>(q^u)</td>
<td>Penalty costs for each unit when cumulated available capacity undershoots cumulated minimum required capacity.</td>
</tr>
<tr>
<td>(F_Q(.))</td>
<td>CDF (Cumulated distribution function) of random variable (Q).</td>
</tr>
<tr>
<td>(F_Q^{-1}(.)</td>
<td>Inverse of the CDF of random variable (Q).</td>
</tr>
<tr>
<td>(FC)</td>
<td>Forecast for the total number of order lines forwarded in the planning horizon.</td>
</tr>
</tbody>
</table>
4.2. Situation consideration

This section considers four situations to introduce the reader to the capacity planning problem considered in this report. We assume all situations are deterministic and thus $D(t)$ and $A(t)$ are known for all periods $t = \{1, ..., T\}$. We also assume, only in this section, that in all situations no orders are forwarded with a due date in another planning horizon; hence, $\bar{A}(T) = \bar{D}(T)$.

4.2.1. Situation 1

There is just one due date, which is in period $T (= 10)$ and for which required capacity is known; the minimum required capacity $D(T)$ is 30 man-hours. Because only one due date is considered, the cumulated minimum required capacity in period $T$ is equal to the minimum required capacity in period $T$; hence, $\bar{D}(T) = D(T) = 30$ and $D(t) = \bar{D}(t) = 0$ for all periods other than $T: \{1, ..., T - 1\}$. We assume that all orders are forwarded and received by the system before the start of the planning horizon; hence, $A(0) = D(T) = 30$ and $A(t) = 0$ for all periods $t = \{1, ..., T\}$. Therefore, the cumulated maximum useful capacity is known for all periods and is equal to $\bar{D}(T)$; hence, $\bar{A}(t) = 30$ for all $t = \{1, ..., T\}$. The described situation is illustrated in Figure 19.

To produce everything on time, the optimal decision for $\omega(t)$ equalizes total available capacity $\hat{\omega}(T)$ to the total minimum required capacity $\bar{D}(T)$, hence $\hat{\omega}(T) = \bar{D}(T) = 30$. Logically in this case, the cumulated available capacity $\hat{\omega}(t)$ for all periods should be lower or equal to the cumulated maximum useful capacity $\bar{A}(t)$; hence, $\hat{\omega}(t) \leq \bar{A}(t)$ for all $t = \{1, ..., T\}$. The possible optimal determination $\hat{\omega}(t)$ for all periods $t = \{1, ..., T\}$ lies in the marked area in Figure 19.

![Figure 19 Visualization of $\bar{A}(t)$ and $\bar{D}(t)$ in situation 1](image)

4.2.2. Situation 2

Let us now expand situation 1 and let us consider the following situation:

Instead of one due date, there are multiple due dates in the planning horizon for which required capacity is known; the minimum required capacity $D(t)$ is known for all $t = \{1, ..., T\}$ and is shown in Figure 20. Because multiple due dates are considered, the cumulated minimum required capacity in period $t$ is equal to the sum of all minimum required capacities for the periods from 1 to $t$; hence, $\bar{D}(t) = \sum_{t'=1}^{t} D(t')$ for all $t = \{1, ..., T\}$. We still assume that all orders are forwarded and received before the start of the planning horizon; hence, $A(0) = \bar{D}(T) = 30$ and $A(t) = 0$ for all periods $t = \{1, ..., T\}$. Therefore, the cumulated maximum useful capacity is still known for all periods and is equal to $\bar{D}(T)$, hence $\bar{A}(t) = \bar{D}(T) = 30$ for all $t = \{1, ..., T\}$. The described situation is illustrated in Figure 20.

To produce everything on time, the optimal decision still equalizes total available capacity $\hat{\omega}(T)$ to total minimum required capacity $\bar{D}(T)$, hence $\hat{\omega}(T) = \bar{D}(T) = 30$. And still, the cumulated available capacity for all periods should be lower or equal to the cumulated maximum useful capacity, $\hat{\omega}(t) \leq \bar{a}(t)$ for all $t = \{1, ..., T\}$. However, to produce everything on time in this situation, the cumulated available capacity has to be higher than or equal to the cumulated minimum required capacity for all periods, hence $\hat{\omega}(t) \geq \bar{a}(t)$ for all $t = \{1, ..., T\}$. The possible optimal determination $\hat{\omega}(t)$ for all periods $t = \{1, ..., T\}$ lies in the marked area in Figure 20.

![Figure 20 Visualization of $\bar{A}(t)$ and $\bar{D}(t)$ in situation 2](image)
4.2.3. Situation 3

Let us now expand situation 1 in another way as in situation 2 and let us consider the following situation:

There is just one due date, which is in period $T$ $(= 10)$ and for which required capacity is known; the minimum required capacity $D(T)$ is 30 man-hours. Because only one due date is considered, the cumulated minimum required capacity in period $T$ is equal to the minimum required capacity in period $T$; hence, $\tilde{D}(T) = D(T) = 30$ and $\tilde{D}(t) = \tilde{D}(t) = 0$ for all periods other than $T$: $\{1, \ldots, T - 1\}$. We assume that no orders are forwarded and received before the start of the planning horizon. However, we do know the amount of forwarded orders within all periods in advance; hence, $A(0) = 0$ and $A(t)$ is known for all periods $t = \{1, \ldots, T\}$ and is shown in Figure 21. Therefore, also the cumulated maximum useful capacity $\tilde{A}(t)$ is known for all $t = \{1, \ldots, T\}$. The described situation is illustrated in Figure 21.

To produce everything on time, the optimal decision still equalizes total available capacity $\tilde{A}(T)$ to total minimum required capacity $\tilde{D}(T)$, hence $\tilde{A}(T) = \tilde{D}(T) = 30$. And still, the cumulated available capacity for all periods should be lower or equal to the cumulated maximum useful capacity, $\tilde{A}(t) \leq \tilde{A}(t)$ for all $t = \{1, \ldots, T\}$. The possible optimal determination $\tilde{A}(t)$ for all periods $t = \{1, \ldots, T\}$ lies in the marked area in Figure 21.

4.2.4. Situation 4

Let us now bring situation 2 and 3 together and let us consider the following situation:

There are multiple due dates in the planning horizon for which required capacity is known; thus, the minimum required capacity $D(t)$ is known for all $t = \{1, \ldots, T\}$. Because multiple due dates are considered, the cumulated minimum required capacity in period $t$ is equal to the sum of all minimum required capacities for the periods from 1 to $t$; hence, $\tilde{D}(t) = \sum_{t' = 1}^{t} D(t')$ for all $t = \{1, \ldots, T\}$, this is shown Figure 22. We assume that no orders are forwarded and received before the start of the planning horizon. However, we do know the amount of forwarded orders within all periods in advance; hence, $A(0) = 0$ and $A(t)$ is known for all periods $t = \{1, \ldots, T\}$. Therefore, also the cumulated maximum useful capacity $\tilde{A}(t)$ is known for all $t = \{1, \ldots, T\}$. The situation is illustrated in Figure 22.

To produce everything on time, the optimal decision still equalizes total available capacity $\tilde{A}(T)$ to total minimum required capacity $\tilde{D}(T)$, hence $\tilde{A}(T) = \tilde{D}(T) = 30$. And still, the cumulated available capacity for all periods should be lower or equal to the cumulated maximum useful capacity, $\tilde{A}(t) \leq \tilde{A}(t)$ for all $t = \{1, \ldots, T\}$. However, to produce everything on time in this situation, the cumulated available capacity has to be higher than or equal to the cumulated minimum required capacity for all periods, hence $\tilde{A}(t) \geq \tilde{D}(t)$ for all $t = \{1, \ldots, T\}$. The possible optimal determination $\tilde{A}(t)$ for all periods $t = \{1, \ldots, T\}$ equalizes the marked area in Figure 22.

To reach 100% employee utilization, and thus to avoid overcapacity (without making corrective recourse actions), the cumulated available capacity $\tilde{w}(t)$ has to be lower than or equal to the cumulated maximum useful capacity $\tilde{A}(t)$ for all periods $t = \{1, \ldots, T\}$. In this case, all available capacity is useful and thus utilization is optimized. At the same time, to reach 100% service level, and
thus to avoid undercapacity (without making corrective recourse actions), the cumulated available capacity $\bar{\omega}(t)$ has to be higher or equal to the cumulated minimum required capacity $\bar{D}(t)$ for all periods $t = \{1, \ldots, T\}$. In this case, all required capacity is fulfilled in time and thus the service level is optimized. In short, in order to accomplish this, the following restriction should hold for all periods:

$$\bar{D}(t) \leq \bar{\omega}(t) \leq \bar{A}(t)$$

This restriction was graphically shown as the marked area in all four Figures 19, 20, 21 and 22 for each situation respectively. For example, when the line of $\bar{\omega}(t)$ should be visualized in Figure 22 it should not cross the line of $\bar{A}(t)$ and it should not cross the line of $\bar{D}(t)$. A straight line with equal slopes of $\bar{\omega}(t)$ is desired when there are costs for having different capacity levels $\omega(t)$ from one period $t$ to another period $t$. However, we assume that there are no costs for changing the capacity levels $\omega(t)$ from one period $t$ to another period $t$. Therefore, no extra costs are caused when, for example, $\bar{\omega}(t)$ has a steep slope early in the planning horizon and a moderate slope late in the planning horizon.

### 4.3. Optimization problem

Section 4.3.1 discusses an optimization problem in which we have to decide upon $\{\varphi_s\}$ in a deterministic environment. Section 4.3.2 translates the method from section 4.3.1 to a stochastic environment and discusses the issues arising in this case.

#### 4.3.1. Deterministic optimization problem

The optimal solution in the four situations considered in section 4.2 could easily be accomplished as far as no restrictions hold for $\bar{\omega}(t)$ and as far as $\bar{D}(t)$ and $\bar{A}(t)$ are known in advance. However, $\bar{\omega}(t)$ is restricted when someone has to decide upon the number of employees available for each shift $\{\varphi_s\}$. Imaginable, situations could occur in which it is impossible to satisfy the restriction $\bar{D}(t) \leq \bar{\omega}(t) \leq \bar{A}(t)$ for all periods $t = \{1, \ldots, T\}$. Occurrences in which this restriction is violated should be minimized. As often used in literature, we could model the violations of such a restriction in terms of penalty costs in an objective function. Two penalty costs could be distinguished: one for so called ‘overcapacity’ ($q^o$); and one for so called ‘undercapacity’ ($q^u$). These are defined by:

$q^o$: when cumulated available capacity $\bar{\omega}(t)$ exceeds cumulated maximum useful capacity $\bar{A}(t)$.

$q^u$: when cumulated available capacity $\bar{\omega}(t)$ undershoots cumulated minimum required capacity $\bar{D}(t)$.

Then, the penalty costs for ‘overcapacity’ are equal to $q^o (\bar{\omega}(t) - \bar{A}(t))$ when $\bar{\omega}(t) > \bar{A}(t)$ and are zero otherwise. The penalty costs for ‘undercapacity’ are equal to $q^u (\bar{D}(t) - \bar{\omega}(t))$ when $\bar{D}(t) > \bar{\omega}(t)$ and are zero otherwise. The objective function, in which total penalty costs should be minimized, will then be:

$$G(\{\bar{\omega}(t)\}) = \sum_{t=1}^{T} q^o [\bar{\omega}(t) - \bar{A}(t)]^+ + q^u [\bar{D}(t) - \bar{\omega}(t)]^+$$

Where $[X]^+$ denotes the maximum of $[X]$ and 0. The optimization problem can now be formulated in the following form:

$$\min_{\bar{\omega}(t) \geq 0} G(\{\bar{\omega}(t)\})$$

We already mentioned that, as far as no restrictions hold for $\bar{\omega}(t)$, the optimal solution is reached when $\bar{D}(t) \leq \bar{\omega}(t) \leq \bar{A}(t)$ holds for all $t = \{1, \ldots, T\}$. In this case the total penalty costs are zero; $G(\{\bar{\omega}(t)\}) = 0$. However, in our capacity planning problem we have to decide upon the number of employees for each shift $\varphi_s$. We know from section 4.1 that $\bar{\omega}(t) = \sum_{t=1}^{T} \sum_{s=1}^{S} \varphi_s \cdot x_s(t')$. Now we are able to decide for $\{\varphi_s\}$; the objective function will be:

$$G(\{\varphi_s\}) = \sum_{t=1}^{T} q^o \left[ \left( \sum_{t=1}^{T} \sum_{s=1}^{S} \varphi_s \cdot x_s(t') \right) - \bar{A}(t) \right]^+ + q^u \left[ \bar{D}(t) - \left( \sum_{t=1}^{T} \sum_{s=1}^{S} \varphi_s \cdot x_s(t') \right) \right]^+$$
The optimization problem can be formulated in the following form:
\[
\min_{\varphi \in \Phi} G(\varphi)
\]
The formulation of the problem provides insights in the essences of the planning problem we are dealing with. However, this optimization problem still assumes a deterministic environment which is one of the basic weaknesses of linear programming approaches (Silver et al., 1998). Additionally, the number of possible capacity plans \( \{\varphi_s\} \) could grow extensively for large \( S \). Therefore, a large \( S \) can affect the degree of practical computational feasibility when someone is trying to find the optimal solution for this deterministic optimization problem.

### 4.3.2. Stochastic optimization problem

Section 4.3.1 discussed a deterministic environment; in a stochastic environment both the forwarded orders \( A(t) \) and the minimum required capacity \( D(t) \) for all \( t = \{1, ..., T\} \) are uncertain. The difference for the objective function is that all \( A(t) \) and \( D(t) \) are now considered as random variables; consequently, \( \tilde{A}(t) \) and \( \tilde{D}(t) \) in the objective function are random variables as well. The problem is now a stochastic optimization problem due to the random variables in the objective function. Again, solving the problem for each \( \{\varphi_s\} \) could result in an excessive high solution state space for large \( S \). Moreover, one should determine the probabilities for each value of \( D(1), ..., D(T) \) and \( A(1), ..., A(T) \) in order to calculate the expected penalty costs for fixed values of \( \{\varphi_s\} \). Assuming dependent and identically distributed random variables \( A(t) \) and \( D(t) \) may not be realistic. First, the variables \( A(t) \) restrict the movements for the variables \( D(t) \); this is because the orders required up to period \( t \), \( \tilde{D}(t) \), cannot be higher than the amount of orders that is forwarded and received by the system until period \( t \), \( \sum_{t'=1}^{t} A(t') \). Additionally, we cannot exclude that observations for the variable \( A(t) \) in period \( t \) does not affect the probability for observations of \( A(t) \) in future periods \( t \) in the planning horizon. Also the probability for observations of \( A(t) \) and \( D(t) \) could depend on the forecast value of total demand; we cannot simply assume the same probability distributions for \( A(t) \) and \( D(t) \) for different forecast values. In the situation just sketched, looking for functions describing the probability functions for all \( D(1), ..., D(T) \) and \( A(1), ..., A(T) \) is an intractable proposition for large \( T \) when one tries to resemble reality. This has the result that, in terms of decision support, this cost-optimization model is not computationally practical.

Besides, Van Houtum and Zijm (2000) state that service level models are more appropriate from a practical point of view. For example, a well-known drawback to the assumption of penalty costs in a pure-cost model is that these are hard to quantify (Van Houtum & Zijm, 2000). One could also imagine imperfect knowledge of penalty costs in our situation since corrective recourse actions are not considered. For a variety of models Van Houtum and Zijm (2000) show that a problem of minimizing penalty costs in a pure cost model is equivalent to a problem of minimizing penalty costs in a model under a service level constraint.

Decomposition reduces the complexity of the planning challenge and is well-known in literature to help solving complex problems. In order to improve computational practicality of the method we could focus on service level optimization and decompose the initial optimization problem into several sub-problems. Therefore, we drop the pure cost-optimization problem and we develop a method in section 4.4 and 4.5 which decomposes the general problem into several smaller sub-problems.

### 4.4. Conceptual method design

From section 4.3 we know that one single cost-optimization model does not meet our requirements of computational practicality. Therefore, we develop a method which decomposes the problem in several smaller subproblems. From the analysis in chapter 3 we know that the capacity planning problem had two important challenges: deciding upon the size of total available capacity and deciding upon the timing of available capacity throughout the planning horizon. These decisions are taken into account by decomposing the problem.
4.4.1. Subproblem 1

When a company can forecast the total minimum required capacity in the planning horizon, the size of total available capacity could be set based on the expected value for total minimum required capacity. One can now determine a target total capacity level by taking into account the random variable of the expected total minimum required capacity. Basically, the target total capacity level determines the safety margin someone is planning over the complete horizon. In our problem decomposition we therefore define the first subproblem as: **Determine the total target capacity level for the complete planning horizon according to the expected total minimum required capacity.**

4.4.2. Subproblem 2

The next subproblem considers the timing of available capacity throughout the planning horizon. The second subproblem therefore should determine how the total target capacity level should be distributed over all planning periods in the planning horizon. The second subproblem is defined as: **Determine the cumulated target capacity level for each planning period in the planning horizon.**

We know from the deterministic situation that the cumulated capacity levels should be anywhere between a minimum and a maximum. We have seen in section 4.3.1 that, instead of in the deterministic situation, the optimal cumulated available capacity levels are hard to determine in a stochastic cost-optimization model. Cost-optimization models are shown to be equivalent to service level models (Van Houtum & Zijm, 2000); therefore, we assume that the optimal cumulated available capacity levels are equally hard to determine in a stochastic service level model as in stochastic cost-optimization models. This is because the bottleneck of stochasticity is present in both situations. As a consequence, instead of looking for one optimal solution, we present and compare several options to determine the cumulated target capacity levels for all planning periods in the planning horizon. Three options are distinguished and presented for which in each option the cumulated target capacity levels are set considering the maximum, minimum or average of those two. The three options are:

2a **Consider the cumulated maximum useful capacity levels.**

With this option, the method determines the target capacity levels according to the maximum useful capacity levels. This option works according to the idea that orders should be processed as soon as they are forwarded. This option takes a risk that if relatively less orders are forwarded, available capacity will become unutilized.

2b **Consider the cumulated minimum required capacity levels.**

With this option, the method determines the target capacity levels according to the minimum required capacity levels. It works according to the idea that orders should be processed and finished just in time; which shows similarities to the chase strategy for aggregate production planning mentioned in Silver et al. (1998). This option takes a risk that if relatively more capacity is required, available capacity is not enough to meet the service levels.

2c **Consider the average between the cumulated minimum required capacity levels and the cumulated maximum useful capacity levels.**

Option 2a and 2b are based on the maximum and minimum respectively; this option considers the average between the maximum of option 2a and the minimum of option 2b. This method takes both utilization and service level into account.

The target capacity levels determined in the options 2a, 2b and 2c are illustrated in Figure 23. Option 2a places the emphasis on available capacity early in the planning horizon, while option 2b places the emphasis on available capacity late in the planning horizon. Option 2c compromises between option 2a and 2b and places the emphasis on spreading available capacity equally throughout the planning horizon.
4.4.3. Subproblem 3

As the second subproblem determined cumulated target capacity levels for all planning periods in the planning horizon, the third subproblem considers the number of employees for each shift based on the cumulated target capacity levels determined in subproblem 2. The purpose of this subproblem is to get the available capacity levels as close as possible to the target capacity levels. We define the third subproblem as: **Determine the number of employees for each shift according to the cumulated target capacity levels.** This subproblem should minimize the difference between the cumulated target capacity levels $\tilde{c}(t)$ and the cumulated available capacity levels $\tilde{w}(t)$. Two options are presented:

3a **Consider the cumulated target capacity levels as a minimum (hard constraint).**
With this option the cumulated available capacity levels $\tilde{w}(t)$ cannot be smaller than cumulated target capacity levels $\tilde{c}(t)$ for all periods in the planning horizon.

3b **Consider the cumulated target capacity level as a maximum (hard constraint).**
With this option the cumulated available capacity levels $\tilde{w}(t)$ cannot be higher than cumulated target capacity levels $\tilde{c}(t)$ for all periods in the planning horizon.

The target capacity levels, available capacity levels and constraints for both option 3a and 3b are illustrated in Figure 24 and Figure 25 respectively. The cumulated target capacity levels in both figures are equal. The line of cumulated available capacity levels in Figure 24 (option 3a) is always above the line of cumulated target capacity levels. The line of cumulated available capacity levels in Figure 25 (option 3b) is always below the line of cumulated target capacity levels.

**Black line:** $\tilde{c}(t) = \text{cumulated target capacity levels}.$
**Purple line:** $\tilde{w}(t) = \text{cumulated available capacity levels}$

**Red marked area = Hard constraint; below black line (3a), or above black line (3b)**
**Green marked area = Objective function; difference between black line and purple line.**

---

**Figure 23** Target capacity levels determined according to the options 2a, 2b and 2c.

**Figure 24** Cumulated target capacity levels and cumulated available capacity levels according to option 3a

**Figure 25** Cumulated target capacity levels and cumulated available capacity levels according to option 3b
4.4.4. Summary of conceptual method

In short, the developed method is split into these three subproblems:

- **Subproblem 1**: Determine the total target capacity level for the complete planning horizon according to the expected total minimum required capacity.
- **Subproblem 2**: Determine the cumulated target capacity level for each planning period in the planning horizon; three options are presented.
- **Subproblem 3**: Determine the number of employees for each shift according to the cumulated target capacity levels; two options are presented.

4.5. Detailed method design

The method developed in section 4.4 is now translated into a detailed design for each subproblem respectively:

4.5.1. Subproblem 1

- **Determine the total target capacity level** for the complete planning horizon according to the expected total minimum required capacity.

The total target capacity level \( \tilde{c}(T) \) should take into account the expected value for total required capacity \( \tilde{D}(T) \). In a deterministic situation, the total target capacity level should equalize the expected total required capacity level; hence, \( \tilde{c}(T) = E[\tilde{D}(T)] \). However, we should deal with the random variable \( \tilde{D}(T) \) because the expected value of total required capacity \( E[\tilde{D}(T)] \) may be incorrect. The realization of total required capacity will exceed the expected value \( E[\tilde{D}(T)] \) with a certain probability. We should aim to satisfy the following constraint:

\[
\tilde{c}(T) \geq \tilde{D}(T)
\]

This states that, when \( \tilde{c}(T) \geq \tilde{D}(T) \), the total target capacity level, \( \tilde{c}(T) \), should be higher or equal to the total required capacity level, \( \tilde{D}(T) \). We now introduce, as we call, the safety variable \( \alpha \). In this subproblem the safety variable affects the safety margin of satisfying the constraint \( \tilde{c}(T) \geq \tilde{D}(T) \). The total target capacity level \( \tilde{c}(T) \) to fulfill total required capacity \( \tilde{D}(T) \) with probability \( \alpha \) \( (F_{\tilde{D}(T)}(\tilde{c}(T)) \leq \alpha) \) is calculated by:

\[
\tilde{c}(T) = F_{\tilde{D}(T)}^{-1}(\alpha)
\]

If, for example, \( \alpha \) is set to 0.9, then \( \tilde{c}(T) \) includes a safety margin to fulfill \( \tilde{D}(T) \) with 90% probability. In other words, a 90% probability of satisfying the constraint \( \tilde{c}(T) \geq \tilde{D}(T) \); the higher the value of \( \alpha \), the less risk is taken regarding violating the constraint \( \tilde{c}(T) \geq \tilde{D}(T) \). This works for all distributions of \( \tilde{D}(T) \) for which an inverse cumulative distribution function is available. The safety margin is thus depending on \( \alpha \) for which the finally used value depends on the situation and user-specific requirements.

4.5.2. Subproblem 2

- **Determine the cumulated target capacity level** for each planning period in the planning horizon; three options are presented.

Subproblem 1 determined \( \tilde{c}(T) \), the target level for total capacity. Subproblem 2 should determine \( \tilde{c}(t) \) for all \( t = \{1, \ldots, T\} \), the target levels for cumulated capacity for each planning period in the planning horizon. Subproblem 2 should work for all possible inputs from subproblem 1, and thus \( \tilde{c}(t) \) should be determined by taking into account the value of \( \tilde{c}(T) \). Therefore we introduce the variable \( \tilde{c}(t) \) which defines the cumulated target capacity level as a percentage of total target capacity level \( \tilde{c}(T) \). In this case the next formula holds:

\[
\tilde{c}(t) = \tilde{c}(t) \ast \tilde{c}(T).
\]

Thus, finding the values for all \( \tilde{c}(t) \) makes it possible to determine the values for corresponding \( \tilde{c}(t) \) by taking into account the value of \( \tilde{c}(T) \) determined in subproblem 1. The way \( \tilde{c}(t) \) is determined is different for all three options considered in subproblem 2 and are presented respectively:
2a: Maximum required capacity levels

The values for $\bar{c}(t)$, the cumulated target capacity levels in period $t$ as a percentage of total target capacity level, are determined according to the random variables $\bar{A}(t)$ for all $t = 1, ..., T$. The variable $\bar{A}(t)$ is defined as the cumulated maximum useful capacity level in period $t$ as a percentage of total useful capacity level $\bar{A}(T)$. In a deterministic situation we know that the cumulated target capacity levels $\bar{c}(t)$ should satisfy the following constraint:

$$\bar{c}(t) \leq \bar{A}(t)$$

This states that, when $\bar{c}(T) \leq \bar{A}(T)$, the percentage of target capacity available at the end of period $t$, $\bar{c}(t)$, should be lower or equal to the percentage of maximum required capacity at the end of period $t$, $\bar{A}(t)$. We should deal with the random variables $\bar{A}(t)$ because the realizations are uncertain. We now introduce the risk variable $\beta$. In this option the risk variable affects the probability of satisfying the constraint $\bar{c}(t) \leq \bar{A}(t)$. The target capacity level $\bar{c}(t)$ to stay below the maximum required capacity level $\bar{A}(t)$ with probability $\beta \ (F_{\bar{A}(t)}(\bar{c}(t)) \leq 1 - \beta)$ for each period $t = 1, ..., T$ is calculated by:

$$\bar{c}(t) = F_{\bar{A}(t)}^{-1}(1 - \beta) \times \bar{c}(T).$$

In essence, the same logic as used in subproblem 1 is applied, but now for all periods $t$ instead of only the total value. If, for example, the risk variable $\beta$ is set to 0.9, then $\bar{c}(t)$ includes a 10% risk probability to be higher or equal to $\bar{A}(t)$ and thus $\bar{c}(t)$ includes a 90% probability to be smaller to $\bar{A}(t)$. In other words, a 90% probability of satisfying the constraint $\bar{c}(t) \leq \bar{A}(t)$; the higher the value of $\beta$, the less risk is taken regarding violating the constraint $\bar{c}(t) \leq \bar{A}(t)$. For subproblem 2a, the cumulated target capacity levels for each planning period in the planning horizon are now calculated by:

$$\bar{c}(t) = F_{\bar{A}(t)}^{-1}(1 - \beta) \times \bar{c}(T).$$

This works for all distributions of $\bar{A}(t)$ for which an inverse cumulative distribution function is available. The timing of capacity now depends on $\beta$ for which the finally used value depends on the situation and user-specific requirements.

2b: Minimum required capacity levels

The values for $\bar{c}(t)$, the cumulated target capacity levels in period $t$ as a percentage of total target capacity level, are determined according to the random variables $\bar{D}(t)$. The variable $\bar{D}(t)$ is defined as the cumulated minimum required capacity level in period $t$ as a percentage of total required capacity level $\bar{D}(T)$. In a deterministic situation, the cumulated target capacity levels $\bar{c}(t)$ should satisfy the following constraint:

$$\bar{c}(t) \geq \bar{D}(t)$$

This states that, when $\bar{c}(T) \leq \bar{D}(T)$, the percentage of target capacity available at the end of period $t$, $\bar{c}(t)$, should be higher or equal to the percentage of minimum required capacity at the end of period $t$, $\bar{D}(t)$. We should deal with the random variables $\bar{D}(t)$ because the realizations are unknown. The risk variable $\beta$ is used in this option as well. In this option the risk variable affects the probability of violating the constraint $\bar{c}(t) \geq \bar{D}(t)$. The target capacity level $\bar{c}(t)$ to stay above the cumulated minimum required capacity $\bar{D}(t)$ with probability $\beta \ (F_{\bar{D}(t)}(\bar{c}(t)) \leq \beta)$ is calculated by:

$$\bar{c}(t) = F_{\bar{D}(t)}^{-1}(\beta).$$

If, for example, $\beta$ is set to 0.9, then $\bar{c}(t)$ includes a 90% probability to be higher or equal to $\bar{D}(t)$. In other words, a 90% probability of satisfying the constraint $\bar{c}(t) \geq \bar{D}(t)$; the higher the value of $\beta$, the less risk is taken regarding violating the constraint $\bar{c}(t) \geq \bar{D}(t)$. Thus, for subproblem 2b, the cumulated target capacity levels for each planning period in the planning horizon are now calculated by:

$$\bar{c}(t) = F_{\bar{D}(t)}^{-1}(\beta) \times \bar{c}(T).$$
This works for all distributions of $D(t)$ for which an inverse cumulative distribution function is available. Like in option 2a, the timing of capacity now depends on $\beta$ for which the finally used value depends on the situation and user-specific requirements.

2c: Average between minimum and maximum required capacity levels

For this option both the minimum and maximum capacity levels are considered. For each individual period $t$, the value for $\bar{c}(t)$ is determined according to the average of the values of $\bar{c}(t)$ in option 2a and 2b. This is visually presented in Figure 26. In this figure a vertical line is drawn for each period $t$ from the $\bar{c}(t)$ determined in option 2b to the $\bar{c}(t)$ determined in option 2a. For each period $t$, the value of $\bar{c}(t)$ in this option lies exactly at the middle of the vertical line. This means for option 2c that the cumulated target capacity levels for each planning period in the planning horizon are calculated by:

$$\bar{c}(t) = \frac{F^{-1}_{D(t)}(1 - \beta) + F^{-1}_{A(t)}(\beta)}{2} \ast \bar{c}(t).$$

Instead of the vertical average visualized in Figure 26, one could consider the horizontal average between the values of $\bar{c}(t)$ determined in option 2a and 2b, see Figure 27. However, the data points available from option 2a and 2b are limited, causing that the average will not lie on the end of each period; while $\bar{c}(t)$ is defined as cumulated available capacity up to and including period $t$, i.e. at the end of each period. In order to determine the horizontal average we are required to jump to estimates of data points lying between the original data points. When the values of $\bar{c}(t)$ for each period $t$ individually are determined in the horizontal way it makes the data unclear and unreliable, therefore this option is left out of scope.

4.5.3. Subproblem 3

- Determine the number of employees for each shift according to the cumulated target capacity levels; two options are presented.

In this subproblem the objective function $G$ depends upon the values for $\{q_s\}$ and should minimize the difference between cumulated available capacity levels $\bar{w}(t)$ and cumulated target capacity levels $\bar{c}(t)$. The optimization problem for subproblem 3 is defined as:

$$\min_{\{q_s\} \geq 0} G(\{q_s\})$$

Compared to non-linear optimization problems, linear optimization problems are much more easy to solve (Chinneck; 2006). To keep the optimization problem linear, this subproblem considers two options to deal with the objective function $G(\{q_s\})$. In the first option we consider the target levels $\bar{c}(t)$ as a minimum and in the second option we consider the target levels $\bar{c}(t)$ as a maximum. We know from section 4.1 that available capacity for each period $t$ depends on the available number of employees for all shifts, and so cumulated available capacity at the end of period $t$ is defined as:

$$\bar{\omega}(t) = \sum_{t' = 1}^{t} \omega(t') = \sum_{t' = 1}^{t} \sum_{s = 1}^{S} q_s * x_s(t')$$
Moreover, the following restrictions should hold for both options:

- \( \phi_s \in \mathbb{N} \) for all \( \phi_s, s = \{1, \ldots, S\} \)
- \( \tilde{c}(t) \geq 0 \) for all \( t = \{1, \ldots, T\} \)
- \( x_s(t) \in \{0,1\} \) for all \( t = \{1, \ldots, T\} \) and for all \( s = \{1, \ldots, S\} \)

The first restriction let the amount of employees available for each shift be a collection of natural numbers. The second restriction let the cumulated values for \( \tilde{c}(t) \) be nonnegative. The third restriction let the variable \( x_s(t) \), which shows whether planning period \( t \) is covered in shift \( s \), be Yes (=1) or No (=0). The way how \( \{\phi_s\} \) is determined is different for both options 3a and 3b and are presented respectively:

4.5.3.1. **Option 3a: Target capacity levels as minimum**

In this option a hard constraint is considered in which the cumulated available capacity levels \( \tilde{\omega}(t) \) are always higher or equal to the cumulated target capacity levels \( \tilde{c}(t) \). Hence, the hard constraint that is added to the optimization problem is defined as \( \tilde{\omega}(t) \geq \tilde{c}(t) \), thus:

\[
\sum_{t=1}^{T} \sum_{s=1}^{S} \phi_s * x_s(t') \geq \tilde{c}(t)
\]

The objective function should decide upon the values for \( \{\phi_s\} \) and should consider the difference between cumulated available capacity levels and cumulated target capacity levels, hence the objective function in this option is formulated as:

\[
G(\{\phi_s\}) = \sum_{t=1}^{T} \tilde{\omega}(t) - \tilde{c}(t) = \sum_{t=1}^{T} \left( \sum_{t'=1}^{T} \sum_{s=1}^{S} \phi_s * x_s(t') \right) - \tilde{c}(t)
\]

4.5.3.2. **Option 3b: Target capacity levels as maximum**

In this option a hard constraint is considered in which the cumulated available capacity levels \( \tilde{\omega}(t) \) are always smaller or equal to the cumulated target capacity levels \( \tilde{c}(t) \). Hence, the hard constraint that is added to the optimization problem is defined as \( \tilde{\omega}(t) \leq \tilde{c}(t) \), thus:

\[
\sum_{t=1}^{T} \sum_{s=1}^{S} \phi_s * x_s(t') \leq \tilde{c}(t)
\]

The objective function should decide upon the values for \( \{\phi_s\} \) and should consider the difference between cumulated available capacity levels and cumulated target capacity levels, hence the objective function in this option is formulated as:

\[
G(\{\phi_s\}) = \sum_{t=1}^{T} \tilde{c}(t) - \tilde{\omega}(t) = \sum_{t=1}^{T} \left( \tilde{c}(t) - \left( \sum_{t'=1}^{T} \sum_{s=1}^{S} \phi_s * x_s(t') \right) \right)
\]

4.6. **Method development summary**

The method developed in this chapter is developed as a decision support tool for a situation where the number of employees for each shift in a given day should be determined. Due to time constraints the method in this report is not extended to a multi-process production system; therefore, the method only considers capacity planning for a single-process production system. To produce such a capacity plan, the method presents three subproblems which should be executed consecutively. The method involves a number of options which are free to choose by the user of the method; three options in subproblem 2 and two options in subproblem 3. The method also involves two parameters (\( \alpha \) and \( \beta \)) for which the user is free to choose the value. Each situation or user could prefer another set of options and parameter values. However, one could only prefer certain decisions when the consequences, risks and performance for these decisions are known. The method should therefore be evaluated for the different decisions one could take. Therefore, chapter 5 evaluates the decisions by performing a case study for CEVA.
5. Case study

The method in this report is developed as a decision support tool for a situation where the number of employees for each shift in a given day should be determined. The method developed in chapter 4 should be used to provide insights in how these short-term capacity decisions should be taken. The method developed in chapter 4 let the user free in several decisions. First of all, in subproblem 2 of the method one could choose between 3 options; moreover, in subproblem 3 of the method one could choose between 2 options. Subsequently, values should be chosen for multiple parameters. For some parameters the value one should use follows directly from its practice situation. For other parameters, like $\alpha$ and $\beta$, the values are free to choose. Each practical situation requires its own ‘best’ options and parameter values. We do not know yet what the ‘best’ choices for CEVA are. To be able to support the choices one should have insights in the consequences, risks and performance of these choices. The purpose of this chapter is to perform a case study in which the performance of the developed method is evaluated for multiple scenarios in CEVA’s environment. A scenario is defined as a combination of choices between the possible options in subproblem 2 and 3 of the method and choices for values of parameters which are free to choose. The planners of CEVA currently have no insights into the consequences of their decisions. With the case study we are able to provide more insights in the consequences of short-term capacity decisions because comparisons are possible. Additionally, it provides the basis for the development of a useful decision support tool.

For making comparisons we could simulate and compare the performance for each scenario. Monte-Carlo simulation for example is a widely used technique that could be used. The values of random variables in this technique are generated according to their probability distribution functions. However, from section 4.3.2 we know that assuming independent and identically distributed random variables $A(t)$ and $D(t)$ may not provide realistic data; therefore, historical data is used to evaluate the scenarios. More details about the tests, dataset, performance, scenarios etc. are found further in this chapter. Basically, the following question will be answered in the case study:

What will the consequences be if scenario X was used in the developed method?

As was said, a scenario is a combination of choices made for options and parameter values one is free to choose in the developed method. Scenarios are compared with each other by evaluating each scenario for the same data set. Considering multiple scenarios helps exploring your choices and parameter settings, it gains insight into their consequences and visualizes risks in the planning process. Anticipating several possible demand realizations helps to adapt and implement a capacity plan that most closely resembles the needs. To process the case study the following parts are executed:

First, section 5.1 presents the case study preparation: the scope of the case study is delineated, it is examined whether and how the developed method should be adapted for CEVA’s practice environment, assumptions are presented and possible parameter values are discussed. Then, section 5.2 describes the case study approach, it discusses respectively: how a capacity plan should be generated from the developed method, which scenarios are compared, how the data set is constructed and how performance is measured. Subsequently, section 5.3 presents a case study verification and section 5.4 presents the results of the case study.

5.1. Case study preparation

The case study is prepared in this section. Consecutively, the scope is delineated to understand the boundaries of the case study. Then, the practical usage of the developed method is examined; the method is adapted to CEVA’s practice situation where necessary. To make clear the case study environment, assumptions are presented and possible parameter values are discussed.
5.1.1. Scope delineation
The production system at CEVA is a multi-process system. The method developed in chapter 4 only considers a single-process production system; therefore, the case study considers one single process. A choice has to be made: which of the multiple processes of CEVA to consider in the case study? As we already know, three main processes could be distinguished: picking, packing and marshaling. On average, marshaling only accounts for 7% of total planned capacity while picking accounts for 49% and packing for 44% of total planned capacity, see section 3.1.2. Considering the picking as the single process will provide the most gains. Moreover, picking is the first process in the process flow and therefore influences the other processes, see also section 3.1.4. Therefore picking is considered in our case study. As we know from the analysis, the picking process could be split into three competencies. The analysis showed that the percentage of forwarded order lines per picking competency is rather constant from day to day and is rather constant from DD group to DD group, see section 3.2.4. The analysis also revealed that employees are relatively easily interchangeable within the three picking competencies. Therefore we aggregate the three picking competencies and consider these as one single ‘picking’ process in the case study. Furthermore, the planning horizon is one day which is split into 24 periods of 1 hour; capacity is always used in terms of man-hours.

5.1.2. Method adaptations
The method developed in chapter 4 contains these three subproblems:

- **Subproblem 1**: Determine the total target capacity level for the complete planning horizon according to the expected total minimum required capacity.
- **Subproblem 2**: Determine the cumulated target capacity level for each planning period in the planning horizon.
- **Subproblem 3**: Determine the number of employees for each shift according to the cumulated target capacity levels.

In the following sections the practicality of each subproblem is discussed individually and modified where necessary.

5.1.2.1. **Subproblem 1**
Subproblem one deals with the forecast and the random variable of total minimum required capacity level \( \hat{D}(T) \). For the current situation total forwarded order lines are being forecasted by the model described in Appendix G. This model forecasts \( \hat{A}(T) \) instead of \( \hat{D}(T) \). The difference between these two is the amount of orders forwarded after cut-off time. CEVA strives to finish all orders at the end of the day, either forwarded before or after cut-off time. Therefore we do not adapt the original forecast model for orders arrived before cut-off time but use \( \hat{A}(T) \) instead of \( \hat{D}(T) \). When total forwarded order lines are known, the required capacity level can be determined by dividing the number of lines by its productivity level, which will be defined by \( \pi \). The productivity level \( \pi \) is assumed to be constant and equal for all employees. A forecast for the required capacity level can be determined in a similar way; dividing the forecast by its productivity level \( \pi \). The analysis in section 3.2.2 revealed that the probability function of the forecast error can be seen as a normal distribution with \( \mu^{FE} \) and \( \sigma^{FE} \) both in percentages. According to the characteristics of a continuous random variable (Montgomery and Runger, 2010) we can determine that the total capacity level \( \hat{A}(T) \) can be seen as a normal distribution with expected capacity level \( E[\hat{A}(T)] = \frac{FC}{\pi} \cdot \mu^{FE} + \frac{FC}{\pi} \) and standard deviation \( \sigma[\hat{A}(T)] = \frac{FC}{\pi} \cdot \sigma^{FE} \); see Appendix J.9. Where \( FC \) is the forecast of total forwarded order lines in the planning horizon and \( \pi \) is the productivity value in order lines per period. The values for \( E[\hat{A}(T)] \) and \( \sigma[\hat{A}(T)] \) are required in the calculation of \( c(T) \). The total target capacity level \( \hat{c}(T) \) to fulfill all orders with probability \( \alpha \) can now be calculated with \( F_{\hat{c}(T)}^{-1}(\alpha) \) since the probability function of \( \hat{A}(T) \) is known.
5.1.2.2. Subproblem 2

Subproblem 2a

Subproblem 2a determines \( \tilde{c}(t) \) by considering the random variable \( \tilde{A}(t) \):

\[
\tilde{c}(t) = F_{\tilde{A}(t)}^{-1}(1 - \beta) \ast \tilde{c}(T)
\]

We would like to select a particular distribution that best fits the random process of \( \tilde{A}(t) \) so we can determine \( \tilde{c}(t) \). The distributions compared in our analysis executed in Appendix K.1 are: Weibull, Gamma, Beta and Exponential. All values for \( \tilde{A}(t) \) lie between or at 0 and 1; the beta distribution is a continuous probability distribution which could be defined on the interval from [0,1]. Moreover, the results show that the Beta distribution is the probability distribution that has the best fit with most \( \tilde{A}(t) \), see Appendix K.1. For a period \( t \) in which the best fit of \( \tilde{A}(t) \) is not the Beta distribution, the log-likelihood for the Beta distribution does not significantly differ from the log-likelihood for the best fitted distribution. Therefore we choose the Beta distribution for all \( \tilde{A}(t) \) in the planning horizon. As a result, cumulated target capacity levels \( \tilde{c}(t) \) for all periods \( t = \{1, \ldots, T\} \) in subproblem 2a can now be determined for a chosen value of \( \beta \).

Subproblem 2b

Subproblem 2b determines \( \tilde{c}(t) \) by considering the random variable \( \tilde{D}(t) \):

\[
\tilde{c}(t) = F_{\tilde{D}(t)}^{-1}(\beta) \ast \tilde{c}(T)
\]

In a similar way to \( \tilde{A}(t) \), we would like to select a particular distribution that best fits the random process of \( \tilde{D}(t) \). The distributions compared in our analysis executed in Appendix K.2 are: Weibull, Gamma, Beta and Exponential. All values for \( \tilde{D}(t) \) lie between or at 0 and 1; the beta distribution is a continuous probability distribution which could be defined on the interval from [0,1]. Moreover, the results show that the Beta distribution is the probability distribution that has the best fit with most \( \tilde{D}(t) \), see Appendix K.2. For a period \( t \) in which the best fit of \( \tilde{D}(t) \) is not the Beta distribution, the log-likelihood for the Beta distribution does not significantly differ from the log-likelihood for the best fitted distribution. Therefore we choose the Beta distribution for all \( \tilde{D}(t) \) in the planning horizon. As a result, cumulated target capacity levels \( \tilde{c}(t) \) for all periods \( t = \{1, \ldots, T\} \) in subproblem 2b can now be determined for a chosen value of \( \beta \).

Subproblem 2c

Subproblem 2c deals with the random variables of both cumulated minimum and maximum required capacity levels \( \tilde{A}(t) \) and \( \tilde{D}(t) \). We now know the probability functions with the best fit for both variables. As a result, cumulated target capacity levels for all periods \( t = \{1, \ldots, T\} \) in subproblem 2c can be determined as originally stated:

\[
\tilde{c}(t) = \frac{\left( F_{\tilde{A}(t)}^{-1}(1 - \beta) + F_{\tilde{D}(t)}^{-1}(\beta) \right)}{2} \ast \tilde{c}(T).
\]

5.1.2.3. Subproblem 3

Both subproblem 3a and subproblem 3b deal with a linear programming (LP) problem which determines the number of available employees \( \varphi_s \) for all shifts \( s = \{1, \ldots, S\} \). The two LP problems developed in section 4.4.3 describe the problem in its general application. However, in practice restrictions exist for the determination of \( \varphi_s \). The restrictions relevant for CEVA and considered in this case study are:

- One cannot have more employees available in the planning horizon than the total pool size. 
- There is a limited number of employees available that one could use, therefore this restriction should be added to the LP problem:
  - \( \sum_{s=1}^{S} \varphi_s \leq PS \)

Where \( PS \) is the total pool size in the planning horizon.
The number of employees available simultaneously in one period should be smaller or equal to the maximum number of employees per period. According to equipment limitations, the number of employees available simultaneously in one planning period is restricted by a maximum. Therefore the following restriction should be added to the LP problem:

\[ \sum_{s=1}^{S} \varphi_s \cdot x_s(t) \leq MNE \quad \text{for all } t \{t = 1, \ldots, T\} \]

Where \( MNE \) is the maximum number of employees per planning period.

For the case study these two restrictions have been added to both LP problems in respectively option 3a and 3b.

### 5.1.3. Parameter values

Values for all parameters should be determined when one uses the developed method to create a capacity plan. The possible values for all parameters in the CEVA case study are discussed in this section and summarized in Table 6. For some parameters one value approximation is determined, for other parameters multiple values are possible.

The parameter for the forecast \( FC \) of total order lines in the planning horizon could basically have all values equal to a natural number \( N \).

The forecast analysis in section 3.2.2 revealed that the forecast error \( FE \) is distributed normally with \( \mu^{FE} = -0.019 \) and \( \sigma^{FE} = 0.166 \). These parameter values are used in the case study.

The scope delineation determined that the case study considers the three picking competencies as one single ‘picking’ process. Therefore, one picking productivity value should be determined. The analysis in section 3.2.4 presented the average percentage of order lines per picking competency and a productivity value for each picking competency individually. These values are used in Appendix L to determine the productivity value in the case study to be 21.5 order lines per period.

The parameter \( \alpha \) in subproblem 1 could basically have all values between or equal to 0 and 1. Similar for the parameter \( \beta \) in subproblem 2.

The scale and parameter values for the Beta distributed variables \( \hat{A}(t) \) for all \( t \) are presented in Appendix K.1. The scale and parameter values for the Beta distributed variables \( \hat{D}(t) \) for all \( t \) are presented in Appendix K.2.

The parameters for the set of shifts and its characteristics \( x_s(t) \) are defined based on current situation at CEVA. Basically, each shift has a length of 9 periods and starts between or at period 6 to 15. The exact values for all \( x_s(t) \) are presented in Appendix M. There are ten different shifts for which employees could be planned for; in other words, there are 10 different decision variables \( \varphi_s \) for which one could choose a value. The restrictions for the values of \( \{\varphi_s\} \) are already discussed in section 5.1.2.3.

The total pool size \( PS \) is set to 60. The maximum number of employees that could be available simultaneously in one planning period \( (MNE) \) is set to 19.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( FC )</td>
<td>( FC \in \mathbb{N} )</td>
<td>( \hat{A}(t) )</td>
<td>See Appendix K.1.</td>
</tr>
<tr>
<td>( \mu^{FE} )</td>
<td>-0.019</td>
<td>( \hat{D}(t) )</td>
<td>See Appendix K.2.</td>
</tr>
<tr>
<td>( \sigma^{FE} )</td>
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<td>( S )</td>
<td>10</td>
</tr>
<tr>
<td>( \pi )</td>
<td>21.5 order lines per period</td>
<td>( x_s(t) )</td>
<td>See appendix M</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>( [0, \ldots, 1] )</td>
<td>( PS )</td>
<td>60</td>
</tr>
<tr>
<td>( \beta )</td>
<td>( [0, \ldots, 1] )</td>
<td>( MNE )</td>
<td>19</td>
</tr>
<tr>
<td>( {\varphi_s} )</td>
<td>See restrictions in LP problem of subproblem 3</td>
<td>Section 4.5.3 and 5.1.2.3</td>
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</tr>
</tbody>
</table>

**Table 6 Parameter values for case study**
5.1.4. Assumptions

This section presents a summary of all assumptions made in the CEVA case study:

1. **The planning horizon is one day.**
   - One day takes 24 hours, each planning period takes 1 hour; $T = 24$.

2. **Forwarded orders within a planning period are available for processing at the end of each planning period.**
   - All forwarded orders within the same period are aggregated and subsequently assumed to be forwarded at the end of the corresponding period, see section 4.1 for explanation.

3. **Required capacity per period should be fulfilled at the end of the preceding period.**
   - Capacity required for all due dates within the same period is aggregated and subsequently assumed to be required at the end of the preceding planning period, see section 4.1 for explanation.

4. **Each planning horizon starts in a ‘clean’ state:**
   - **No orders are forwarded before the start of the planning horizon.**
     - At the beginning of each planning horizon no backlog from previous planning horizon is assumed. In this case each planning horizon is independent from one another and no assumptions about the initial backlog have to be made.
   - **Backlog at the end of the planning horizon is lost.**
     - No corrective recourse actions are taken into account to correct for the backlog. The planning horizon is one day and there is no initial backlog at the start of a planning horizon; therefore backlog at the end of the planning horizon is lost.

5. **Employees are being hired per shift.**
   - When an employee is planned to work he/she is hired to work for the periods according to one shift $s$ as shown in Appendix M.

6. **All employees have equal and constant productivity value $\pi = 21.5$.**
   - No distinction is made to correct for employees with a higher or lower productivity because this makes the problem be an individual staff assignment which is outside the scope of this project.

7. **Only contingent employees are considered**
   - Although the capacity plan in practice considers restrictions related to permanent employees, the case study is interested in the ‘best’ capacity plan without considering permanent employees.

5.2. Case study approach

The case study approach is presented in this section. Consecutively, the scenarios compared in the case study are discussed. Subsequently, the dataset used in the case study is discussed and the way of performance measurement is presented.

5.2.1. Scenario comparisons

Not all possible scenarios are compared because there are an infinitely number of possible scenarios and some scenarios does not make sense to consider. This section discusses the scenarios that are compared in the case study.

Choices between options should be made within subproblem 2 and subproblem 3 of the method, but we do not know yet the consequences of these choices. In subproblem 2 one could choose between three options (2a, 2b & 2c). In subproblem 3 one could choose between two options (3a & 3b). In total six, as we now define, choice-combinations (cc) are possible: 2a-3a, 2a-3b, 2b-3a, 2b-3b, 2c-3a and 2c-3b. Subproblem 2a determines the target $\tilde{c}(t)$ as being a maximum. In this case, it is contradictory to consider $\tilde{c}(t)$ in subproblem 3a as a minimum at the same time. Therefore, the choice-combination 2a-3a is left out of scope. The same logic holds for the choice combination 2b-3a, since it is contradictory to determine $\tilde{c}(t)$ as a minimum in subproblem 2 and
consider it as a maximum at the same time in subproblem 3. Thus, the four choice-combinations considered in the case study are: 2a-3b, 2b-3a, 2c-3b and 2c-3a.

We have seen in section 5.1.3 that several parameter values are still not determined; these are the parameters \( FC, \alpha, \beta \). The forecast value \( FC \) is input for which the value is out of our control; the method should be able to process all possible values of \( FC \). The parameter \( \alpha \) directly affects the total capacity, and thereby the safety margin that is used for planning; the higher \( \alpha \) the higher the safety margin. We do not know yet the exact performance for the possible values of \( \alpha \). As a logical consequence, comparisons should be made for different values of \( \alpha \). The analysis from section 3.1.2 revealed that current average safety margin of CEVA is about 7%. This safety margin equals \( \alpha = 0.7 \); see Appendix J.10 for the calculations. From section 2.1.1.1 we know there is minimum and maximum for the number of order lines CEVA should be able to process each day. The minimum equals \( \alpha = 0.22 \) and the maximum equals \( \alpha = 0.85 \); see Appendix J.10 for the calculations. Therefore, three values for \( \alpha \) are considered in the case study: 0.22, 0.7 and 0.85.

The parameter \( \beta \) directly affects how capacity is allocated throughout the planning horizon. We do not know yet the performance for the possible values of \( \beta \). Similarly to \( \alpha \), comparisons for different values of \( \beta \) should be made. For all three options in subproblem 2, the values for \( \beta \) directly affect the place in the planning horizon capacity will be planned. In subproblem 2a, \( \beta \) directly affects the risk of \( \bar{c}(t) \) being higher or equal to \( \bar{A}(t) \). In subproblem 2b, \( \beta \) directly affects the risk of \( \bar{c}(t) \) being smaller or equal to \( \bar{D}(t) \). Subproblem 2c takes the average of both 2a and 2b. The lower the value of \( \beta \) the more risk is taken, one would expect better results for the highest \( \beta \). Therefore, in the first place, we are not interested in low values of \( \beta \). Although, in order to verify and to get a sense of the affect for the value of \( \beta \) it is reasonable to consider the following three values of \( \beta \) in the case study: 0.5, 0.7 and 0.9. In summary:

- Four choice-combinations (cc) are considered:
  - \( cc = 1: \) (2a-3b), Maximum in subproblem 2, Maximum in subproblem 3
  - \( cc = 2: \) (2b-3a), Minimum in subproblem 2, Minimum in subproblem 3
  - \( cc = 3: \) (2c-3b), Average in subproblem 2, Maximum in subproblem 3
  - \( cc = 4: \) (2c-3a), Average in subproblem 2, Minimum in subproblem 3

- Three values for \( \alpha \) are considered: 0.22, 0.7 and 0.85
- Three values for \( \beta \) are considered: 0.5, 0.7 and 0.9

This makes it that in total 36 (= \( 4 \times 3 \times 3 \)) individual scenarios are compared. Each scenario is defined by a number \( x \) for which each \( x \) is characterized by its own choice-combination \( cc^x \), and parameter values \( \alpha^x \) and \( \beta^x \). All scenarios are presented individually in Appendix N.

Next to the 36 scenarios, there is one extra scenario that is used as a reference scenario. A combination of consultations with current capacity planners and capacity plans used in last months (January to March 2015) has resulted in a reference scenario. We assume that these capacity plans resembles CEVA’s current method of capacity planning.

### 5.2.2. Dataset

Scenarios are compared with each other by running each scenario for the same data set. A dataset includes data for multiple days where for each day the following data is available:

- \( FC \) = The forecast value;
- \( \{A(t)\} = \) The set of values for all \( A(t) \) \( t = 1, ..., T; \)
- \( \{D(t)\} = \) The set of values for all \( D(t) \) \( t = 1, ..., T. \)

From section 4.3.2 we know that assuming the random variables \( A(t) \) and \( D(t) \) to be independent and identically distributed is not realistic. Therefore, generating values from the random variables \( A(t) \) and \( D(t) \) based on the best fitting distribution function does not give a realistic test environment. Therefore, we choose to use historical data to create a realistic data set. The forecast values \( FC \) and values for all \( \{A(t)\} \) and \( \{D(t)\} \) are stored by CEVA. The data set considered in the case study covers all working days in 2014. The data set finally covers 250 days where for each day the values for \( FC, \{A(t)\} \) and \( \{D(t)\} \) are known.
5.2.3. Performance measurement

The term *performance* is mentioned multiple times, but what is *performance* in the CEVA case study? How should be determined that one scenario is performing ‘better’ than another one? The method produces a capacity plan which subsequently should be brought into practice. In this case, what are the possible consequences? Which consequences are desired and which consequences should be avoided? As mentioned in section 4.3, the optimal plan, which we desire, satisfies the following constraints for all periods in the planning horizon:

\[
\tilde{D}(t) \leq \tilde{a}(t) \leq \tilde{A}(t)
\]

In this case the available capacity is always enough to satisfy the minimum required capacity while at the same time the available capacity does not exceed the maximum useful capacity. Situations, however, occur in which the restrictions are violated; these situations should be avoided. Now we can answer the question how to determine that a certain scenario is performing ‘better’ than another one, because the ‘best’ scenario will have the least situations in which the mentioned restrictions are violated. The performance of a capacity plan can thus be measured with the available capacity and the minimum required and maximum useful capacity for each planning horizon. In section 4.3 we discussed an optimization problem taking into account these variables.

We could consider using the objective function of this optimization problem since it measures the penalty costs for situations when cumulated available capacity exceeds cumulated maximum useful capacity and it measures situations when cumulated available capacity undershoots cumulated minimum required capacity.

There is however one issue not taken into account in this objective function. The size of effective production should be enough to fulfill the minimum required capacity. In this case, the size of effective production is not equal to the available capacity because available capacity is lost when it exceeds the maximum useful capacity. Apparently, the cumulative available capacity only is not appropriate to check whether minimum required capacity is fulfilled since it does not reflect the exact size of effective production. Therefore, in order to define the performance of a capacity plan, we should be able to measure the size of effective production in each period of the planning horizon. With this information we are able to measure the size of lost capacity and the size of work not fulfilled in time for each planning horizon. The notation used in the performance measurements are shown in Table 7 and is visualized in Figure 28.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\omega(t))</td>
<td>Available capacity value for planning period (t).</td>
</tr>
<tr>
<td>(d(t))</td>
<td>Realization of minimum required capacity at the end of planning period (t).</td>
</tr>
<tr>
<td>(a(t))</td>
<td>Realization of forward orders at the beginning of planning period (t).</td>
</tr>
<tr>
<td>(wip(t))</td>
<td>Work in progress at the end of planning period (t).</td>
</tr>
<tr>
<td>(l(t))</td>
<td>Lost capacity at the end of planning period (t).</td>
</tr>
<tr>
<td>(p(t))</td>
<td>Effective production in planning period (t).</td>
</tr>
<tr>
<td>(s(t))</td>
<td>Stock of finished work at the end of planning period (t).</td>
</tr>
<tr>
<td>(f(t))</td>
<td>Work not fulfilled in time at the end of planning period (t).</td>
</tr>
</tbody>
</table>

Table 7 Definition of parameters and variables used in performance measurement

![Figure 28 Visualization of performance measurement per period](image)

- The total size of lost capacity in the planning horizon is now equal to: \(\sum_{t=1}^{T} l(t)\).
- **Overcapacity**
- The total size of work not fulfilled in time in the planning horizon is now equal to: \(\sum_{t=1}^{T} f(t)\).
- **Undercapacity**
Because we assume each planning horizon to start ‘clean’. we assume \( wip(0) = 0 \) and \( s(0) = 0 \). In the formulation \( [X]^+ \) denotes the maximum of \( [X] \) and \( 0 \); \( \text{Min}[X; Y] \) denotes the minimum between \([X]\) and \([Y]\). The performance of a scenario will thus be visualized with two values. One value representing lost capacity and another value representing work not fulfilled in time. In other words, we consider these values as representing the size of overcapacity and the size of undercapacity respectively.

### 5.3. Case study verification

This section discusses the verification of the case study. In the case study several distribution functions are used. Additionally, the case study uses the computer program MS Excel to produce the results of the case study. These two issues are discussed in this section.

*In subproblem 1*, the Shapiro-Wilk test for normality in section 3.2.2 revealed that the probability of the forecast error can be seen as a normal distribution with \( \mu_{PE} = -0.019 \) and \( \sigma_{PE} = 0.166 \). The dataset used to determine the probability function of the forecast error comes from the same dataset used in the case study. Therefore we know that the parameter values used in subproblem 1 of the method are representative for the forecast error and thus also for the forecasted demand used in the case study. In the future, CEVA should study whether the parameters are still representative for the situation at that moment and adjust the parameters when necessary.

*In subproblem 2*, the analysis in Appendix K revealed that the random variables \( \tilde{A}(t) \) and \( \tilde{D}(t) \) can be seen as a beta distribution with parameter values \( a \) and \( b \) for each period as presented in Appendix K.1 and Appendix K.2. The dataset used to determine the probability function of the forecast error comes from the same dataset used in the case study. Therefore we know that the parameter values used in subproblem 2 of the method are representative for the data used in the case study. Also in this case, CEVA should study whether the parameters are still representative for the situation at that moment and adjust the parameters when necessary.

*In subproblem 3*, the linear programming problem is implemented in MS Excel according to the model presented in section 4.4.3. and its adjustments in section 5.1.2.3. Appendix O.1 presents a verification whether the solution of the implemented model is error free and successfully satisfies all constraints.

The performance measurements are implemented in MS Excel according to the formulas presented in section 5.2.3 Appendix O.2 presents a correctness test for the measurements by evaluating the results for each set of input values.

The results of the case study are discussed in section 5.4. It will be discussed whether the results are reasonable. The relationship between input and output is discussed to verify the logic from the conceptual model, known as face validity (Sargent, 2005).

### 5.4. Case study results

This section discusses the results of the case study. For completeness, appendix P presents how exactly the results of the case study are retrieved step by step.

The main purpose of the case study is to provide insights into the consequences of the capacity decisions a user of the method could make. With the case study we try to reveal the ‘best’ decisions for CEVA. Therefore, this section discusses the results for the following question:

*What will the consequences be if scenario X was used in the developed method?*

According to section 5.2.3 performance is measured by the amount of overcapacity and the amount of undercapacity, both in terms of man-hours. Therefore, according to section 5.2.3, we evaluate the following averages values for each scenario denoted by:

- \( U \) = The average size of overcapacity in one planning horizon (in terms of man-hours).
- \( O \) = The average size of undercapacity in one planning horizon (in terms of man-hours).

The reference scenario, as mentioned in section 5.2.1, resembles current way of capacity planning. The planners of CEVA mention that they experience in current situation relatively more overcapacity (\( O \)) and less to no undercapacity (\( U \)). The case study results for the reference scenario...
match with the expectations because the case study results show an average size of overcapacity in one planning horizon \( O = 36,80 \) and an average size of undercapacity in one planning horizon \( U = 2,49 \). CEVA does not provide reliable data to verify these figures with reality. However, the real values for \( O \) and \( U \) for the reference scenario are approximated by using the approximated numbers for planned capacity and used capacity for each day in the period from week 27 to week 50 of 2014. According to these figures \( O = 33,61 \) and \( U = 2,21 \). Although we cannot make hard conclusions from this data, the approximated values are rather similar to the case study values. Moreover, the behavior of the input-output relationship is reasonable and thus the logic in the method seems to be verified for the reference scenario.

The results for the average size of overcapacity and the average size of undercapacity for each scenario individually are shown in Table 8 and are visualized as a scatterplot in Figure 29. The concept of an efficient frontier is drawn in Figure 29. The concept of the efficient frontier, introduced by Markowitz (1952) and generally used in financial mathematics, helps to illustrate the trade-off between the factors of undercapacity and overcapacity. In this case, the efficient frontier overlaps the scenarios that offers the lowest size of undercapacity for a given size of overcapacity, and lies at the bottom of all considered scenarios. The efficient frontier thereby provides a reference line in order to optimize the parameter values. Given the scenarios defined in section 5.2.1, the consequences of changing a parameter value are discussed now.

![Efficient frontier](image)

**Figure 29** Visualization of the efficient frontier and the average size of overcapacity \( (O) \) and the average size of undercapacity \( (U) \) for each scenario individually.

Looking back to the problem analysis in chapter 3, two major challenges for our capacity planning problem were outlined. The first challenge is deciding on the size of total available capacity. This choice depends on the value for \( \alpha \) since this value directly affects the total size of available capacity. The choice for the value of \( \alpha \) is a trade-off between the average size of overcapacity \( (O) \) and the average size of undercapacity \( (U) \). For all instances, we expect that choosing a higher value for \( \alpha \) causes a decrease in the size undercapacity \( (U) \) and an increase in the size of overcapacity \( (O) \). This is in line with the results from our case study; when keeping fixed values for \( cc \) and \( \beta \), choosing a higher \( \alpha \) decreases undercapacity and increases overcapacity, see also the Figures 30, 31, 32 and 33. We can state that, also for these results, the behavior of the input-output relationship is reasonable and thus the logic in the method seems to be correct.

The second challenge is deciding on the timing of available capacity throughout the day. This choice depends on the choice combination \( cc \) and depends on the value for \( \beta \) since both affect the timing of available capacity during the day. The choice for \( cc \) directly affects the way how available capacity is spread during the day. The value for \( \beta \) is a variable which affects the risk taken within each choice combination \( cc \).
<table>
<thead>
<tr>
<th>Scenario</th>
<th>( cc^x - \alpha^x - \beta^x )</th>
<th>( O )</th>
<th>( U )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference scenario</td>
<td>⋄</td>
<td>36.80</td>
<td>2.48</td>
</tr>
<tr>
<td>1</td>
<td>1 - 0.22 - 0.5</td>
<td>□</td>
<td>18.35</td>
</tr>
<tr>
<td>2</td>
<td>1 - 0.22 - 0.7</td>
<td>□</td>
<td>13.85</td>
</tr>
<tr>
<td>3</td>
<td>1 - 0.22 - 0.9</td>
<td>⋄</td>
<td>7.99</td>
</tr>
<tr>
<td>4</td>
<td>1 - 0.70 - 0.5</td>
<td>●</td>
<td>34.69</td>
</tr>
<tr>
<td>5</td>
<td>1 - 0.70 - 0.7</td>
<td>●</td>
<td>28.26</td>
</tr>
<tr>
<td>6</td>
<td>1 - 0.70 - 0.9</td>
<td>●</td>
<td>21.45</td>
</tr>
<tr>
<td>7</td>
<td>1 - 0.85 - 0.5</td>
<td>▲</td>
<td>46.40</td>
</tr>
<tr>
<td>8</td>
<td>1 - 0.85 - 0.7</td>
<td>▲</td>
<td>40.09</td>
</tr>
<tr>
<td>9</td>
<td>1 - 0.85 - 0.9</td>
<td>▲</td>
<td>32.36</td>
</tr>
<tr>
<td>10</td>
<td>2 - 0.22 - 0.5</td>
<td>□</td>
<td>10.99</td>
</tr>
<tr>
<td>11</td>
<td>2 - 0.22 - 0.7</td>
<td>□</td>
<td>8.70</td>
</tr>
<tr>
<td>12</td>
<td>2 - 0.22 - 0.9</td>
<td>□</td>
<td>8.30</td>
</tr>
<tr>
<td>13</td>
<td>2 - 0.70 - 0.5</td>
<td>●</td>
<td>31.03</td>
</tr>
<tr>
<td>14</td>
<td>2 - 0.70 - 0.7</td>
<td>●</td>
<td>28.24</td>
</tr>
<tr>
<td>15</td>
<td>2 - 0.70 - 0.9</td>
<td>●</td>
<td>26.90</td>
</tr>
<tr>
<td>16</td>
<td>2 - 0.85 - 0.5</td>
<td>▲</td>
<td>47.94</td>
</tr>
<tr>
<td>17</td>
<td>2 - 0.85 - 0.7</td>
<td>▲</td>
<td>46.26</td>
</tr>
<tr>
<td>18</td>
<td>2 - 0.85 - 0.9</td>
<td>▲</td>
<td>44.57</td>
</tr>
<tr>
<td>19</td>
<td>3 - 0.22 - 0.5</td>
<td>□</td>
<td>5.58</td>
</tr>
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<td>□</td>
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<td>16.71</td>
</tr>
<tr>
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<td>3 - 0.70 - 0.7</td>
<td>●</td>
<td>16.34</td>
</tr>
<tr>
<td>24</td>
<td>3 - 0.70 - 0.9</td>
<td>●</td>
<td>15.87</td>
</tr>
<tr>
<td>25</td>
<td>3 - 0.85 - 0.5</td>
<td>▲</td>
<td>25.62</td>
</tr>
<tr>
<td>26</td>
<td>3 - 0.85 - 0.7</td>
<td>▲</td>
<td>25.54</td>
</tr>
<tr>
<td>27</td>
<td>3 - 0.85 - 0.9</td>
<td>▲</td>
<td>25.40</td>
</tr>
<tr>
<td>28</td>
<td>4 - 0.22 - 0.5</td>
<td>□</td>
<td>12.19</td>
</tr>
<tr>
<td>29</td>
<td>4 - 0.22 - 0.7</td>
<td>□</td>
<td>11.03</td>
</tr>
<tr>
<td>30</td>
<td>4 - 0.22 - 0.9</td>
<td>□</td>
<td>9.09</td>
</tr>
<tr>
<td>31</td>
<td>4 - 0.70 - 0.5</td>
<td>●</td>
<td>30.56</td>
</tr>
<tr>
<td>32</td>
<td>4 - 0.70 - 0.7</td>
<td>●</td>
<td>28.91</td>
</tr>
<tr>
<td>33</td>
<td>4 - 0.70 - 0.9</td>
<td>●</td>
<td>26.80</td>
</tr>
<tr>
<td>34</td>
<td>4 - 0.85 - 0.5</td>
<td>▲</td>
<td>49.92</td>
</tr>
<tr>
<td>35</td>
<td>4 - 0.85 - 0.7</td>
<td>▲</td>
<td>46.02</td>
</tr>
<tr>
<td>36</td>
<td>4 - 0.85 - 0.9</td>
<td>▲</td>
<td>43.41</td>
</tr>
</tbody>
</table>

Table 8 Case study results for \( U \) and \( O \)

The results show that, when keeping fixed values for \( \alpha \) and \( \beta \), \( cc = 4 \) minimizes undercapacity and \( cc = 3 \) minimizes overcapacity. The figures show that purely on the quantitative results \( cc = 1 \) and \( cc = 2 \) are always outperformed either by \( cc = 3 \) or \( cc = 4 \). In our developed method the random variable for minimum required capacity \( D(t) \) is ignored when \( cc = 1 \); the random variable for maximum useful capacity \( A(t) \) is ignored when \( cc = 2 \). Apparently, better results are achieved when both the random variables for the minimum required capacity and the
maximum useful capacity levels are considered. In fact this is not surprisingly since the major problem of our capacity planning problem is that both variables are highly uncertain.

The parameter $\beta$ was introduced as a risk parameter which affects the risk one is taking regarding overcapacity and/or undercapacity. One would therefore expect better results for the highest $\beta$ in our case study for both overcapacity and undercapacity. The results match with our expectation; when keeping fixed values for $cc$ and $\alpha$, a higher value of $\beta$ always causes a lower value in both the size of undercapacity ($U$) and the size of overcapacity ($O$).

5.4.1. Cost saving opportunities compared to current situation

The exact costs for overcapacity and undercapacity are not easy to determine. In the past, operators left the company because of the high rate of downscaling, resulting in training costs for new operators. Other costs for overcapacity are included in a decrease of employee utilization. Undercapacity causes penalty costs of not meeting the SLA or could be corrected by upscaling actions. Upscaling actions causes employees need to work overtime, which is usually considered more expensive than usual working time. When the costs for overcapacity and undercapacity are equally weighted scenario 30 is preferred and cost savings of 56% could be achieved (compared to the reference scenario). This scenario makes it able to reduce the average size of overcapacity from 36.8 to 9.09 man-hours; however, this also means that the average size of undercapacity increases from 2.48 to 8.80 man-hours. The costs for undercapacity are generally considered higher than the costs for overcapacity. We do not know the exact costs for overcapacity and undercapacity. Although, we can determine the maximum possible cost savings for different cost ratios between overcapacity and undercapacity. Figure 34 visualizes the maximum possible cost savings for different cost ratios between overcapacity and undercapacity. It shows that when the costs for undercapacity are, for example, 3 times larger than the costs for overcapacity, cost savings of 20% could be achieved by applying scenario 24 instead of applying the reference scenario. In consultation with CEVA we approximate the costs for undercapacity not more than eight times as large as the costs for overcapacity. In this view, minimum cost savings of 8% could be achieved by applying scenario 33 instead of applying the reference scenario.

![Figure 34 Maximum possible cost savings per cost-ratio (overcapacity:undercapacity) compared to reference scenario](image)

Apparently, CEVA currently runs the risk of ignoring significant cost savings to base its capacity decisions on an intuitive sense. This is quantified by the results of the case study performed in this research. However, the choice among the preferred cost savings, and thereby the preferred scenario, should not only be based on the possible cost savings. Managers should not ignore qualitative factors such as practical usefulness and for example employee morale. The practical usefulness of a scenario partially depends on the abilities CEVA has for its corrective recourse actions. Changing the abilities of upscaling could generally not be achieved in the short-run and therefore requires long-term strategic capacity decisions which is not in the scope of this research. The practical usefulness therefore partially depends on the results for undercapacity. However, without significantly increasing the average size of undercapacity (from 2.48 to 3.17), the average size of overcapacity could be reduced from 36.80 to 26.80. Depending on CEVA’s cost ratio between overcapacity and undercapacity this could cause a **minimum cost saving of 8% and a maximum cost savings of 31%**, without having to significantly change the abilities of upscaling.
6. Implementation plan

This chapter shortly describes how the developed method should be used as a decision support tool for CEVA. At the end of the week, the capacity levels for each of the working days of the next week should be determined. A forecast, as originally generated, is required for the number of order lines for each of these days. The tool considers each day individually. The output of the tool generates a capacity plan presenting the number of employees which should be available for each shift. Appendix Q shows a screenshot of the output screen from the decision support tool. From the fact that the output of the method should be used as decision support, the planner of CEVA is free to adjust the capacity plan. However, the planner should be aware that adjustments also have it effects on the performance of the capacity plan. In advance of actually using the decision support tool, the following parameter values should be determined:

- The CDF and its corresponding parameter values explaining the distribution of the forecast error.

The performance of the forecast method possibly changes in the future. Consequently, the expected forecast error $\mu^{FE}$ and standard deviation $\sigma^{FE}$ changes and should be adjusted accordingly. The sample size to determine these values is advised to cover at least 25 weeks of forecast errors (125 data points).

- The productivity rate for the process in scope.

The productivity rate directly affects the solution of available capacity levels. Current productivity rate is determined in Appendix L and should be adjusted according to changes in the parameters used to determine the productivity rate. In our case study one average productivity rate is used, an interesting further research direction will be to distinguish between employees having different productivity rates.

- The CDF and its corresponding parameter values explaining the distribution of $\hat{A}(t)$ and $\hat{D}(t)$ for all periods $t = \{1, ..., T\}$.

The variation of all random variables $\hat{A}(t)$ and $\hat{D}(t)$ possibly change in the future. Consequently, the parameter values should be adjusted accordingly. The sample size to determine these values is advised to cover at least 25 weeks of data (125 data points).

- The values $x_s(t)$ for all $t = \{1, ..., T\}$ and for all $s = \{1, ..., S\}$ explaining the shifts employees could be planned for.

All values for $x_s(t)$ considered in the capacity planning problem should be adjusted accordingly when either the set of planning periods or the set of shifts changes. In our case study only shifts including 9 periods are considered, an interesting further research direction will be to consider other sets of shifts, for example shifts including less periods.

- The value for $PS$ explaining the total pool size for the process in scope.

This value should only be adjusted when the total pool size for the process in scope changes.

- The value for $MNE$ explaining the maximum number of employees that could be available simultaneously in one planning period for the process in scope.

Logically, this value should only be adjusted when the maximum number of employees that could be available simultaneously in one planning period for the process in scope changes.

For CEVA the values for all these parameters are already determined in section 5.1.3 and could be set according to it. These values should be updated each month in order to keep the tool up-to-date. Subsequently, the values for $cc$, $\alpha$ and $\beta$ should be chosen. The best parameter values depend on the situation in which the tool need to be applied. CEVA could choose its parameter values according to the case study results presented in section 5.4. Additionally, CEVA should examine the possibilities they have for their corrective recourse actions in both upscaling and downscaling and should examine the capacity plans each scenario creates in more detail. According to the results of CEVA’s examination they can make a conscious choice for the values $cc$, $\alpha$ and $\beta$. In our case study only 36 scenarios are considered, CEVA could investigate other scenarios by itself when they are interested in it.
7. Conclusions

This research was initiated because CEVA faces difficulties in their short-term capacity planning process. In order to reduce the costs and improve supply chain performance, CEVA is looking for a way in which current decisions taken in labour capacity planning could be improved. The results of this report should support CEVA in making proper capacity planning decisions in the short term. Therefore the research assignment of this project was stated as:

“Develop a decision support tool which provides insights for a short-term labour capacity planning problem in a make-to-order environment with multiple due dates in the planning horizon.”

This report presents a decomposition method to support on labour capacity decisions in the short-term. The method is specifically designed for a short-term make-to-order environment with multiple due dates. For CEVA, the developed method is implemented as a decision support tool in MS Excel. With this tool CEVA is able to create capacity plans in a more consistent manner compared to the manual planning method. The managers of CEVA have the possibility to adjust three parameters in this tool. The results from the case study gained useful insights in the consequences and risks for the parameter values. In order to fulfill the research assignment, the execution of the project was split in three phases; an analysis phase, a development phase and a case study phase.

The analysis phase revealed that uncertainty is the main factor which makes it difficult to balance the available capacity with the required capacity. Two core challenges were distinguished which are illustrative for the type of problem we are dealing with. The first challenge is to determine the right amount of total available capacity that should be planned in the planning horizon. The second challenge is to determine the right levels of available capacity at the right time in the planning horizon.

The method developed in the development phase provides support to decide upon the total size and timing of available capacity. The method provides insights in how these short-term capacity decisions should be taken for a make-to-order environment given a set of fixed due dates in the planning horizon. One single cost-optimization model turned out to be computationally impractical in terms of decision support. Therefore, an alternative method was developed which decomposed the problem in three distinct subproblems:

- The first subproblem decides upon a target level for total available capacity.
- The second subproblem decides upon target levels of available capacity throughout the planning horizon.
- The third subproblem determines a capacity plan which most closely satisfies the target levels from subproblem 1 and subproblem 2.

The developed method left three parameters open for determination because each work environment requires its own ‘best’ parameter values. In order to consciously choose the values for these parameters a case study is conducted applied to CEVA.

In the case study phase 36 scenarios of capacity planning were compared with a reference scenario. The main purpose of the case study was to help exploring the choices for parameter values and subsequently to gain insight into their consequences and to visualize the risks in the capacity planning problem. As was already mentioned, the main trade-off in the capacity planning problem is having excess capacity or insufficient capacity available. This could either be in total values for the complete horizon or for shorter time periods in the planning horizon. The method did not take into account the corrective recourse actions (downscaling and upscaling) that could be taken during the planning horizon. In terms of corrective recourse actions, the trade-off between having excess capacity available or insufficient capacity available is equal to the trade-off between undercapacity or overcapacity. The results of the case study visualizes the consequences each scenario has with respect to the mentioned trade-offs. The optimal scenario therefore also depends on the costs for undercapacity and overcapacity. The discussion of the results revealed the consequences of changing each of the three parameters individually. The optimal scenario for CEVA also depends on
the flexibility it has regarding upscaling and downscaling its available capacity during the planning horizon.

7.1. Practical contributions
The main purpose of this project was to provide support to the short-term capacity planning problem. The practical usefulness of the developed decisions support tool lies in the consistent way in which the planners are now able to make a capacity plan; instead of making capacity decisions on an intuitive sense. In addition, the consequences and risks of current capacity planning method, in terms of the trade-off between overcapacity and undercapacity are visualized. Apparently, CEVA currently runs the risk of ignoring significant cost savings to base its capacity decisions on an intuitive sense. This is quantified by the results of the case study performed in this research. The results of the case study makes it able to consciously change parameters in the decision support tool in order to consciously aim to the desired trade-off point between overcapacity and undercapacity. The best balanced scenario from our case study (scenario 24), when counting with equal weights in the trade-off, makes it able to reduce the average size of overcapacity from 36.80 to 9.09 man-hours; however, this also means that the average size of undercapacity increases from 2.48 to 8.80 man-hours. It has to be mentioned that this scenario requires another flexibility from CEVA. Moreover, managers should not ignore qualitative factors such as practical usefulness and for example employee morale. The practical usefulness of a scenario partially depends on the flexibility CEVA has for corrective recourse actions. Changing the abilities of upscaling could generally not be achieved in the short-run and therefore requires long-term strategic capacity decisions. The practical usefulness of a scenario therefore partially depends on the results for undercapacity. However, without significantly increasing the average size of undercapacity, from 2.48 to 3.17, the average size of overcapacity could be reduced from 36.80 to 26.80. Depending on CEVA’s cost ratio between overcapacity and undercapacity this could cause an expected minimum cost saving of 8% and an expected maximum cost saving of 31% without having to significantly change the abilities of upscaling.

7.2. Theoretical contributions
The available literature regarding short-term capacity planning for logistic providers is still limited. Available research showed that there is room for research in short-term capacity problems in a make-to-order environment with multiple due dates in the planning horizon. This research contributes to current literature by proposing a decomposition method to produce capacity plans which takes into account three aspects of uncertainty; uncertainty of total required capacity, uncertainty of required capacity at several fixed time points in the planning horizon, and uncertainty of useful capacity levels at different time points in the planning horizon. The method is designed that it could be adapted for different sizes of the planning horizon and different sizes of planning periods. Also the set of available shifts could be adapted. Future research should apply those instances to strengthen the robustness of the method.

7.3. Limitations and further research directions
The main limitations of this research must be noted and are described in this section.

- The developed method only considers a single-process system, while CEVA operates in a multi-process system. The capacity planned for each of the processes is dependent on each other. Therefore, it is interesting for further research to extend the method to a multi-process system.
- It is assumed that all employees have equal productivities. In practice, employees does not have the same average productivities, see section 3.2.7. To cope with this issue a planner could change the input value for the average productivity rate according to the planned employees.
This study does not include individual staff allocation. The decision support tool could be extended by including constraints regarding individual staff allocation. However, the ELSA of CEVA deals with this issue and is therefore not interesting for CEVA.

This study only considers contingent employees, while CEVA has to deal with both permanent and contingent employees. Therefore it is interesting for further research to include restrictions regarding permanent employees as hard constraints in step 3 of the method.

The re-order system of Sandvik causes higher demand at the first week of each month, see section 3.2.1. Further research should reveal whether the performance of the planning scenarios differs in the first week of each month compared to the other weeks of the month.

The results reveal that a higher $\beta$ causes a better performance. The scenarios in our case study only considers $\beta = 0.5; 0.7$ and $0.9$; therefore it is interesting to consider scenarios with $\beta > 0.9$.

The scenarios in our case study only considers $\alpha = 0.22; 0.7$ and $0.85$. CEVA may be interested in other safety margins and therefore it is interesting to consider other values for $\alpha$ in further research.

Step two of the method considers three options to determine the target capacity levels during the planning horizon. It is interesting for further research to consider other options in order to determine the target capacity levels. For example considering the horizontal average of option 2a and 2b as discussed in section 4.5.2.

Only one set of shifts is considered in which each shift has the same length. Other sets of shifts could generate more flexibility regarding corrective recourse actions. Further research should therefore reveal whether other set of shifts affects the performance of the method.

The developed method is non-reactive and therefore does not consider corrective recourse actions. In further research a reactive anticipated model could be developed according to the concept of Schneeweis (2003) which considers possible corrective recourse actions in the base-level with respect to the top-level’s instructions, see the introduction of chapter 4.

A normal distribution was assumed for $\dot{\lambda}(T)$ and Beta distributions were assumed for all $\dot{\lambda}(t)$ and $D(t)$. The behavior of these variables could change over time and should therefore be assessed constantly to keep the values valid.

This study assumes that each day starts in a ‘clean’ state, while this is hardly ever the case for CEVA. To cope with this issue, CEVA could adjust the initial capacity plans for each day at the end of its preceding day according to the backlog. Further research could relax this assumption by extending the planning horizon to multiple days.

The case study aggregates the three picking competencies to one single process. The capacity plan generated by the method is not competency based but process based, while CEVA plans its capacity competency based. Therefore, it is interesting for further research to generate capacity plans and indicate the performance per competency individually.
Abbreviations

- **3PL**: Third-party logistics provider
- **cc**: Choice combination
- **DD group**: Due Date group
- **ELSA**: External labour supply agency
- **FE**: Forecast error
- **LP**: Linear programming
- **KPI**: Key performance indicator
- **MTO**: Make-to-order
- **SKU**: Stock keeping unit
- **SLA**: Service level agreement
- **WMS**: Warehouse Management System

Definitions

- **Competency**: A set of defined behaviors used to complete a process.
- **Corrective recourse action**: An action which modifies the original capacity plan to correct for unanticipated disruptions.
- **Customer order**: An order forwarded by Sandvik and initiated by a direct customer of Sandvik.
- **Cut-off time**: The last possible point of time on a day until an order could be forwarded by Sandvik such that it will have a **marshal by time** at the same day it is forwarded. Logically, when an order is forwarded after its cut-off time it will have a **marshal by time** on a date later than its forwarded date.
- **Cycle time**: The period required to complete a task.
- **DD group**: A group of orders with equal pick by time, pack by time, marshal by time and cut-off time.
- **Downscaling**: An action to decrease the original capacity levels to correct for overcapacity.
- **Due date**: Date/time at which a process has to be finished.
- **Forecast**: A prediction of an unknown result.
- **Forwarded order**: An order is forwarded at the time Sandvik confirms an order and is received in the WMS of CEVA.
- **Make-to-order**: An production approach where items are not processed until a confirmed order for the items is received.
- **Marshal by time**: The last possible point of time on a day until an order could be marshalled such that it will be on time regarding the SLA.
- **Marshalling**: the process of moving packed items to the right location on dock such that the order is ready for shipment.
- **Order**: A customer request including one or multiple order lines.
- **Order line**: An unique item in a certain quantity.
- **Overcapacity**: A situation of excess capacity in relation to the level of order that could be processed.
- **Pack by time**: The last possible point of time on a day until an order could be packed such that it will be on time regarding the SLA.
- **Packing**: The process of checking, wrapping and confirming a picked item.
- **Pick by time**: The last possible point of time on a day until an order could be picked such that it will be on time regarding the SLA.
- **Picking**: The process of retrieving items from stock and deliver them to a packing station.
- **Picking lead time**: The time between an order is forwarded and the time this order should be picked according to its *pick by time*.
- **Pick movement**: The time in the system when an employee scans an item and simultaneously retrieves this item physically from stock.
- **Planning horizon**: The future time period for which a capacity plan determines the requirements.
- **Planning period**: A certain time period in the planning horizon.
- **Productivity**: The number of processed order lines per hour.
- **Replenishment order**: An order forwarded by Sandvik and initiated by one of the other consolidation hubs of Sandvik.
- **Sandvik Outbound**: Department of CEVA Eindhoven responsible for the outbound logistics for Sandvik.
- **Scenario**: A certain way of determining the capacity plan according to an identical combination of parameter values $a$, $b$ and $cc$.
- **Shift**: A time period during the day for which an employee could be planned to work.
- **Undercapacity**: A situation of insufficient capacity in relation to the level of orders that should be processed.
- **Upscaling**: An action to increase the original capacity levels to correct for undercapacity.
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Bibliography


Website: www.cevalogistics.com (Retrieved August 28, 2014)
Appendix A: Map of the warehouse

Figure 35 shows a map of the warehouse in which the execution areas of all competencies in scope of this research are roughly indicated.

Appendix B: Order structure

Figure 36 presents the structure of one order in more detail; it represents one order with number C319669 which includes 3 order lines. Each order line involves one identical SKU-number and a quantity for this SKU; apparently, this order includes 120 items in total. Each individual order could include one or multiple order lines; each order line could include one or multiple items.

<table>
<thead>
<tr>
<th>Order line</th>
<th>SKU nr.</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>- 1</td>
<td>5635</td>
<td>105</td>
</tr>
<tr>
<td>- 2</td>
<td>9875</td>
<td>2</td>
</tr>
<tr>
<td>- 3</td>
<td>0048</td>
<td>13</td>
</tr>
</tbody>
</table>

Figure 36 Order example
Appendix C: Due Date groups

Table 9 shows the cut-off time, pick by time, pack by time and marshal by time for each Due Date group.

<table>
<thead>
<tr>
<th>DD group</th>
<th>Cut-off time</th>
<th>Pick by time</th>
<th>Pack by time</th>
<th>Marshal by time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12:00</td>
<td>13:00</td>
<td>14:00</td>
<td>15:00</td>
</tr>
<tr>
<td>2</td>
<td>13:15</td>
<td>13:30</td>
<td>14:30</td>
<td>15:00</td>
</tr>
<tr>
<td>3</td>
<td>14:30</td>
<td>14:45</td>
<td>15:00</td>
<td>15:30</td>
</tr>
<tr>
<td>4</td>
<td>13:15</td>
<td>15:00</td>
<td>15:30</td>
<td>16:00</td>
</tr>
<tr>
<td>5</td>
<td>16:15</td>
<td>16:30</td>
<td>16:30</td>
<td>17:00</td>
</tr>
<tr>
<td>6</td>
<td>16:30</td>
<td>16:45</td>
<td>17:00</td>
<td>17:30</td>
</tr>
<tr>
<td>7</td>
<td>17:15</td>
<td>17:30</td>
<td>18:00</td>
<td>18:30</td>
</tr>
<tr>
<td>8</td>
<td>17:15</td>
<td>18:00</td>
<td>18:30</td>
<td>19:00</td>
</tr>
<tr>
<td>9</td>
<td>17:15</td>
<td>18:15</td>
<td>18:45</td>
<td>19:15</td>
</tr>
<tr>
<td>10</td>
<td>20:00</td>
<td>21:00</td>
<td>21:30</td>
<td>22:00</td>
</tr>
<tr>
<td>11</td>
<td>22:00</td>
<td>23:00</td>
<td>23:30</td>
<td>0:00</td>
</tr>
</tbody>
</table>

Table 9 The cut-off time, pick by time, pack by time and marshal by time per DD group

Appendix D: Order processing example.

With an order example will be explained in detail how an order should be processed such that it meets the service level agreement. We look at order C319669, information about this order is shown in Table 10 and Figure 37.

- Order is allocated to DD group 1.
  - See Table 10 for the cut-off time, pick by time, pack by time and marshal by time of this order.
- Order is forwarded at 08:45, which is before cut-off time
  - Within red line of Figure 37.
- Order could be picked from its forward time to its pick by time (13:00).
  - Within green line of Figure 37
- Order is picked at 10:31 which is before its pick by time (13:00), which thus is in time.
- Order could be packed from its picked time (10:31) to its pack by time (13:00).
  - Within purple line of Figure 37.
- Order is packed at 12:45 which is before its pack by time (13:00), which thus is in time.
- Order could be marshaled from its packed time (12:45) to its marshal by time (14:00)
  - Within orange line of Figure 37.
- Order is marshaled at 13:12 which is before its marshal by time (14:00), which is in time.
- This order meets the service level agreements.
  - An order does not meet the service level agreements when either the picking, packing or marshalling process is not finished in time.

| Cut-off time: | 12:00 | Forward time: | 08:45 |
| Pick by time | 13:00 | Picked time: | 10:31 |
| Pack by time | 13:00 | Packed time: | 12:45 |
| Marshal by time | 14:00 | Marshalled time: | 13:12 |

Table 10 Information about order example C319669
Appendix E: Historical capacity plans

Table 11 shows the amount of capacity (in man-hours) planned for ten days which all had a forecast value between 3700 and 3800 order lines. The total capacity for these days were planned between 376 and 514 man-hours. It shows that a consistent way of using a safety margin is not applied.

<table>
<thead>
<tr>
<th>Date</th>
<th>2-7-2014</th>
<th>3-7-2014</th>
<th>6-8-2014</th>
<th>11-8-2014</th>
<th>4-9-2014</th>
<th>9-10-2014</th>
<th>3-11-2014</th>
<th>4-11-2014</th>
<th>5-11-2014</th>
<th>4-12-2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast</td>
<td>3750</td>
<td>3750</td>
<td>3800</td>
<td>3700</td>
<td>3700</td>
<td>3800</td>
<td>3750</td>
<td>3750</td>
<td>3800</td>
<td>3800</td>
</tr>
<tr>
<td>Total planned capacity (man-hours)</td>
<td>514</td>
<td>506</td>
<td>452</td>
<td>376</td>
<td>492</td>
<td>444</td>
<td>420</td>
<td>428</td>
<td>444</td>
<td>382</td>
</tr>
</tbody>
</table>

Table 11 Total planned capacity for 10 days with a forecast value between 3700 and 3800 order lines

Appendix F: KPI figures

Table 12 presents a concise version of a detailed KPI report on a monthly level for April to August 2014. More reason codes are available in a complete KPI report but are not presented in here.

<table>
<thead>
<tr>
<th>KPI CEVA - Sandvik</th>
<th>2014</th>
<th>April</th>
<th>May</th>
<th>June</th>
<th>July</th>
<th>August</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order lines created</td>
<td>67418</td>
<td>67664</td>
<td>67534</td>
<td>70294</td>
<td>64245</td>
<td></td>
</tr>
<tr>
<td>Order lines missed (CEVA uncontrollable)</td>
<td>12694</td>
<td>12253</td>
<td>14402</td>
<td>10600</td>
<td>13805</td>
<td></td>
</tr>
<tr>
<td>Order lines missed (CEVA controllable)</td>
<td>2848</td>
<td>4841</td>
<td>6600</td>
<td>2920</td>
<td>3403</td>
<td></td>
</tr>
<tr>
<td>Total KPI performance</td>
<td>95,8%</td>
<td>92,8%</td>
<td>90,2%</td>
<td>92,4%</td>
<td>94,7%</td>
<td></td>
</tr>
</tbody>
</table>

Reason codes

- 3.1 Capacity: Orders packed on time, but too late for CS and M&S
- 3.2 Capacity: High variance (Sandvik)
- 3.3 Capacity: Resources (employees)
- 3.4 Capacity: Planning / forecast
- 18.1 Variance agreed with Sandvik exceeded/too high workload

Table 12 Outbound KPI Figures on a monthly level

Table 13 presents a concise version of a detailed KPI report on a daily level for the month Augustus 2014.

<table>
<thead>
<tr>
<th>KPI CEVA - Sandvik</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order lines created</td>
<td>67418</td>
</tr>
<tr>
<td>Order lines missed (CEVA uncontrollable)</td>
<td>12694</td>
</tr>
<tr>
<td>Order lines missed (CEVA controllable)</td>
<td>2848</td>
</tr>
<tr>
<td>Total KPI performance</td>
<td>95,8%</td>
</tr>
</tbody>
</table>

Reason codes

- 3.1 Capacity: Orders packed on time, but too late for CS and M&S
- 3.2 Capacity: High variance (Sandvik)
- 3.3 Capacity: Resources (employees)
- 3.4 Capacity: Planning / forecast
- 18.1 Variance agreed with Sandvik exceeded/too high workload

Table 13 Outbound KPI figures on a daily level August
Appendix G: Current forecasting method

The forecast method CEVA currently uses can be described by the following formula:

\[ FC_{m,w,d} = MF_m \times WF_w \times DF_d \]

Where:
- \( m \)  Month number of the year \( \{ m = 1, \ldots, 12 \} \).
- \( w \)  Week number of a month \( \{ w = 1, \ldots, 5 \} \).
- \( d \)  Working day number of the week \( \{ d = 1, \ldots, 5 \} \).
- \( MF_m \)  Expected average number of order lines forwarded per day in month \( m \).
- \( WF_w \)  Week factor for week number \( w \) of the month.
- \( DF_d \)  Day factor for day number \( d \) of the week.
- \( FC_{m,w,d} \)  Forecasted number of order lines forwarded for day \( d \) in week \( w \) of month \( m \) in 2014.

The values of the factors used in 2014 are presented in Table 14.

<table>
<thead>
<tr>
<th>Month</th>
<th>m</th>
<th>MF_m</th>
<th>Week</th>
<th>w</th>
<th>WF_w</th>
<th>Day</th>
<th>d</th>
<th>DF_d</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>1</td>
<td>3100</td>
<td>Wk1</td>
<td>1</td>
<td>123%</td>
<td>Mo</td>
<td>1</td>
<td>109%</td>
</tr>
<tr>
<td>Feb</td>
<td>2</td>
<td>3100</td>
<td>Wk2</td>
<td>2</td>
<td>102%</td>
<td>Tu</td>
<td>2</td>
<td>103%</td>
</tr>
<tr>
<td>Mrt</td>
<td>3</td>
<td>3100</td>
<td>Wk3</td>
<td>3</td>
<td>95%</td>
<td>Wed</td>
<td>3</td>
<td>102%</td>
</tr>
<tr>
<td>Apr</td>
<td>4</td>
<td>3200</td>
<td>Wk4</td>
<td>4</td>
<td>90%</td>
<td>Thur</td>
<td>4</td>
<td>102%</td>
</tr>
<tr>
<td>Mei</td>
<td>5</td>
<td>3200</td>
<td>Wk5</td>
<td>5</td>
<td>89%</td>
<td>Fri</td>
<td>5</td>
<td>84%</td>
</tr>
<tr>
<td>Jun</td>
<td>6</td>
<td>3200</td>
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</tr>
<tr>
<td>Jul</td>
<td>7</td>
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<td>Aug</td>
<td>8</td>
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<td></td>
<td></td>
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</tr>
<tr>
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<td>3300</td>
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<td></td>
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<tr>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Nov</td>
<td>11</td>
<td>3400</td>
<td></td>
<td></td>
<td></td>
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<td>Dec</td>
<td>12</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 14 Factor values used in 2014 for the forecast model
Appendix H: Average percentage of capacity per process

The average percentage of capacity that should be planned for each process in the process flow is calculated by the figures shown in Table 15.

<table>
<thead>
<tr>
<th>Task</th>
<th>Target productivity (order lines per hour)</th>
<th>% of total demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOPT picking</td>
<td>23</td>
<td>51%</td>
</tr>
<tr>
<td>Reach picking</td>
<td>10</td>
<td>12%</td>
</tr>
<tr>
<td>Shelving picking</td>
<td>30</td>
<td>37%</td>
</tr>
<tr>
<td>Parcel packing</td>
<td>22.5</td>
<td>78%</td>
</tr>
<tr>
<td>Plywood packing</td>
<td>30</td>
<td>22%</td>
</tr>
<tr>
<td>Marshaling</td>
<td>160</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 15 Target productivity and % of total demand per competency

\[
\text{Average \% of picking capacity} = \frac{0.51}{23} + \frac{0.12}{10} + \frac{0.37}{30} + \frac{0.78}{22.5} + \frac{0.22}{30} + \frac{1}{160} = 0.49
\]

\[
\text{Average \% of packing capacity} = \frac{0.51}{23} + \frac{0.12}{10} + \frac{0.37}{30} + \frac{0.78}{22.5} + \frac{0.22}{30} + \frac{1}{160} = 0.44
\]

\[
\text{Average \% of marshalling capacity} = \frac{0.51}{23} + \frac{0.12}{10} + \frac{0.37}{30} + \frac{0.78}{22.5} + \frac{0.22}{30} + \frac{1}{160} = 0.07
\]

Appendix I: Historical capacity plans

Table 16 and Table 17 both shows the amount of capacity (in hours) planned per competency per day. The days shown in Table 16 all had a forecast between 3700 and 3800 number of order lines. The days shown in Table 17 all had a total capacity planned between 388 and 392 hours.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Week</td>
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<td>27</td>
<td>32</td>
<td>33</td>
<td>36</td>
<td>41</td>
<td>45</td>
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<td>31</td>
<td>31</td>
<td>31</td>
<td>31</td>
<td>31</td>
<td></td>
</tr>
<tr>
<td>Forecast</td>
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<td>3750</td>
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<td>3700</td>
<td>3700</td>
<td>3800</td>
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<td>31</td>
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<td>112</td>
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<td>112</td>
<td>112</td>
<td>112</td>
<td>112</td>
<td></td>
</tr>
<tr>
<td>REACH</td>
<td>104</td>
<td>104</td>
<td>104</td>
<td>64</td>
<td>88</td>
<td>80</td>
<td>72</td>
<td>80</td>
<td>80</td>
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<td>80</td>
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<td>80</td>
<td>80</td>
<td>80</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SHELVING</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>24</td>
<td>16</td>
<td>16</td>
<td>16</td>
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<td>16</td>
<td>16</td>
<td>16</td>
<td>16</td>
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<td></td>
</tr>
<tr>
<td>PLYWOOD</td>
<td>160</td>
<td>160</td>
<td>144</td>
<td>120</td>
<td>192</td>
<td>168</td>
<td>152</td>
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<td>152</td>
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<td>32</td>
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<td>44</td>
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<td></td>
</tr>
<tr>
<td>TOTAL</td>
<td>514</td>
<td>506</td>
<td>452</td>
<td>376</td>
<td>492</td>
<td>444</td>
<td>420</td>
<td>428</td>
<td>444</td>
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</tr>
</tbody>
</table>

Table 16 Capacity plans for days with a forecast level between between 3700 and 3800 number of order lines.

<table>
<thead>
<tr>
<th>Date</th>
<th>8-7-2014</th>
<th>9-7-2014</th>
<th>23-7-2014</th>
<th>28-7-2014</th>
<th>29-7-2014</th>
<th>30-7-2014</th>
<th>31-7-2014</th>
<th>1-8-2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week</td>
<td>28</td>
<td>28</td>
<td>30</td>
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<td>31</td>
<td>31</td>
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<td>40</td>
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<td>24</td>
<td>24</td>
<td>24</td>
<td>24</td>
<td>24</td>
</tr>
<tr>
<td>TOTAL</td>
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<td>390</td>
<td>392</td>
<td>392</td>
<td>392</td>
<td>392</td>
<td>388</td>
</tr>
</tbody>
</table>

Table 17 Capacity plans for days with total capacity planned between 388 and 392 hours.
Appendix J: Statistical tests

Appendix J.1: Total forwarded order lines per day by quarter of 2014

Table 18 shows the forecasted and realized average of total forwarded order lines per day for each quarter in 2014. Although a growing trend throughout the year was forecasted, realized figures show the absence of a growing trend. According to these figure one would assume no significant differences between the averages of each quarter.

<table>
<thead>
<tr>
<th>Quarter of 2014</th>
<th>Forecasted average</th>
<th>Realized average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3100</td>
<td>3163</td>
</tr>
<tr>
<td>2</td>
<td>3200</td>
<td>3117</td>
</tr>
<tr>
<td>3</td>
<td>3300</td>
<td>3132</td>
</tr>
<tr>
<td>4</td>
<td>3400</td>
<td>3180</td>
</tr>
</tbody>
</table>

Table 18 Forecasted and realized averages of forwarded order lines per day for each quarter of 2014

A one-way analysis of variance, explained in Field (2000), is used to compare the average values of total forwarded demand for the four different quarters of the year 2014. The results are shown in Table 19. The F-test in the ANOVA table tests whether there are any significant differences amongst the averages. The P-value of the F-test is greater than 0,05 which tells us that there is no statistically significant difference between the average of total demand per day from one quarter to another at the 95,0% confidence level.

<table>
<thead>
<tr>
<th>Demand per day</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>153160,091</td>
<td>3</td>
<td>51053,364</td>
<td>.089</td>
<td>.966</td>
</tr>
<tr>
<td>Within Groups</td>
<td>144513917,659</td>
<td>251</td>
<td>573467,927</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>144667077,750</td>
<td>254</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 19 ANOVA Table to test for differences of forwarded order lines per day between each quarter of 2014

Appendix J.2: Forwarded order lines per day by week number of a month

Table 20 shows the realized average of total forwarded order lines per day for each week number of a month. A decreasing trend throughout the month was forecasted. According to these figure one would only assume a higher average for the first week of each month.

<table>
<thead>
<tr>
<th>Week number of the month</th>
<th>Realized average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3655</td>
</tr>
<tr>
<td>2</td>
<td>3111</td>
</tr>
<tr>
<td>3</td>
<td>3060</td>
</tr>
<tr>
<td>4</td>
<td>2971</td>
</tr>
<tr>
<td>5</td>
<td>2974</td>
</tr>
</tbody>
</table>

Table 20 Realized averages of forwarded order lines for each week number of a month.

A one-way analysis of variance is used to compare the average values for the five possible week numbers of a month. The results are shown in Table 21. The F-test in the ANOVA table tests whether there are any significant differences amongst the averages. The P-value of the F-test is smaller than 0,05 which tells us that there is a statistically significant difference between the average of total forwarded order lines per week number of a month from one to another at the 95,0% confidence level.
A multiple comparison test is used to determine which averages are significantly different. Tamhane’s post-hoc procedure is the method used for this test because no equal variances can be assumed. The findings indicate that total forwarded order lines per day for week 1 is significantly different from the other weeks of the month. No significant differences are found between total average demand of the other weeks of the month.

**Table 22 Multiple comparisons to test for differences between total daily forwarded order lines by week number of a month.**

A one-way analysis of variance is used to compare the average values of total forwarded demand per day for the different days of the week. The results are shown in Table 24. The F-test in the ANOVA table tests whether there are any significant differences amongst the averages. The P-value of the F-test is smaller than 0.05 which tells us that there is a statistically significant difference.
between the average of total demand per day of the week from one to another at the 95.0% confidence level.

**ANOVA**

<table>
<thead>
<tr>
<th>Demand per day</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>6411302.530</td>
<td>4</td>
<td>1602825.633</td>
<td>3.335</td>
<td>.011</td>
</tr>
<tr>
<td>Within Groups</td>
<td>119206388.537</td>
<td>250</td>
<td>480670.922</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>125617691.067</td>
<td>254</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 24 ANOVA Table to test for differences of demand per day between the different days of the week.

A multiple comparison test is used to determine which averages are significantly different. Tamhane’s post-hoc procedure is the method used for this test because no equal variances can be assumed. The findings indicate that total forwarded order lines per day on Tuesdays is significantly different from Fridays. No significant differences are found between the other days of the week.

**Multiple Comparisons**

<table>
<thead>
<tr>
<th>(I) Day of the week</th>
<th>Mean Difference (I-J)</th>
<th>Std. Error</th>
<th>Sig.</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower Bound</td>
<td>Upper Bound</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday</td>
<td>-137.80538</td>
<td>139.84040</td>
<td>.981</td>
<td>-539.0346</td>
</tr>
<tr>
<td>Tuesday</td>
<td>137.80538</td>
<td>139.84040</td>
<td>.981</td>
<td>263.4239</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-267.06146</td>
<td>154.46237</td>
<td>.495</td>
<td>-729.2240</td>
</tr>
<tr>
<td>Thursday</td>
<td>187.45608</td>
<td>143.59295</td>
<td>.885</td>
<td>598.6369</td>
</tr>
<tr>
<td>Friday</td>
<td>480.99608</td>
<td>133.29310</td>
<td>.005</td>
<td>263.4239</td>
</tr>
<tr>
<td></td>
<td>-223.7248</td>
<td>598.6369</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday</td>
<td>-193.93462</td>
<td>141.49080</td>
<td>.852</td>
<td>-333.4857</td>
</tr>
<tr>
<td>Tuesday</td>
<td>193.93462</td>
<td>141.49080</td>
<td>.852</td>
<td>211.8599</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-99.60538</td>
<td>151.23337</td>
<td>.999</td>
<td>-333.4857</td>
</tr>
<tr>
<td>Thursday</td>
<td>293.54000</td>
<td>129.53747</td>
<td>.229</td>
<td>664.7933</td>
</tr>
<tr>
<td>Friday</td>
<td>-331.74000</td>
<td>116.03345</td>
<td>.051</td>
<td>-664.0792</td>
</tr>
<tr>
<td></td>
<td>-211.8599</td>
<td>599.7292</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* The mean difference is significant at the 0.05 level.

Table 25 Multiple comparisons to test for differences between total daily forwarded order lines by day of the week

**Appendix J.4: Forecast error checked for time-related factors.**

A one-way analysis of variance is used to check for a relation between the forecast error and different time periods, according to the three time related factors in the forecast model. We hypothesize that the forecast error is different across the quarters of the year, different across the week numbers of the month, and different across the days of the week. Therefore, three independent one-way ANOVA tests are performed in a similar fashion as performed in Appendix J.1, J.2 and J.3. The results are shown in Table 26, Table 27 and Table 28 respectively. For all three tests the P-value of the F-test is higher than 0.05 which tells us that there is no statistically significant difference between any of the different time periods at the 95% confidence level.
ANOVA

<table>
<thead>
<tr>
<th></th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>823,314</td>
<td>3</td>
<td>274,438</td>
<td>1,005</td>
<td>.391</td>
</tr>
<tr>
<td>Within Groups</td>
<td>68523,113</td>
<td>251</td>
<td>273,000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>69346,427</td>
<td>254</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Table 26 ANOVA Table to test for differences of the forecast error between the different quarters of the year

ANOVA

<table>
<thead>
<tr>
<th></th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>863,272</td>
<td>4</td>
<td>215,818</td>
<td>.788</td>
<td>.534</td>
</tr>
<tr>
<td>Within Groups</td>
<td>68483,155</td>
<td>250</td>
<td>273,933</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>69346,427</td>
<td>254</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 27 ANOVA Table to test for differences of the forecast error between the different week number of the month

ANOVA

<table>
<thead>
<tr>
<th></th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between Groups</td>
<td>1035,978</td>
<td>4</td>
<td>258,995</td>
<td>.948</td>
<td>.437</td>
</tr>
<tr>
<td>Within Groups</td>
<td>68310,449</td>
<td>250</td>
<td>273,242</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>69346,427</td>
<td>254</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 28 ANOVA Table to test for differences of the forecast error between the different days of the week.

Appendix J.5: Forwarded order lines per DD group

A Box-and-Whisker Plot is presented in Figure 38. The plot shows us that the amount of forwarded order lines per DD group fluctuates in a fairly large range for DD groups which represent a reasonable proportion of total forwarded order lines. For example, considering the inter-quartile range of DD group two, 50% of the days the amount of forwarded order lines is between ±500 and ±900 order lines. The other 50% of the days, the amount of forwarded order lines is between ±200 and ±500 order lines or between ±900 and ±1400 order lines.

![Box-and-Whisker Plot](image)

Figure 38 Box-and-Whisker Plot of forwarded order lines per DD group
Table 29 shows for each combination of DD group and region the average percentage of total forwarded order lines per day. We can see that, except for Europe, most of forwarded order lines for within a region belongs to one specific DD group.

<table>
<thead>
<tr>
<th>DD group</th>
<th>Africa + TR</th>
<th>APAC</th>
<th>CIS</th>
<th>Europe</th>
<th>Latin America + MX</th>
<th>North America</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4,2%</td>
<td>0,9%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5,1%</td>
</tr>
<tr>
<td>2</td>
<td>0,1%</td>
<td>20,1%</td>
<td>0,7%</td>
<td>1,2%</td>
<td></td>
<td></td>
<td>22,2%</td>
</tr>
<tr>
<td>3</td>
<td>0,7%</td>
<td>0,1%</td>
<td>0,1%</td>
<td></td>
<td></td>
<td></td>
<td>0,9%</td>
</tr>
<tr>
<td>4</td>
<td>0,5%</td>
<td>0,4%</td>
<td>0,6%</td>
<td>0,2%</td>
<td>0,2%</td>
<td></td>
<td>2,0%</td>
</tr>
<tr>
<td>5</td>
<td>0,2%</td>
<td>0,3%</td>
<td></td>
<td>0,1%</td>
<td></td>
<td></td>
<td>0,0%</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td>2,2%</td>
<td></td>
<td></td>
<td>2,2%</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td>0,2%</td>
<td>0,1%</td>
<td>9,4%</td>
<td></td>
<td>25,3%</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td>2,4%</td>
<td></td>
<td></td>
<td>2,4%</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td></td>
<td></td>
<td>7,0%</td>
<td></td>
<td></td>
<td>7,0%</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td>7,1%</td>
<td></td>
<td></td>
<td>7,1%</td>
</tr>
<tr>
<td>11</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10,2%</td>
<td>10,2%</td>
</tr>
<tr>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>15,2%</td>
<td>15,2%</td>
</tr>
<tr>
<td>Total</td>
<td>16,5%</td>
<td>21,7%</td>
<td>5,1%</td>
<td>30,8%</td>
<td>10,5%</td>
<td>15,4%</td>
<td>100,0%</td>
</tr>
</tbody>
</table>

Table 29: Average percentage of total forwarded order lines per day for each DD group - region combination

Table 30 presents the amount of forwarded order lines per day for eight randomly chosen customers for the period from 29-9-2014 to 12-12-2014. Different kind of behaviors can be distinguished. Some customers forward their orders in an intermittent behavior while others forward their orders in a more constant behavior. We can see that the number of customers is dynamic; customer 2 could be considered as a new customer from 10-11-2014 while customer seven stopped forwarding orders from 14-11-2014.

Table 30: Demand per day for eight random customers (from 29-9-2014 to 12-12-2014) in number of order lines.

The reasoning from section 3.2.3 let us hypothesize that positive correlations should exist between DD groups two, seven and twelve. Correlations between all DD groups are examined in a rank correlation analysis in order to reject or confirm these hypotheses. Spearman’s rank correlation coefficient is non-parametric, is appropriate for discrete variables and less sensitive to outliers than Pearson’s correlation coefficients. Therefore, Spearman’s rank correlation matrix is used to test whether there are statistical significant correlations across the DD groups. The output is presented in
Table 31. The third number in each location shows the P-value. A P-value is below 0.05 indicates a significant non-zero correlation at the 95% confidence level. The general null-hypothesis for a Spearman correlation is: $H_0 = \text{There is no correlation between the two variables}$. When analyzing 78 combinations at a 95% confidence level we can expect approximately four Type I errors. A Type I error occurs when a null hypothesis is rejected incorrectly. From all 78 analyzed combinations, seven combinations significantly correlate; we assume that no Type I error is expected for the three combinations with the lowest P-value. These three combinations are found between DD group two and seven, between DD group two and twelve, and between DD group seven and twelve. These results confirm our hypotheses that positive correlations exist between DD groups two and seven, between DD group two and twelve, and between DD group seven and twelve.

Spearman Rank Correlations

<table>
<thead>
<tr>
<th>DD group</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.0429</td>
<td>-0.0742</td>
<td>-0.037</td>
<td>0.1339</td>
<td>-0.0544</td>
<td>-0.014</td>
<td>-0.2459</td>
<td>-0.0782</td>
<td>-0.0347</td>
<td>0.0275</td>
<td>0.0005</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.583</td>
<td>-0.4063</td>
<td>0.3912</td>
<td>-0.131</td>
<td>0.5448</td>
<td>0.9022</td>
<td>-0.0053</td>
<td>0.3842</td>
<td>0.6989</td>
<td>0.7589</td>
<td>0.9244</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-0.0742</td>
<td>-0.1722</td>
<td>-0.1259</td>
<td>-0.1447</td>
<td>0.3434</td>
<td>0.1536</td>
<td>-0.0733</td>
<td>-0.0166</td>
<td>0.0314</td>
<td>0.3474</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-0.123</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td>-0.0742</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td>-0.4063</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>-0.0733</td>
<td>0.2713</td>
<td>-0.1437</td>
<td>-0.5634</td>
<td>0.4169</td>
<td>0.4467</td>
<td>-0.5728</td>
<td>0.0921</td>
<td>0.7409</td>
<td>0.6393</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.0772</td>
<td>-0.0683</td>
<td>-0.1665</td>
<td>0.0415</td>
<td>0.0936</td>
<td>0.0014</td>
<td>0.8982</td>
<td>0.0082</td>
<td>0.0269</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
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<td>-0.122</td>
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<td>-0.122</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>-0.1392</td>
<td>-0.0532</td>
<td>-0.0227</td>
<td>-0.0117</td>
<td>0.0227</td>
<td>0.1236</td>
<td>0.0661</td>
<td>0.1949</td>
<td>0.1529</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>-0.610</td>
<td>-0.5634</td>
<td>-0.4063</td>
<td>-0.3634</td>
<td>-0.1896</td>
<td>-0.0053</td>
<td>0.1622</td>
<td>0.0017</td>
<td>0.3691</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>0.3804</td>
<td>0.5634</td>
<td>0.4063</td>
<td>0.3634</td>
<td>0.1896</td>
<td>-0.0053</td>
<td>0.1622</td>
<td>0.0017</td>
<td>0.3691</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td>-0.0185</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>0.9022</td>
<td>0.0001</td>
<td>-0.0041</td>
<td>0.0684</td>
<td>0.8333</td>
<td>0.1894</td>
<td>0.6167</td>
<td>0.9885</td>
<td>0.2631</td>
<td>0.7398</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>-0.2499</td>
<td>0.1536</td>
<td>0.0174</td>
<td>0.0411</td>
<td>-0.0661</td>
<td>-0.0227</td>
<td>0.0416</td>
<td>-0.0062</td>
<td>0.0008</td>
<td>0.0005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td>-0.122</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td>-0.0018</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td>-0.5634</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For each location:

Correlation

(Sample Size)

P-Value

Table 31 Spearman’s Rank Correlations table for DD groups

68
Appendix J.6: Percentage of order lines forwarded after/before cut-off time

Table 32 shows per DD group the percentage of order lines forwarded either after or before cut-off time.

<table>
<thead>
<tr>
<th>DD group</th>
<th>% of order lines forwarded after cut-off time</th>
<th>% of order lines forwarded before cut-off time</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>35.29%</td>
<td>64.71%</td>
<td>100.00%</td>
</tr>
<tr>
<td>2</td>
<td>10.37%</td>
<td>89.63%</td>
<td>100.00%</td>
</tr>
<tr>
<td>3</td>
<td>11.71%</td>
<td>88.29%</td>
<td>100.00%</td>
</tr>
<tr>
<td>4</td>
<td>31.97%</td>
<td>68.03%</td>
<td>100.00%</td>
</tr>
<tr>
<td>5</td>
<td>8.97%</td>
<td>91.03%</td>
<td>100.00%</td>
</tr>
<tr>
<td>6</td>
<td>2.74%</td>
<td>97.26%</td>
<td>100.00%</td>
</tr>
<tr>
<td>7</td>
<td>2.86%</td>
<td>97.14%</td>
<td>100.00%</td>
</tr>
<tr>
<td>8</td>
<td>1.15%</td>
<td>98.85%</td>
<td>100.00%</td>
</tr>
<tr>
<td>9</td>
<td>2.06%</td>
<td>97.94%</td>
<td>100.00%</td>
</tr>
<tr>
<td>10</td>
<td>1.48%</td>
<td>98.52%</td>
<td>100.00%</td>
</tr>
<tr>
<td>11</td>
<td>9.21%</td>
<td>90.79%</td>
<td>100.00%</td>
</tr>
<tr>
<td>12</td>
<td>0.66%</td>
<td>99.34%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Total</td>
<td>7.10%</td>
<td>92.90%</td>
<td>100.00%</td>
</tr>
</tbody>
</table>

Table 32 Percentage of order lines forwarded either after or before cut-off time, per DD group.

Appendix J.7: Cycle time for picking shelving

The data used in the analysis of this appendix covers three days of picking shelving cycle times. The results are used as indicative and not as hard conclusions. For three days the average cycle time is measured. The cycle time for picking one order line is measured by the time between two pick movements in the system. A pick movement in the system is the time when an employee scans, and thus retrieves, an item from stock. The time between two pick movements is therefore assumed to be equal to the cycle time of one order line.

Table 33 shows that there exist reasonable differences in the average cycle time per employee. Employee 3 and 8 shows an excellent average cycle time while employee 9 shows an average cycle time which is almost twice as slow. A possible reason for a lower average cycle time is that these employees may have more experience, but also other factors could play a role.

<table>
<thead>
<tr>
<th>Employee</th>
<th>Average cycle time (sec)</th>
<th>Employee</th>
<th>Average cycle time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>137</td>
<td>7</td>
<td>136</td>
</tr>
<tr>
<td>2</td>
<td>112</td>
<td>8</td>
<td>88</td>
</tr>
<tr>
<td>3</td>
<td>83</td>
<td>9</td>
<td>159</td>
</tr>
<tr>
<td>4</td>
<td>129</td>
<td>10</td>
<td>113</td>
</tr>
<tr>
<td>5</td>
<td>105</td>
<td>11</td>
<td>115</td>
</tr>
<tr>
<td>6</td>
<td>106</td>
<td>Average</td>
<td>122</td>
</tr>
</tbody>
</table>

Table 33 The average cycle time per employee in seconds

Table 34 shows that there exist reasonable differences in the average cycle time for different quantities per line. Employees need to count the items in order to retrieve the exact required amount. Counting more items logically requires more time and therefore more items per line causes a larger cycle time.
Table 34 The average cycle time per quantity of an order line

Table 35 shows that there exist reasonable differences in the average cycle time for different row heights per order line. For the picking shelving competency employees need a stepladder to retrieve items from the shelving on the highest rows. There are a limited number of stepladders available in the shelving area and thus it takes extra time to grab the stepladder, use it, and put it back in place.

Table 35 The average cycle time per row height of an order line

Table 36 shows that there exist, but relatively small, differences between the average cycle time for different DD groups. DD group 5 and 8 show a reasonable higher average cycle time than the other DD groups but these DD groups account for a relatively small part of the total. From these figures we therefore do not assume differences between the average cycle time per DD group.

Because the volume and weight of spare parts CEVA handles fluctuates in a relatively large range one could hypothesize the average cycle time to be dependent on the volume and weight as well. This is in line with what the employees indicate; however, no reliable data is available for analyze this issue.
Appendix J.8: Picking lead times per DD group

Table 37 presents the average picking lead time per DD group. It also shows the average percentage of orders per DD group which has a picking lead of a certain time period. The standard deviations are presented as well. For example, for one day, the average percentage of order lines within DD group 1 with a picking lead time between 0 and 1 hours is 18%.

### Table 37: Average and standard deviation of picking lead times per DD group

<table>
<thead>
<tr>
<th>Remaining processing time (hours)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>Avg</td>
<td>St.dev</td>
<td>Avg</td>
<td>St.dev</td>
<td>Avg</td>
<td>St.dev</td>
<td>Avg</td>
<td>St.dev</td>
<td>Avg</td>
<td>St.dev</td>
<td>Avg</td>
<td>St.dev</td>
<td>Avg</td>
</tr>
<tr>
<td>0-1</td>
<td>1%</td>
<td>2%</td>
<td>1%</td>
<td>3%</td>
<td>2%</td>
<td>4%</td>
<td>1%</td>
<td>3%</td>
<td>2%</td>
<td>4%</td>
<td>1%</td>
<td>3%</td>
<td>1%</td>
</tr>
<tr>
<td>1-2</td>
<td>2%</td>
<td>3%</td>
<td>2%</td>
<td>3%</td>
<td>2%</td>
<td>4%</td>
<td>1%</td>
<td>3%</td>
<td>2%</td>
<td>4%</td>
<td>1%</td>
<td>3%</td>
<td>1%</td>
</tr>
<tr>
<td>2-3</td>
<td>5%</td>
<td>6%</td>
<td>5%</td>
<td>6%</td>
<td>5%</td>
<td>6%</td>
<td>5%</td>
<td>6%</td>
<td>5%</td>
<td>6%</td>
<td>5%</td>
<td>6%</td>
<td>5%</td>
</tr>
<tr>
<td>3-4</td>
<td>2%</td>
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<td>2%</td>
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### Appendix J.9: Determination of $E[\bar{T}]$ and $\sigma[\bar{T}]$

The total useful capacity $\bar{T}$ equals the forecast for the total useful capacity ($\frac{FC}{\pi}$) plus the error of the forecast ($\frac{FC}{\pi} + FE$) and thus: $\bar{T} = \frac{FC}{\pi} + \frac{FC}{\pi} + FE$, where $FE$ and $\bar{T}$ are random variables and $FC$ and $\pi$ are constants. According to the analysis of section 3.2.2 we know that the random variable $FE$ is normal distributed with $\mu_{FE}$ and $\sigma_{FE}$. According to the characteristics of a continuous random variable (Montgomery and Runger, 2010) we know that if $Y = aX + b$, where $X$ and $Y$ are random variables and $a$ and $b$ are constants, then:

$$\mu = E[X];$$
$$E[Y] = aE[X] + b;$$
$$\sigma[Y] = |a|\sigma[X].$$

In this case, for the expected value of $\bar{T}$ holds that:

$$E[\bar{T}] = \frac{FC}{\pi} + \mu_{FE} + \frac{FC}{\pi}.$$

For the standard deviation of $\bar{T}$ holds that:

$$\sigma[\bar{T}] = \left|\frac{FC}{\pi}\right| + \sigma_{FE}.$$
Appendix J.10: Determination $\alpha$ according to a safety margin.

In this section we determine $\alpha$ according to a certain safety margin for planned capacity. In section 3.1.2 we stated that the safety margin is calculated by

$$Safety \ Margin = \frac{(Planned \ capacity - required \ capacity)}{required \ capacity}$$

In our case, $\bar{\alpha}(T)$ is in terms of required capacity for total forwarded orders in the planning horizon, $\bar{\epsilon}(T)$ is a target for total planned capacity in the planning horizon. The safety margin is now calculated by:

$$Safety \ Margin = \frac{(\bar{\epsilon}(T) - \bar{\alpha}(T))}{\bar{\alpha}(T)}$$

In section 5.1.2.1 we defined $\bar{\epsilon}(T) = F_{\bar{\alpha}(T)}^{-1}(\alpha)$ and thus:

$$Safety \ Margin = \frac{(F_{\bar{\alpha}(T)}^{-1}(\alpha) - \bar{\alpha}(T))}{\bar{\alpha}(T)}$$

In order to calculate the safety margin for a certain value of $\alpha$ we need to rearrange the formula:

$$\left(\left(Safety \ Margin \cdot \bar{\alpha}(T)\right) + \bar{\alpha}(T)\right) = F_{\bar{\alpha}(T)}^{-1}(\alpha)$$

If $\bar{\epsilon}(T) = F_{\bar{\alpha}(T)}^{-1}(\alpha)$ we know that $F_{\bar{\alpha}(T)}\left(\bar{\epsilon}(T)\right) \leq \alpha$ and thus:

$$F_{\bar{\alpha}(T)}\left(\left(Safety \ Margin \cdot \bar{\alpha}(T)\right) + \bar{\alpha}(T)\right) \leq \alpha$$

The analysis from section 3.1.2 revealed that CEVA’s average safety margin is about 7%. From section 2.1.1.1 we know there is minimum ($FC \cdot 0,85$) and maximum ($FC \cdot 1,15$) for the number of order lines CEVA should be able to process each day. Therefore, we are interested in the safety margins -0,15; 0,07 and 0,15:

$$F_{\bar{\alpha}(T)}\left(-0,15 \cdot \bar{\alpha}(T)\right) + \bar{\alpha}(T) \leq 0,22$$

$$F_{\bar{\alpha}(T)}\left(0,07 \cdot \bar{\alpha}(T)\right) + \bar{\alpha}(T) \leq 0,70$$

$$F_{\bar{\alpha}(T)}\left(0,15 \cdot \bar{\alpha}(T)\right) + \bar{\alpha}(T) \leq 0,85$$
Appendix K: Distribution determination for $A(t)$ and $D(t)$

Appendix K.1: $A(t)$

A dataset is used with 125 measurements of $A(t)$ for all $t$ in the planning horizon. First we checked the data for outliers and we did not need to correct the data. The value for $A(t)$ ranges between 0 and 1 because $A(t)$ represents a fraction of $A(T)$. A well-known continuous distribution function for which the range of the data ranges between 0 and 1 is the Beta distribution. Other well-known continuous distribution for which the data is equal or larger than 0 are the Gamma, Weibull and Exponential distribution. Therefore, the probability distributions compared in our tests are the Gamma, Beta, Weibull and Exponential distribution. The parameter estimations upon each distribution are obtained using Maximum Likelihood Estimation. We now compare the log-likelihood value of the four selected distributions with the data set for each period independently. The results are presented in Table 38. The results are presented for the periods 5 to 23 (5 to $T-1$) because $A(t)$ equals zero for period $t = \{1,...,4\}$ for all values in the dataset and because $A(24)$ always equals 1. From the results we can see that the Beta distribution has the best fit for 15 of the 19 analyzed periods. In periods for which the best fit of $A(t)$ is not the Beta distribution, the log-likelihood for the Beta distribution does not significantly differ from the log-likelihood for the best fitted distribution. Moreover, all values for $A(t)$ lie between 0 and 1; the beta distribution is a continuous probability distribution which could be defined on the interval from $[0,1]$. Therefore we choose the Beta distribution for all $A(t)$ in the planning horizon. The probability density function of the beta distribution is defined by:

$$ f(x; a, b) = \frac{x^{a-1}(1-x)^{b-1}}{B(a,b)} $$

where $B(a,b)$ is the beta function defined by:

$$ B(a,b) := \int_0^1 y^{a-1}(1-y)^{b-1} dy. $$

The values for $a$ and $b$ for each period $t$ independently are presented in Table 38.

<table>
<thead>
<tr>
<th>Log Likelihood</th>
<th>Beta distribution</th>
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</thead>
<tbody>
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<td>1320,85</td>
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Table 38 Log likelihood results for $A(t)$
Appendix K.2: $\bar{D}(t)$

The due dates (*pick by times*) for the 12 DD groups are presented in Appendix C. We can see that $\bar{D}(t)$ is zero from period 1 to 12, $\bar{D}(t)$ in the periods 19, 20, 22 and 24 are equal to its preceding period since no due dates are in those periods and $\bar{D}(t)$ for period 23 always equals 1 since it is the last period in the planning horizon including a due date. Therefore we would like to choose the type of probability function that best fits the random process of $\bar{D}(t)$ for the periods 13, 14, 15, 16, 17, 18 and 21. A dataset is used with 125 measurements of $\bar{D}(t)$ for the appointed periods. First we checked the data for outliers and we need not need to correct the data. The value for $\bar{D}(t)$ ranges between 0 and 1 because $\bar{D}(t)$ represents a fraction of $\bar{D}(T)$. A well-known continuous distribution function for which the range of the data ranges between 0 and 1 is the Beta distribution. Other well-known continuous distribution for which the data is equal or larger than 0 are the Gamma, Weibull and Exponential distribution. Therefore, the probability distributions compared in our tests are the Gamma, Beta, Weibull and Exponential distribution. The parameter estimations upon each distribution are obtained using Maximum Likelihood Estimation. We now compare the log-likelihood value of the three selected distributions with the data set for each $t$ independently. From the results we can see that the Beta distribution has the best fit for 5 of the 7 analyzed periods. In periods for which the best fit of $\bar{D}(t)$ is not the Beta distribution, the log-likelihood for the Beta distribution does not significantly differ from the log-likelihood for the best fitted distribution. Moreover, all values for $\bar{D}(t)$ lie between or at 0 and 1; the beta distribution is a continuous probability distribution which could be defined on the interval from [0,1]. Therefore we choose the Beta distribution for all $\bar{D}(t)$ in the planning horizon. The values for $a$ and $b$ for each period $t$ independently are presented in Table 39.

<table>
<thead>
<tr>
<th>Period</th>
<th>Log Likelihood</th>
<th>Beta distribution</th>
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Table 39 Log likelihood results for $\bar{D}(t)$
Appendix L: Determination of productivity value $\pi$

The overall productivity for picking is generated according to the percentage of demand per competency and the average productivity per competency; these values were already found by analyzing historical data, see section 3.2.4. The ‘picking’ productivity value will then be:

$$\pi = \frac{1}{\frac{0.51}{23} + \frac{0.12}{10} + \frac{0.37}{30}} = 21.5$$

Appendix M: Set of shifts in simulation

The parameters for the set of shifts $\{S\}$ and its characteristics $x_s(t)$ are defined based on current situation at CEVA. Each shift has a length of 9 periods and starts between or at period 7 to 16. The exact values for all $x_s(t)$ are presented in Table 40. There are ten different shifts for which employees could be planned for.

| $x_s(t)$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 1        | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9        | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 10       | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

Table 40: The values for all $x_s(t)$ used in the case study
Appendix N: Scenarios considered in case study

The choice-combinations \( cc^x \) and the values for \( \alpha^x \) and \( \beta^x \) for all scenarios considered in the case study.

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<th>( \alpha^x )</th>
<th>( \beta^x )</th>
<th>Scenario x</th>
<th>( cc^x )</th>
<th>( \alpha^x )</th>
<th>( \beta^x )</th>
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<td>19</td>
<td>2c-3b</td>
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<td>20</td>
<td>2c-3b</td>
<td>0.22, 0.70</td>
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<td>21</td>
<td>2c-3b</td>
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<td>22</td>
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<td>36</td>
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</table>

Table 41 Choice-combinations \( cc^x \) and the values for \( \alpha^x \) and \( \beta^x \) for each scenario

Appendix O.1: Verification performance measurements

This appendix verifies the performance measurements implemented in MS Excel. For all input values used in the case study is checked whether the output values make sense. The input values for all \( w(t) \), \( d(t) \) and \( a(t) \) for one set of input values are as presented in Table 42; the output values for all \( wip(t) \), \( s(t) \), \( p(t) \), \( l(t) \) and \( f(t) \) for the same set of input values are presented in Table 42as well.

To check for correctness of the output values the following issues are controller for:

- For each period in the planning horizon, the size of effective production should be equal to the size of available capacity minus the size of lost capacity:
  \[ p(t) = w(t) - l(t) \]
  for all \( t \) in planning horizon.
- The size of total demand forwarded should be equal to the size of total effective production plus the size of work still in progress:
  \[ \sum_{t=1}^{T} a(t) = \sum_{t=1}^{T} p(t) + wip(t) \]
- The size of total minimum required demand minus the size of total work not fulfilled in time should be equal to the total size of effective production minus the size of stock at the end of the planning horizon.
  \[ \sum_{t=1}^{T} d(t) - \sum_{t=1}^{T} f(t) = p(t) - s(T) \]

The performance measurement in Excel is verified because no situation is found in which one of the three checks are violated.

<table>
<thead>
<tr>
<th>Scenario x</th>
<th>( cc^x )</th>
<th>( \alpha^x )</th>
<th>( \beta^x )</th>
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</tr>
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</tr>
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<td>18</td>
<td>2b-3a</td>
<td>0.85, 0.90</td>
<td></td>
</tr>
</tbody>
</table>

Table 41 Choice-combinations \( cc^x \) and the values for \( \alpha^x \) and \( \beta^x \) for each scenario

Table 42 Verification performance measurements
Appendix O.2: Verification integer linear programming problem

The linear programming problem is implemented in the Solver Add-in available for MS Excel. This appendix verifies the solutions of the Solver used in subproblem 3 of the method. For all input values used in the case study is checked whether the output values satisfies the constraints. All constraints which are checked for all solutions are summarized:

- The amount of employees available for each shift should be a collection of natural numbers.
  - \( q_s \in \mathbb{N} \) For all \( q_s \ (s=1,...,S) \)

- The cumulated values for \( c(t) \) should always be nonnegative.
  - \( c(t) \geq 0 \) For all \( t \ (t=1,...,T) \)

- The variable \( x_s(t) \), which shows whether planning period \( t \) is covered in shift \( s \) should be Yes (=1) or No (=0).
  - \( x_s(t) \in \{0,1\} \) For all \( t \ (t=1,...,T) \) For all \( s \ (s=1,...,S) \)

- One cannot have more employees available in the planning horizon than the total pool size.
  - \( \sum_{s=1}^{S} q_s \leq PS \)

- The number of employees available simultaneously in one period should be smaller or equal to the maximum number of employees per period.
  - \( \sum_{s=1}^{S} q_s \cdot x_s(t) \leq MNE \) For all \( t \ (t = 1,...,T) \)

There are no solutions in the case study which violates one of the constraints and thus these are verified.

Appendix P: Case study implementation plan

According to chapter 5 there are 37 scenarios that are compared in the case study. The choice-combinations \( cc^x \) and values for \( \alpha^x \) and \( \beta^x \) for each scenario \( x \) are presented in Appendix N and serve as input parameters.

For each individual scenario the same data set is used to simulate and compare the performance. As was said in chapter 5, the dataset is composited with historical values. A forecast value \( FC \) is available for each day in the data set. This causes that a lot of different forecast values are present in this data set. In the developed method, an individual ILP has to be solved for each individual scenario \( x \) combined with a forecast value \( FC \). As a consequence, the case study quickly becomes highly time consuming when the dataset will be large. For the output of the ILP in subproblem 3 of the method it does not make sense to consider forecast values very close to each other because the ILP will then generate approximately identical solutions. A considerable change in the ILP solution will occur when an extra shift has to be planned. The productivity in this case study is determined to be 21.5 order lines per period and one shift is determined to be 9 periods. One extra shift could process 21.5 \( \times 9 = 193.5 \) order lines. The forecast values of the dataset ranges between 2000 and 5000, therefore the following 16 forecast values are considered: 2000, 2200, 2400, 2600, 2800, 3000, 3200, 3400, 3600, 3800, 4000, 4200, 4400, 4600, 4800 and 5000. Thus, for each individual scenario \( x \) the case study develops a dataset with individual ILP solutions for each of the 16 considered forecast values \( FC \). Within each considered scenario \( x \) and for each day in the data set, the case study matches an individual ILP solution with the closest considered \( FC \) value from the generated dataset of ILP solutions.

A capacity plan \( \{q_s\}_{FC}^x \) is determined for each combination of scenario \( x \) and forecast value \( FC \). Subsequently, each planning horizon in the data set is tested for each scenario \( x \). For the complete case study the following is performed:
Set parameter values according to section 5.1.3
For each scenario $x$ the following processes are executed consecutively:

**Subproblem 1:**
- Set $\alpha^x$ according to the considered scenario.
- Determine $\bar{c}(T)^x_{FC}$ for all forecast values $F$ considered in the case study.
  
  $\bar{c}(T)^x_{FC} =$ the target total capacity value for scenario $x$ and forecast value $FC$.

**Output of subproblem 1:** For each forecast value there is now one $\bar{c}(T)^x_{FC}$ value.

**Subproblem 2:**
- Choose one of the possible options according to the considered scenario.
- Set $\beta^x$ according to the considered scenario.
- Determine $\{\bar{c}(t)^x_{FC}\}$ for each $\bar{c}(T)^x_{FC}$ determined in subproblem 1.
  
  $\{\bar{c}(t)^x_{FC}\} =$ the set of cumulated target capacity levels for scenario $x$ and forecast value $FC$.

**Output of subproblem 2:** For each forecast value $FC$ there is now one set of $\{\bar{c}(t)^x_{FC}\}$ values.

**Subproblem 3:**
- Choose one of the possible options according to the considered scenario.
- Determine $\{\varphi_s^x_{FC}\}$ for each set $\{\bar{c}(t)^x_{FC}\}$ determined in subproblem 2 by running the ILP for each set individually.
  
  $\{\varphi_s^x_{FC}\} =$ the set of available employees for scenario $x$ and forecast value $FC$.

**Output of subproblem 3:** For each forecast value $FC$ there is now one capacity plan defined by the set $\{\varphi_s^x_{FC}\}$.

Subsequently, within scenario $x$, the following processes are processed consecutively for day of the data set:

- The dataset has the values for $FC$, $\{A(t)\}$ and $\{D(t)\}$ available for each day. The developed method produced for each forecast value $FC$ an individual capacity plan defined by the set $\{\varphi_s^x_{FC}\}$.

**Test:**
- Determine $\{\omega(t)^x_{FC}\}$ for each $\{\varphi_s^x_{FC}\}$ determined in subproblem 3.
- Determine $\{\omega(t)^x_{FC}\}$: check the forecast value $FC$ of the day and match it with the closest forecast value $FC$ considered in the case study, now choose
  
  $\{\omega(t)^x_{FC}\}$ for $\{\omega(t)^x_{FC}\}$
  
  $\{\omega(t)^x_{FC}\} =$ the set of available capacities for each period of the day by considering scenario $x$ and forecast value $FC$.

- We now have available $\{\omega(t)^x_{FC}\}$, $\{A(t)\}$ and $\{D(t)\}$.

- Determine $\sum_{t=1}^{T}l(t)$ and $\sum_{t=1}^{T}f(t)$ by running the performance measurement method for the considered day of the data set.

**Output of test:** The performance for the considered in the data set is now determined by considering scenario $x$.

The case study is implemented in MS Excel. The integer linear optimization problem which should be solved in subproblem 3 were run with the free Solver Add-in available for MS Excel. The Simplex LP solving algorithm is used to find a global optimal solution for each scenario $x$ and forecast value $FC$. For practical reasons, the computation of the MS Excel Solver add-in is interrupted when after 30 seconds no global optimum is found; we keep the best feasible solution during its 30 seconds search. VBA code is written in order to repeat the method and measure the performance for all scenarios considered in the case study.
Appendix Q: Capacity planning tool

Figure 39 shows the output screen of the decision support tool. The tool should be used by the planners of CEVA to assist them in their capacity planning process. The user first need to fill in a forecast (in order lines) for the next planning horizon in box 1. Then, presses the button ‘Create capacity plan’ in box 2. Subsequently, output is generated in box 3. Additional information is shown in the other parts of the screen which should help the planner. Box 4 visualizes the number of employees available per hour. Box 5 visualizes the expected number of order lines that could be processed with current capacity plan. According to the information shown the planner is free to adapt the values in box 3.

Figure 39 Output screen of the decision support tool