From data to insights

An advice to improve the capacity planning of temporary employees

Master thesis at CEVA Logistics Benelux

University of Twente

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CEVA LOGISTICS

Essentially,
all models are wrong,
but some are useful.

GEORGE E. P. BOX (1976)

Preface

This thesis is written as the graduation assignment for my masters degree of the study Industrial Engineering and Management at the University of Twente. The company, CEVA Logistics Benelux, offered me a place where I could apply my passion for data analysis and my interests in logistics. I worked at the headquarter office in Culemborg and visited various warehouses during my time at the company. Over there, I got the opportunity to formulate my own research as long as the focus was to provide insights in order to improve a logistic process by data analysis. I learned to individually identify a problem, formulate a problem solving approach and to create a model from scratch in the programming software R.

First of all, I would like to thank my family, friends and girlfriend, who supported me with appreciation and understanding. And secondly, my committee members, each of whom has provided patient advice and guidance throughout the research process. Thank you all for your unwavering support.

Management Summary

This research is executed at CEVA Logistics Benelux, they are a logistic service provider with multiple warehouses across The Netherlands. Currently the warehouses facing a high outflow rate of temporary workers. On average, 24% of the pool of temporary workers leave every month. The cost of outflow are defined as the cost of inflow since a temporary worker that is leaving must be replaced by a new one if the demand is increasing. The cost of inflow includes the costs of training and the use of supporting staff. The yearly costs of the outflow rate is approximately ranging between €2.000.000 and €3.100.000 in total. A survey among 1300 temporary employees indicated that receiving less work than desired is one of the main causes a temporary worker decides to leave. In addition to this, the temporary workers are planned as on-call staff, so the temporary workers have a lot of uncertainty how much work they get offered on a weekly base. Given these points, the problem is that it seems that receiving enough work is a very important factor for a temporary employee and currently this is not an important factor as considered by the capacity planning.

The capacity planning determines the amount of work a temporary employee receives on a weekly or monthly base by determining how many temporary employees should be included in the pool. In order to reduce the outflow rate, the capacity planning strategy must be improved such that the preferences of the temporary workers are better represented.

The purpose of this thesis is to provide advice and insights how the capacity planning strategy can be improved such that the outflow rate of the temporary employees can be reduced. This thesis proposed two models. The first model determines the relationship between the estimated outflow rate when receiving less work for a certain period of time. The result of this model is used to formulate an advice about how the pool of temporary workers must change when the demand changes. The second model investigates to what extent demand can be predicted using only time series data in order to adjust the pool size of temporary workers to the forecasted demand in time. To conclude, the first model assumes that future demand is known and provides an advice towards a capacity planning strategy. The second model verifies that assumption by investigating to what extent future demand can be predicted.

The first model is called the outflow rate model. The purpose of the model is to estimate the outflow rate when the pool of temporary workers receive less work. The model operates by identifying the regular amount of work a temporary employee receives. The estimated outflow rate is determined by identifying the amount of times a temporary worker received less work within a certain period than normal, the moments the temporary worker didn't decide to leave and the final moment a temporary worker decided to leave are compared with each other. So, if it happens that a temporary employee left during a period in which the temporary employee received less work than normal, the model indicates this event as outflow due to less work. The output of the outflow rate model is used as input for a regression model. This model generalizes the relationship between the estimated outflow rate and the rate of receiving less work. The result is a linear regression model where the outflow rate increases more if the rate of less work increases. Another way to interpret this outcome is by using the overcapacity. The overcapacity is defined as the surplus of temporary workers in the pool to fulfill demand, a high overcapacity rate means that temporary workers receive less work. The conclusion is that at any overcapacity level, the estimated outflow rate will be higher and undesired outflow of temporary workers occurs. It is assumed that an overcapacity rate between 0% to 15% does not have an influence on the outflow rate. Therefore the conclusion of the outflow rate model is that the overcapacity rate should not exceed the 15%, otherwise undesired outflow of temporary workers occurs.

The second model is called the time series forecasting model. The motivation of this model is that for most of the warehouses a demand forecast with a horizon of three months is unknown. In order to use the advise of the outflow rate model, the three months ahead forecast must be known. The purpose of the forecasting model is to know to what extent it is possible to generate a reasonable accurate three months ahead forecast, using only monthly time series demand data of different clients. The model provides an advice and insights if there are time series forecasting methods that are able to generate a forecast that is accurate enough to accept the advice provided by the outflow rate model.

The three best performing methods from an international forecasting competition are selected for the forecast model. In addition to that, a parameter is proposed in order to improve the selected forecasts methods in case of some typical demand behavior of some clients. The model uses monthly time series demand data that consist of warehouse activities such as the number of orderlines, orders or trucks. In total there are 177 different time series data from different clients available, each consisting of more than 24 monthly observations. For each time series demand data, the model chooses the best forecast method. The forecast accuracy is summarized per client sector. The conclusion of the forecasting model is that in general the clients within the healthcare and industrial sector have a forecast error of 14% to 16% for a three months ahead forecast. The clients within the technology and retail sector have a considerably lower forecast error ranging from 8% to 9%. The conclusion is that the outflow rate model should only be used for clients active in the technology or retail sector, since it is desired to have an three months ahead forecast error of less than 9%.

To conclude the findings by the outflow rate and forecasting model, the advice is that the capacity planning strategy determines that a maximum overcapacity of 15% is allowed, otherwise undesired outflow of temporary workers occur due to receiving less work. The proposed capacity planning strategy is only applicable for clients within the technology or retail sector, or a client that is able to deliver a three months ahead forecast with a forecast error of at most 9% to ensure that the pool of temporary workers can be adjusted in time to the forecasted demand.

For the year 2018, the total costs as a consequence of outflow by less work is estimated at a range from €200.000 to €290.000. The cost savings are determined when the advice was integrated in the capacity planning strategy. Costs can be saved as a result of preventing outflows by adjusting the pool size in time to be within the 15% overcapacity rate. The costs savings are based on the condition that an reasonable accurate demand forecast is available. Altogether, the potential cost savings over 2018 are estimated at a range from €110.000 - €160.000.

The most important recommendation is to incorporate the expected overcapacity level when a warehouse determines the capacity planning of temporary workers. The expected overcapacity level can be made visible with a key performance indicator. There are three options to implement the key performance indicator.

1. **Basic:** Incorporate the actual overcapacity level in the dashboard that a warehouse (supervisor) can use when determining the capacity planning. It is up to the warehouse (supervisor) to make the right decisions.
2. **Premium:** Incorporate the expected overcapacity level in a software tool that provides an advice to the warehouse (supervisor) about the decisions to be made regarding the capacity planning.
3. **Pro:** Incorporate the expected overcapacity level in a programming environment where the outcome for multiple scenario's with different variables are simulated. This lowers the uncertainty of the capacity planning.

This research focused on two input variables of the capacity planning, the estimated outflow rate and the estimated forecast accuracy. The next step is to go from a strategy to implementation. Therefore a model that incorporates these two input variables provides a warehouse with advice about the capacity planning decisions of a live operation. To conclude, the most interesting point of further research is to build a proof of concept model that can be used at a live operation and convinces the warehouses of the opportunities to improve their capacity planning of temporary workers.

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1 | Introduction

The purpose of this thesis is to provide CEVA Logistics Benelux with advice how the capacity planing of temporary employees can be improved. The approach is to perform a quantitative research for multiple CEVA warehouses in the Netherlands. These quantitative research models focuses on exploring the long-term forecasting processes and analyzing the behaviour of temporary employees when their work pattern differs. The Benelux Innovation Team is the main client of this thesis, since they are eager to know which insights can be derived with the current available data and to what extent this thesis contributes with the decision making processes concerning the capacity planning of temporary employees.

1.1 CEVA Logistics

CEVA Logistics is a supply chain management companies that it present in over 160 countries worldwide with an gross revenue of 7.4 billion dollars in the year 2018. The main sectors CEVA Logistics operate are freight management and contract logistics. The freight management sector provides a service for other companies to transport their goods via road, sea or air. The contract logistics sector consists of all the activities concerning warehousing. CEVA Logistics is divided into 11 clusters, one of them is CEVA Logistics Benelux.

1.1.1 CEVA Logistics Benelux

The CEVA Logistics Benelux is a non-asset-based supply chain management company that has 17 warehouses that cover over 600.000m^2 of storage space. An overview of those location can be given in Figure 1.1. Together with 4.000 employees they generated around €480 million revenue in the year 2018. Besides the warehouses, CEVA Logistics Benelux has two control towers that are responsible for freight management. At the time of writing, the major clients of CEVA Logistics Benelux can be found in Figure 1.1.

Figure 1.1: CEVA Logistics Benelux Contract Logistics sites and their main clients.

1.2 Problem statement

Around the end of the year 2018, the Benelux Innovation Board, abbreviated as BIB, is founded. This multidisciplinary team is looking for opportunities to innovate parts of the organisation. One of their interests is to explore the possibilities of a quantitative research. Nowadays companies put more effort in extracting information which could be valuable in order to improve their processes. The BIB team want to go along with this trend, but there are some limitations regarding the capacity to analyse data and knowledge about data analysis methods. Besides, CEVA Logistics Benelux has multiple sites that work most of the time independently for each other when analyzing certain processes. Furthermore, almost all analysis are made in a basic Microsoft Excel worksheet. Fortunately, the current strategy is to centralize most of the warehouse data. This increases the importance for CEVA Logistics Benelux to familiarize themselves with analyzing big data sets. The following sections elaborate on the processes of selecting the research topic, defining the problem formulation and defining the research approach.

1.2.1 Mapping opportunities

The BIB team wants to explore the opportunities regarding quantitative research for the Benelux cluster. The start of this research begun with a value assessment of potential projects that could be investigated via quantitative research. The value assessment is made with the heads of the IT, Customer Engagement and Solution Design departments. The result is listed in Figure 1.2, it must be mentioned that these value are objective.

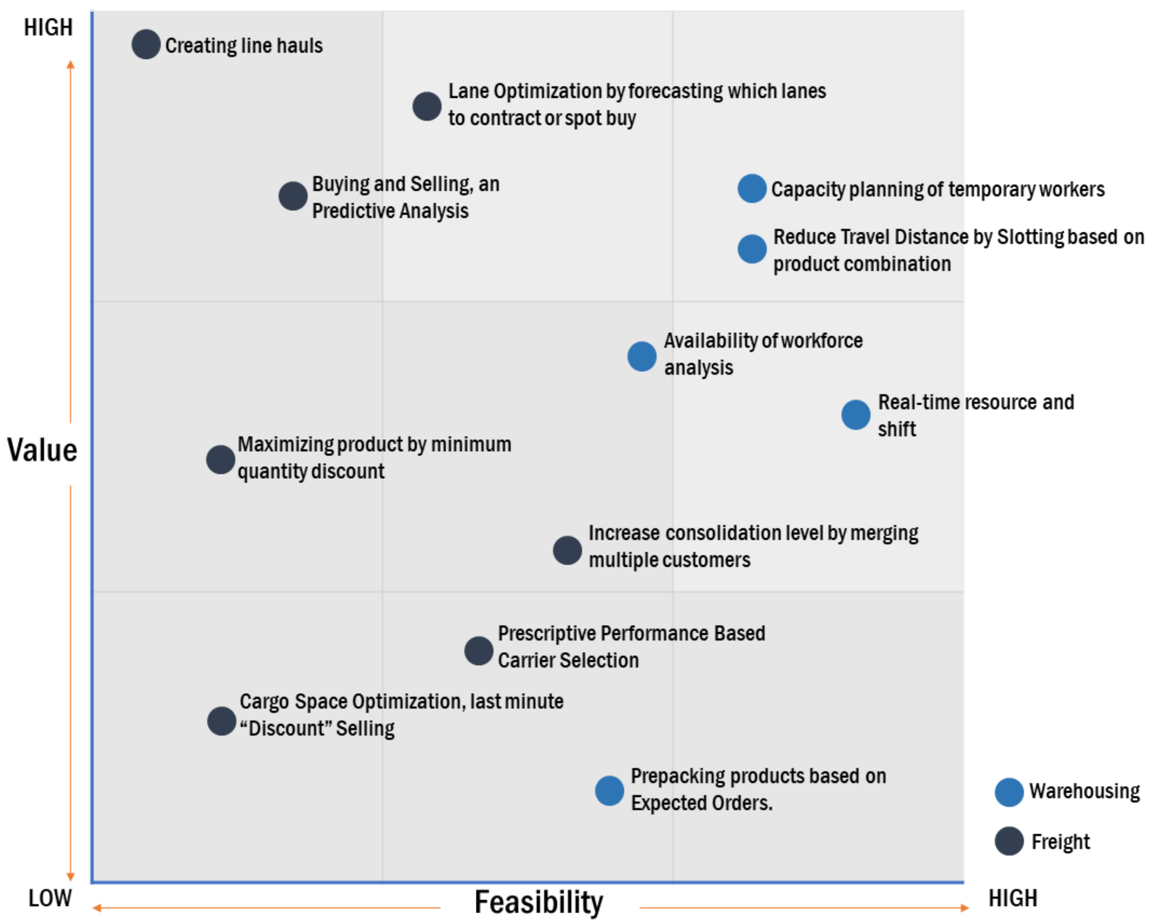


Figure 1.2: A value assessment of projects that could be explored via quantitative based based research.

This assessment indicates the most relevant project to investigate in terms of value creation and feasibility. A high value indicates that a certain project could have a big impact on the organisation in order to save costs, a high feasibility indicates how complex a project can be with respect to data gathering and data processing. The first impression is that the freight activities have less value and less feasibility than the warehousing activities. One of the main reasons why the freight management activities score low on value assessment is because CEVA Logistics Benelux does not own any form of modality. Optimizing these fields would require extensive cooperation with external transport companies. Therefore, only the warehousing activities are within the scope of this thesis.

There are two warehousing activities with a high value and high feasibility, these project are "reduce travel distance by slotting based on product combinations" and "Capacity Planning". Both project can be applied to all Benelux warehouses and the data is available. The reason why the "slotting on product combinations" project scores just a bit less on value is because it is only applicable for existing clients, since new clients have no data or data is outdated. The outcome of the value assessment is that a project concerning the capacity planning of temporary employees seem to have the highest value and the highest feasibility of all other quantitative based projects. From this point on, this thesis focuses on the capacity planning of temporary employees, a topic within the resource planning.

1.2.2 Resource planning

The resource planning problem concerns the decision maker's response to a changing demand pattern over time [7]. In other words, what needs to be the workforce capacity in order to meet the demand and minimize the costs if hiring and firing. In case of a warehouse, the capacity planning problem can be formulated as how many full time equivalent hours (FTE) capacity is needed to process the demand while minimizing the cost of a certain size of the workforce pool.

The capacity planning problem occurs on a tactical decision level within a warehouse, that means over a time frame of a couple of months or quarters of a year as can be seen in Table 1.1. Over there the difference between different types of levels is explained regarding planning and scheduling according to a framework of Hans et al. [1]. It is important to see the differences between the strategical, tactical and operational level, since this thesis focuses on the tactical level.

Table 1.1: Resource planning and scheduling framework [1].

Level	Resource Planning	Review period
Strategic	Case mix planning, capacity dimensioning	Years
Tactical	Block planning, staffing, admission planning and capacity planning	Weeks, months, quarters
Offline Operational	Workforce scheduling	Day-to-day
Online Operational	Monitoring and emergency coordination	Real-time

1.2.3 Problem cluster

The value assessment of section 1.2.1 indicates that the most valuable and feasible project is about improving the capacity planning. In order to know what can be improved of the capacity planning, a problem cluster is needed to identify cause-effect relationships that lead to the core problem of an activity. This methodology to solve a problem by determining it's core problem is useful when identifying an action problem. An action problem is defined as that the result of something that happens differs from the desired outcome [8]. In case of the capacity planning, there are three action problems identified by the management of CEVA. The first one is a high inflow of TEMPs, a TEMP is an temporary employee. The second one is a high outflow of TEMPs and the third one is a high turnover rate of the pool of TEMPs. That means that the whole pool is refreshed at a rather high frequency. Their root-causes are displayed in Figure 1.3, which is called the problem cluster.

Within a warehouse, the workforce pool consists of fixed employees and temporary employees. The idea is that the pool of TEMPs deals with seasonality, if demand increases, then the pool of TEMPs increases as well. At the CEVA warehouses, the ratio between the fixed employees and TEMPs is about 50%-50%. Therefore, the pool of TEMPs also deals with non-seasonal demand, so there are always TEMPs present to fulfill demand. The problem that occurs is that the number of TEMPs that flow in, as well as the

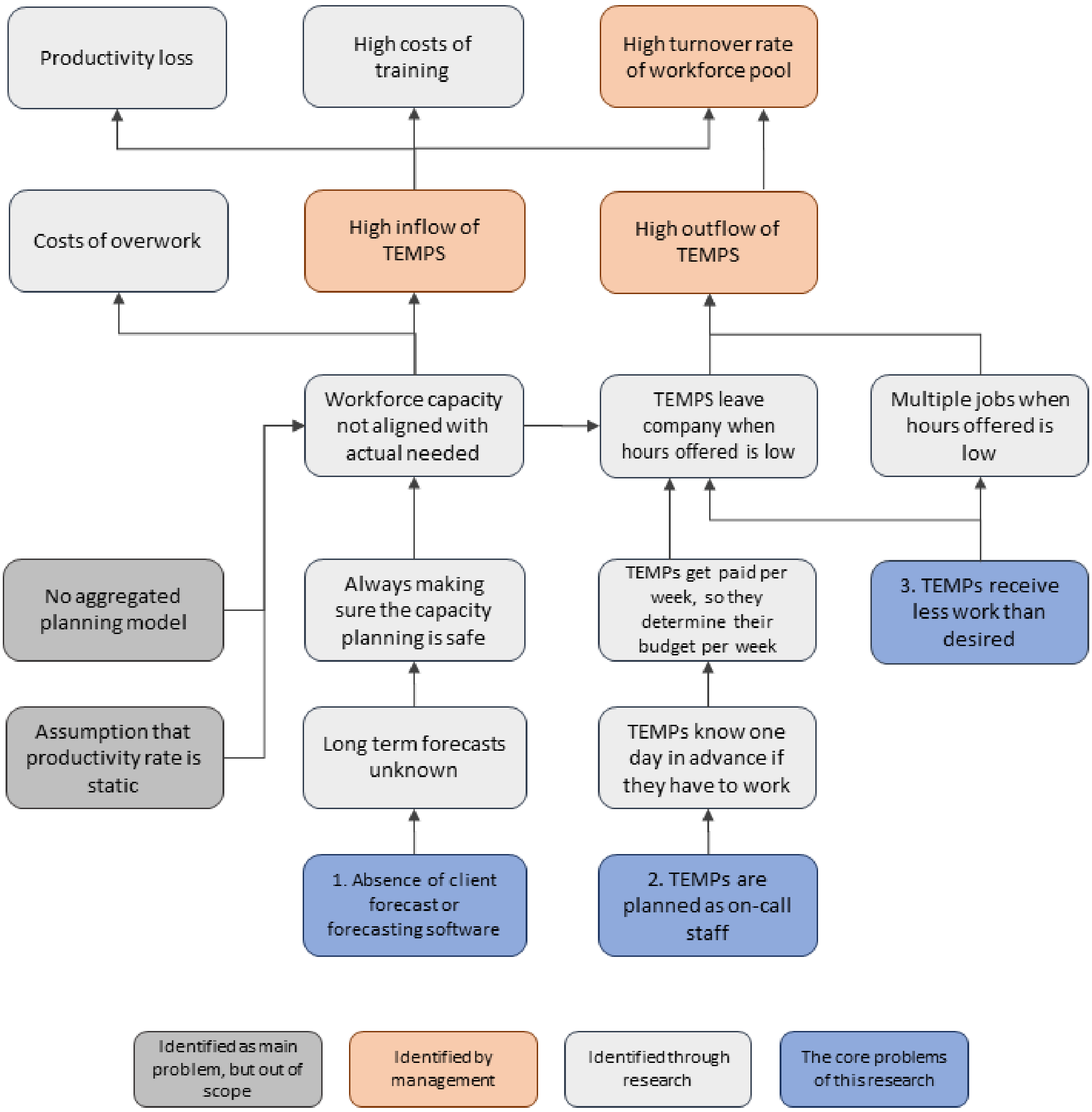


Figure 1.3: The problem cluster regarding the capacity planning problem.

number of TEMPs that flow out, is quite high. This results in a loss of productivity, since a new TEMP need a couple of weeks to get familiar with a new work environment. In addition to that, a high inflow of new TEMPs result in a high costs of training. Even dough the warehouse activities involve low skilled work, a training is needed to explain the tools, processes, lean methodology and continuous improvement program. The root-cause of the actions problems relates all the way to the bottom of the figure, marked in a blue box. These are called the core problems.

The purpose of this thesis is to tackle the core problems, except for two core problems that are out of scope. They require a different research approach and the problem is just too big to handle in one thesis. There are five core problems identified, but only three core problems are solved. These are listed below, in addition to that some further explanation is given. The next section incorporates the core problems and rephrases the problems to questions.

1. *"Absence of client forecast or forecasting software"*: A site depends either on a forecast that is made by their client or by their own. However, at the moment they use often a yearly forecast. This includes the seasonalities, but is does not have a good accuracy on a monthly base. In case a client does not provide a site with a forecast, they can make their own forecast. But this requires a lot of effort and no support of an forecasting company is given. A site will make sure that

there are always enough workforce to cover demand, so in case a forecast is absent or a forecast in inaccurate, a site makes sure that there is extra workforce capacity to cover this uncertainty. The increase in workforce capacity causes an unaligned balance between the workforce pool size and actual workforce needed. This causes TEMPs to leave, which results in more TEMPs that needs to be hired and unnecessary costs will follow.

2. *"TEMPs are planned as on-call staff"*: The TEMPs are hired by employment agencies, but CEVA sends a request to these employment agencies when more TEMPs need to be hired. The problem is that in most cases, the TEMPs receive one day in advance a conformation that they can work. In addition to that, the TEMPs are paid per week. So when they did not work much for a couple of consecutive weeks, they are likely to leave when they have the opportunity to work more elsewhere. The likeliness increases given the fact that they don't have any assurance that they can work the next week more. Therefore the on-call planning of TEMPs is a cause of a high outflow rate.
3. *"TEMPs received less work than desired"*: The most important reason for a TEMP to work is to earn money. Since the hourly wages are not high, it is very important for them that they can work the amount of hours that they desired. That does not mean that every TEMP wants to work 40 hours a week, since there are also part-time TEMPs. As mentioned previously, TEMPs get paid per week so if they get the feeling that they didn't get the opportunity to work their desired hours in the past couple of weeks, they are very likely to leave after a couple of weeks. To compare that with employees who are paid every month, they are less sensitive to weekly changes and will probably decide to stay or leave after a couple of months.

1.3 Research goal

1.3.1 Main research question

The BIB teams want to improve the capacity planning of TEMPs by a quantitative analysis. Two core problems, that were identified in the previous section, are likely to be the cause that the workforce capacity planning is not optimal. This section formulates the research goal that will help to develop insights to improve the capacity planning of TEMPs. The research goal is divided by multiple research questions that provides an answer for the main research question. The main research question is listed below, the answer to that question is formulated in section 6.1.3.

How can the capacity planning of temporary workers at the CEVA Logistics Benelux warehouses be improved by an estimation of the outflow rate and a prediction of demand?

1.3.2 Research questions

The main research question is divided in to two topics. One topic is about the prediction of demand (forecasting) and the other topic is about the estimation of the outflow rate (resource planning). First, a small section introduces the purpose of the topic and then a list of the research questions is added.

1. **Organization**
   CEVA Logistics has multiple warehouses throughout the Benelux, this results in a great amount of available data. Furthermore, a possible solution could increase in value if it can cover all the sites. However, there are some differences among the sites regarding the capacity planning strategy. This section elaborates on the organisational aspect of the main research question.
   (a) *Section 2.1.2:* How does the process of capacity planning of TEMPs currently looks like?
   (b) *Section 2.1.4:* How are the warehouses characterized in terms of size and differences between TEMPs?
   (c) *Section 6.2.1:* How can the result of the capacity planning model and the forecasting model be implemented within the organisation?

2. **Resource planning**
   The capacity planning is part of the tactical planning as explained in Table 1.1. The capacity planning indicates how many TEMPs to include or exclude to and from the pool of TEMPs on a monthly base. As indicated in section 1.2, the capacity planning can be improved by reducing the high outflow rate. In order to reduce high outflow rate, the relationship between the outflow rate and the size of the pool of TEMPs is investigated.

(a) *Section 2.3.1:* How many TEMPs flow out on a monthly base?
(b) *Section 2.3.2:* What are the causes that a TEMP flows out of the organization?
(c) *Section 2.3.3:* What are the estimated costs of outflow and what are the potential savings regarding an improvement of the capacity planning strategy?
(d) *Section 2.4 & section 4.2:* How can the relation between the size of the pool of TEMPs and the outflow rate be modelled?
(e) *Section 3.4:* What are the tools from the literature to interpret the results of the proposed outflow rate model?
(f) *Section 5.2:* If the relation between the size of the pool of TEMPs and the outflow rate is known, how much could potentially be saved in the past when anticipating on this relationship?
(g) *Section 6.1.1:* How can the result of the outflow rate model be incorporated within the strategy towards capacity planning of TEMPs?

3. **Forecasting**
A workforce capacity planning need a certain prediction of the workload for a certain month. This can be a forecast of the demand that the TEMPs need to fulfill. An accurate forecast does not provide the needed workforce capacity, since more variables are involved to determined the needed workforce capacity. Nevertheless, a large amount of uncertainty is involved in this forecast. This makes the workforce capacity planning also uncertain. By reducing the uncertainty of the forecast, the uncertainty of the workforce capacity planning will also be reduced.

(a) *Section 2.4:* How does the current long-term forecasting method perform?
(b) *Section 2.1.3:* Which data is available that could be used by a forecasting model?
(c) *Section 3.1:* Which forecasting method or methods are capable to deliver the best results according to the literature?
(d) *Section 4.1:* How can the best forecasting methods or method from the literature be put into a model to find out what the best possible forecast accuracy is, given the current input data?
(e) *Section 4.1.2:* Is there a way to improve some proposed forecasting methods out of the literature, by adding parameters to deal with specific demand behavior?
(f) *Section 5.1:* How well does the proposed forecasting model perform?
(g) *Section 6.1.2:* Is the performance of the proposed forecasting model good enough or is there a need to search for alternative methods to determine a forecast.

1.4 Research approach

The research approach can be formulated as the problem solving approach. The core problems are already defined in section 1.2.3. There is a high outflow rate of TEMPs and it is likely that the underlying core reasons are that TEMPs receive less work than desired and that TEMPs are planned as on-call staff. These two events are responsible for some part of the high outflow rate, it is assumed that an improved capacity planning can reduce the effect of the two events and lower the outflow rate. An overview of the research approach can be find in Figure 1.4.

There are two models that are key for the problem solving approach. Due to he large number of TEMPs that leave, it is valuable to know the impact of receiving less work on the likeliness that a TEMP leaves. This is modeled as the outflow rate model. With this insight, the size of the pool of TEMPs can be adjusted in order to reduce the high outflow rate. In addition to that, if it is known how the pool of TEMPs should change to fluctuating demand, it must be known how accurate the changes in demand can be predicted. The main reason is that the uncertainty of a forecast influences the accuracy when determining the correct size of the pool of TEMPs in order to reduce the outflow rate. Altogether, the result is a proposed strategy towards the capacity planning of TEMPs. This advises about the ideal size of the pool of TEMPs, under a set of assumptions what the demand forecast is going to do.

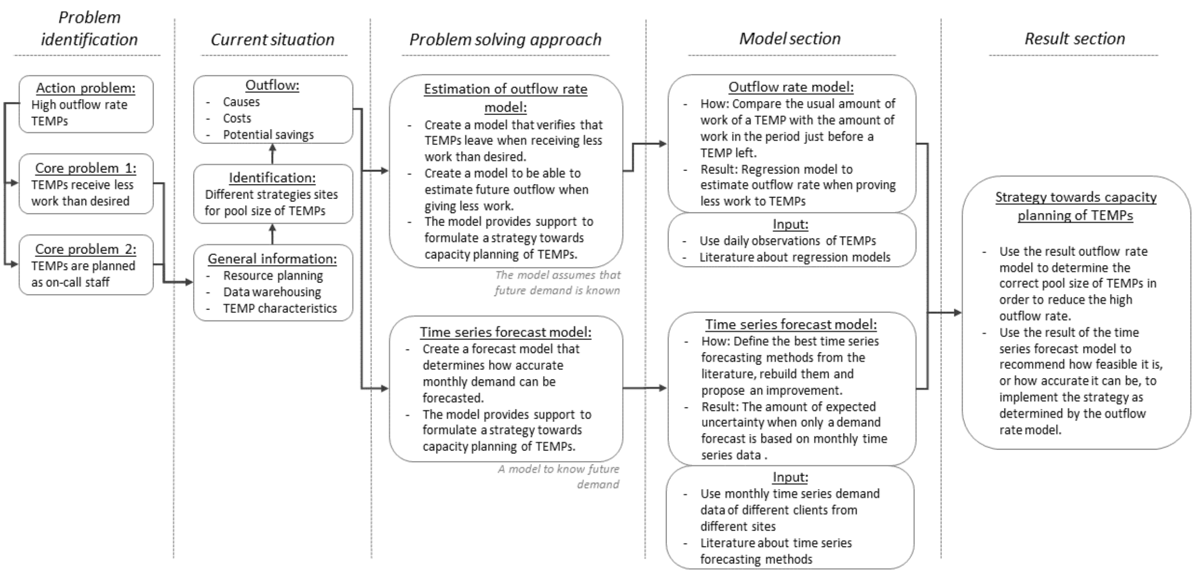


Figure 1.4: An overview of the research approach of this thesis.

1.5 Scope and assumptions

The scope and assumptions are written down in order to explain the conditions and expectations of this thesis. The scope is defined as restriction that are made by the company or are necessary due to time limitations. The assumptions are defined as presumptions that are likely to be true, but they are not 100% verified within this thesis.

Scope

Forecasting

- The forecast horizon will be long term, this mean the model predicts one to three months in advance.
- The forecasting model is programmed in programming language R, this open source analysis tool comes along with a big user community to provide support during the modelling phase.
- The model uses monthly time series demand data of all the warehouses located in the Benelux of a period between the year 2015 and the year 2019.
- The focus is to develop insights based on analysing literature about accurate time series forecast models.
- Building the best forecast model is out of scope, since only demand data is used as input for the forecast. In order to create a better forecast, more data should be used such as information about special events or external influences.

Workforce capacity planning

- This thesis focuses on the tactical resource planning, another word for that is workforce capacity planning or workforce pool size planning.
- A part of this thesis refers to the hiring and firing process of the TEMPs. Another way of expressing this process is the inclusion and exclusion of TEMPs to the pool of TEMPs, since actually TEMPs are not fired, they only receive less to no work for a certain period.
- The costs of one TEMP per hour is kept secret for the reader of this report, but a range of the approximate costs is given. It is assumed that all TEMPs have the same costs per hour.
- The workforce pool consists of fixed blue collar employees and temporary employees, only the TEMPs are considered in this thesis.
- Daily data is gathered from 01-2015 till 05-2019.
- The purpose of the model is to provide insights for a month-to-month planning, the model is not build to use for day-to-day operations.
- Cost savings and improvements towards the satisfaction of TEMPs are the two points of interests.

- The ratio between the amount of fixed employees and the amount of TEMPs must be approximately 50%/50% at a warehouse, this is considered to be a fixed constraint.
- The pool of fixed employees move along with the trend of the demand and the pool of TEMPs move along with the seasonality or fluctuation in demand.
- It can happen that there are cost benefits to have backorders, but the proposed model in this thesis assumes that the demand a warehouse receives must be met.
- The model uses daily data about worked hours of nine warehouses located in the Netherlands. These ones are the most valuable warehouses for CEVA Logistics Benelux, below an overview of these locations.
  - Venray 1
  - Venray 2
  - Venray 3
  - Born 1
  - Born 2
  - Eindhoven
  - Roosendaal
  - Den Haag
  - Maarssen
- The use of TEMPs is different between the Netherlands and Belgium, since they have different employee rights. Therefore the TEMPs that are located in Belgium warehouses are out of scope.

Assumptions

Forecasting

- The forecasting model uses monthly time series data of different warehouse activities. The assumption is that this aggregated monthly demand is representative enough as measure for the trend and seasonality of the workload during a year.
- Special events are not filtered out of the time series data, it is assumed that these special events do not have a big impact on the overall demand behavior.
- Since all CEVA warehouses must operate according to the same standards, it's assumed that the recommendations of this thesis can be used, in most cases, for all warehouses.

Resource planning

- Some warehouse run two or three shifts a day, consisting of approximately 8 hours each.
- The productivity parameters are constant.
- It is assumed that the employment agencies do not share or do not have information about the pool size of TEMPs dedicated for CEVA.
- Overcapacity is defined as the difference between the total capacity of TEMPs on a certain month and the needed amount of TEMPs at that moment.
- The needed amount of TEMPs per month is defined as the actual amount of hours spend in one month multiplied by a factor of 1.14. The reason for that is because the pool must deal with illness and holiday, so it must be 14% higher than the actual needed amount of TEMPs. More about that 14% in section 2.2.
- It is assumed that the required size of the pool of TEMPs per month is big enough to deal with daily fluctuations, since TEMPs
- The results are either shown in a number of TEMPs or the number of FTE. The calculation are performed in FTE, but can be converted in a number of TEMPs by a factor of 1.06. On average, 1 FTE consist of 1.06 TEMP.

Conclusion

This report delivers an advice concerning the capacity planning of TEMPs of the CEVA warehouses located in the Netherlands. There is a high outflow of TEMPs which costs a lot of money. It is likely that an improvement towards the capacity planning can reduce that outflow rate. Two goals are formulated in order to develop a set of recommendations that will help to reduce the high outflow rate. The first goal is to explore the relationship between the size of the capacity planning and the behaviour of TEMPs to leave the company. The second goal is to investigate to what extent monthly demand of multiple clients can be predicted using only the currently available data and which knowledge can be derived from the performance of current forecasting methods. The relation between the two goals is that the first one tells how to react when demand changes and the second one tells how much demand changes. This can be summarized to first determine an optimal strategy for the workforce capacity planning regarding certain changes in demand, then determine to what extent the changes in demand can be predicted so that the optimal strategy for the workforce capacity planning can be effective.

2 | Current situation analysis

This chapter gives an answer to several sub research questions regarding the current situation of the workforce capacity planning of TEMPs at different warehouses. Furthermore this chapter describes which processes are involved in the warehouse operations and which aspects characterize both the problem definition and the CEVA warehouses. First the general processes are explained, then a section explains that their is no mutual strategy towards the capacity of the pool of TEMPs. This is followed by a section that supports the feeling that there is a high rate of inflow and outflow of TEMPs. The end of this chapter summarizes the findings and proposes a the path towards a better capacity planning of TEMPs.

2.1 Introduction to warehousing and resource planning

The upcoming sections give an overview of the mutual processes at the different CEVA warehouses and to what extent the approach differs towards certain processes between sites. First the general warehouse activities are listed, then the resource planning on a operational and a tactical level is discussed. At last, a description how data is gathered, stored and retrieved is written and the characteristics of TEMPs are described.

2.1.1 Warehouse operations

This section describes which processes are common in the CEVA warehouses. This involves the logistic activities, the current process of planning TEMPs and the way how data is gathered. A general overview of the logistic activities within a warehouse is given in Figure 2.1. CEVA Logistics is responsible for the logistic activities of their clients. A product can be ordered from the warehouse from three different sources. These sources can be a local decentralized warehouse, a local store or a customer of the client who ordered something online. CEVA makes sure that the products are picked and shipped within the agreed time.

The clients of CEVA are categorized per sector, this is based on the characteristics of the products that are stored within a warehouse and if a client sells their products to another company or to end consumers. Within the Benelux area, there are four sectors present. An overview of these sectors can be found below, along with some examples of clients that belong to a certain sector.

- Retail
  Companies with physical stores or e-commerce companies, most of them sell fashion items (business to consumer)
- Healthcare
  Companies with medical equipment that can be electronics or dressings (business to business and consumer).
- Technology
  Companies with electrical equipment (business to business and consumer).
- Industrial
  Companies with large products or spare parts (business to business).

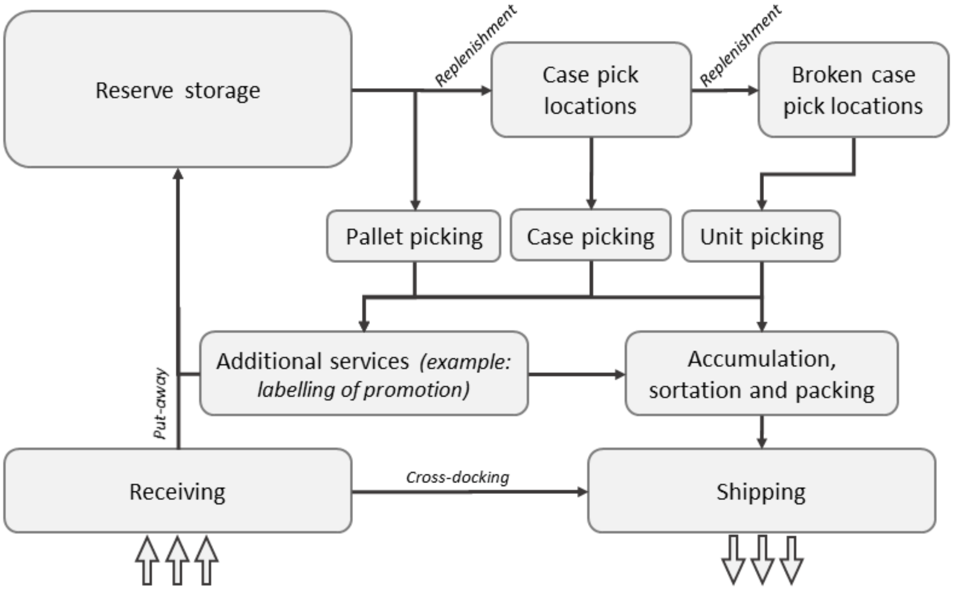


Figure 2.1: A general overview of the logistic activities within a warehouse

2.1.2 Resource planning

This sections answers research question 1a: *How does the process of capacity planning of TEMPs currently looks like?*

There are two types of employees working at the CEVA warehouses, the blue collars and the white collars. The blue collars represent the people that are directly involved with the warehouse operations, so they often perform physical labor. The white collars represent the people that facilitate the blue collars, this is often involved with administrative work. The blue collar employees are hired in two ways. One group that is hired directly by CEVA, they have a fixed contract. The other group is hired by an employment agency, they do not have a fixed contract and are called a temporary blue collar employee (TEMP). Traditionally, the TEMPs are used as flexible workforce that can easily increase during a high season peak or decrease during a period of low demand.

Each day TEMPS are used at the warehouses and that involves decisions on a operational and tactical resource planning level. The challenge of the operational resource planning is to match the right amount of TEMPS to process all the orderlines for that day, without creating overtime. The challenge of the tactical resource planning is to create a workforce pool big enough to have enough flexibility to meet the daily demand, but without creating a workforce pool that is too big which costs a lot of money.

Currently within CEVA there is no aligned strategy of who is responsible for the tactical capacity planning of TEMPs. Some sites give the warehouse supervisors that responsibility, others a resource planner and some give the employment agencies that responsibility. The ownership of this responsibility is important, since a new TEMP must be trained and those costs must be paid by CEVA. The thing that most sites have in common is that they put their focus to the operational resource planning. That consist of the day to day or weekly planning, while the recruitment process may take up to a month regarding advertising, screening and onboarding. Therefore it is important to put also some focus to the tactical research planning. The way the sites currently arrange their resource planning can be seen in Table 2.1 [1].

[1] COP is a Centre of Planning, a company of Manpower that provides as service that they match a certain demand to a number of TEMPs.

Table 2.1: The resource planning process at the sites.

Site	Responsible for resource planning		Planning methodology tactical level
	Operational level	***Tactical level***	
Born	HR, Supervisor	Middle management	Plan based on annual forecast, weekly forecast and one day in advance.
Den Haag	HR, Supervisor	Middle management	Plan based on annual forecast, weekly forecast and one day in advance.
Eindhoven	HR, Supervisor	HR, Supervisor, middle management, COP	There is a 3 month forecast provided by client and supervisors. This is send to the COP and they provide the supervisors with a certain number of employees to include or exclude from the workforce pool. On operational level there is a scheduling tool, but that determines the requirements per day.
Maarssen	HR, Supervisor	HR, Supervisor	Receive forecast of client per week and increase or decrease pool size by experience.
Roosendaal	HR, Resource planner, Supervisors	Middle management	The addition of the resource planner is to match the skills via a competence matrix and to improve the resource planning on operational level.
Venray	HR, Resource planner, Supervisors	Middle management	Determine capacity based on the busiest day of the week or month out of the forecast. The resource planner has the same role as the resource planner of Roosendaal.

The pool of TEMPS must flexible enough in order to minimize the probability of overtime and undertime at the same time it is required to minimize the amount of inflow of a new TEMP. Since a new employee requires training and is not as productive in the first couple of shifts as an experienced TEMP [2]. The challenge to determine the optimal pool size of TEMPS can be described as the problem to know how many TEMPs to include or exclude from the workforce pool.

2.1.3 Data warehousing

This sections answers research question 3b: *Which data is available that could be used by a forecasting model?*

CEVA has multiple systems to store warehouse data. This differs per client since a client has a different portfolio of items, different order volumes and different preferences to store certain information. In general the information about the generic warehouse operations (WMS data) that are mentioned in section 2.1 is available of every client. Since a couple of years, a database exists that collects all the WMS data and makes it available through a QlikView application. Unfortunately, the QlikView application keeps only one year of data. To obtain data over a longer period of time, the QlikView application cannot be used and more effort is needed.

In case more than one year of data is needed, queries are needed to withdrawal data from other servers. This process is not standardized and requires a lot of effort. An overview of the warehouse data systems can be found in Figure 2.2 along with the contents and volume of the data. As Figure 2.2 illustrates, detailed daily data such as orders per store is only available for 90 days, this is due to the General Data Protection Regulation. Further limitations like the one year of available data of QlikView happens due to a trade-off between application speed and application capacity.

In addition to the warehouse data, also employee data is available. This data is stored in a system

[2] An experienced TEMP is defined as a TEMP that meets the required productivity after 20 shifts.

called Protime. This protime data consists of all the activities that employees performed within a warehouse. An example of this can be found in Figure 2.2, over there a table is listed with the contents of the data tables. A warehouse employees register all their activities in the protime system. They are paid by the hours that are stored in the protime system, so that makes the protime data reliable.

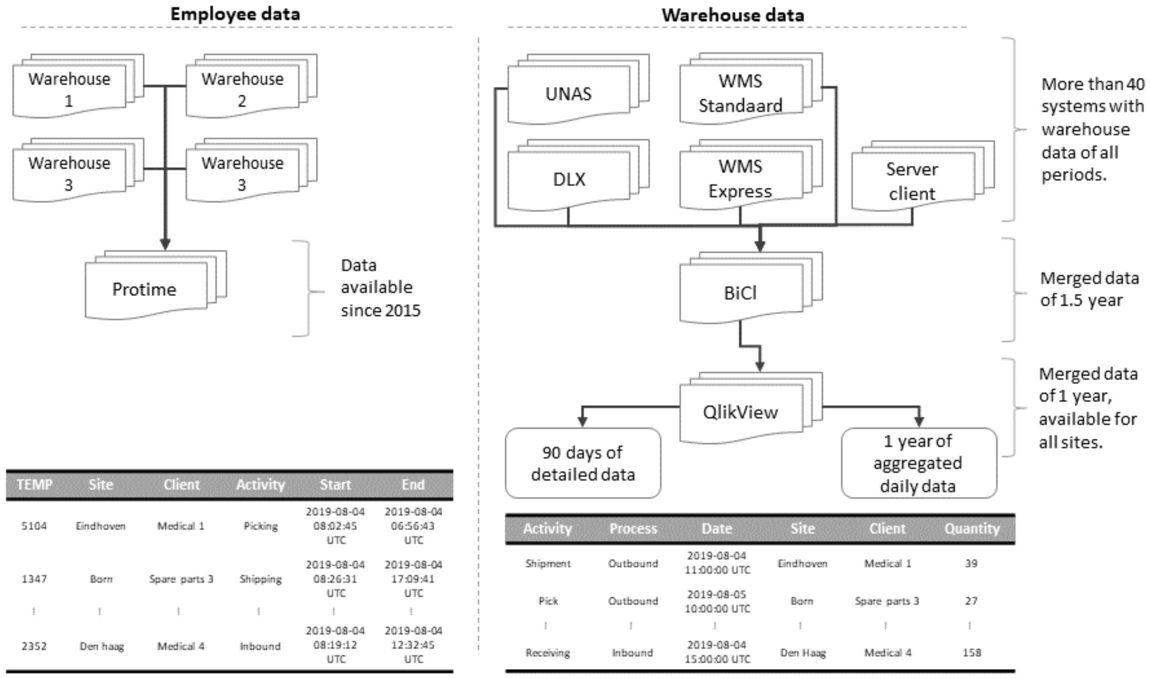


Figure 2.2: An overview of the data warehouse systems and the available data per system.

2.1.4 TEMP characteristics

This sections answers research question 1b: *How are the warehouses characterized in terms of size and differences between TEMPs?*

This section categorizes TEMPs based on hours worked and gives an overview how these categories differ among the sites. The categories are full-time, part-time and not available. The not available TEMPs are TEMPs that worked for less than 20 shifts at CEVA. Most of the TEMPs work five shifts a week for a total of 40 hours a week, this is called a full-time TEMP. But unfortunately, there is no general database present in which the preferences or restrictions regarding the amount of hours a part-time TEMP want to work.

In order to provide an answer how many hours part-time TEMPs want to work in general, an analysis is performed over the fixed employees. The reason to choose for the fixed employees is because the amount of hours that is provided to TEMPs fluctuate, therefore it is hard to determine which TEMPs work on a full-time or part-time base. Sites are focused to give fixed employees the amount of hours as agreed on the contract, based on that it should be more clear to see which employees work on a full-time base and which employees work on a part-time base.

The average amount of hours worked per week and the average number of shifts per week per fixed employee of the year 2018 are plotted in Figure 2.3. In order to determine the average amount of hours worked or the average number of shifts worked, the holiday days must be excluded from the data. That means that if a TEMP didn't show up for more than 7 days, that period is indicated as a holiday for the TEMP and won't be included to calculate the averages. The days when an employee was ill or if there was a public holiday are still included, since the assumption is that this amount is rather low and has little influence to the calculation of the averages. More about the way how this is calculated in section 4.2.

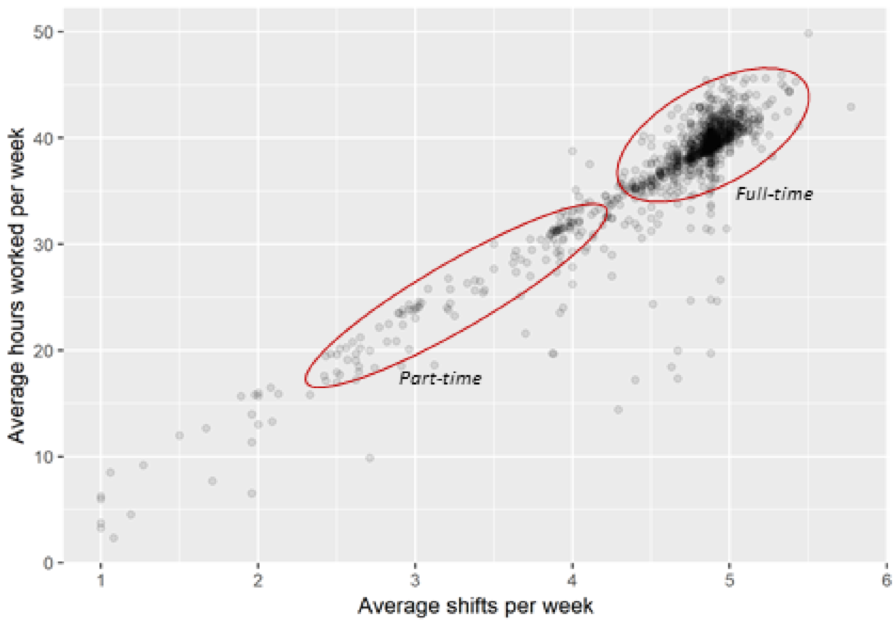


Figure 2.3: A density plot for the amount of hours worked per week and the average number of shifts worked per week of all fixed blue collars in the year 2018.

As indicated in the figure, two area's can be distinguished. The most upper right area are the full-timers and those employees work for around 40 hours a week with an average number of shifts between 4.5 and 5 per week. This indicates that some overtime work occurs, thus TEMPs work sometimes more than 8 hours a days. The area on the left are the part-timers, since they work on average between 12 hours and 34 hours a week. However, this does not give an answer to the question because the range is too big. Based on the most dense area of the part-timers, it can be assumed that most part-time employees work around 32 hours in a bit less than 4 shifts a week. Also, this indicates that overtime work does happen. To conclude the following assumption can be made, the average amount of hours full-time TEMPs work is 40 hours a week and the average amount of hours part-time TEMPs work is 32 hours a week.

Based on the this verification the TEMPs can be distinguished into three types. The third type is not characterized by their average hours worked per week, but by their total employment period. There are a lot of TEMPs that won't achieve the desired productivity after working 20 shifts or don't have a fit with the organisation and quit within 20 shifts. These are called the NA TEMP [3]. The type of TEMPs are enumerated below.

TEMP types:

- They want to work 40 hours a week: Full-time TEMP
- They want to work 32 hours a week: Part-time TEMP
- Worked less than 20 shifts: NA TEMP *(Not Available TEMPs)*

The ratio's of the TEMP types is given in Figure 2.4, in addition to that, to indicate the size of the workforce of each warehouse, the total number of TEMPs worked per year on a site is listed next to it. In 2018 on average it can be concluded that out of every 10 new TEMPs that were hired, 5 are full-time, 2 are part-time and 3 are NA TEMPs. This ratio changes per site, but the ones who are quite similar in size have the same characteristics of the TEMP type ratio.

The smaller sites like Born, Maarssen and Venray 3 have a lot of full-timers in their pool. It is likely to assume that those sites have a non-fluctuating demand and therefore a non-fluctuating workforce pool. Interesting is the high ratio of NA TEMPs. Probably this is caused during a period of high demand. Within a short period of time, a lot of TEMPs needs to be hired. The result of that might be that the quality of TEMPs is not as high as desired. Another reason might be the case where an overreaction takes place to counter a sudden increase in demand, more TEMPs are hired than needed and some need

[3]NA TEMP means a Not Available TEMP since the TEMP worked for less than 20 shifts.

to leave again.

To conclude, there are three TEMP types. A full-time TEMP expects to work 40 hours a week, a part-time TEMP expects to work 32 hours a week and the NA TEMPs worked less than 20 shifts in total for a warehouse. It is not desired to have many NA TEMPs since they do not have many additive value in the long-term. In 2018 on average 50% were full-time TEMPs, 30% were NA TEMPs and 20% were part-time TEMPs. The smaller sites have a higher full-time TEMPs ratio, compared with the bigger sites.

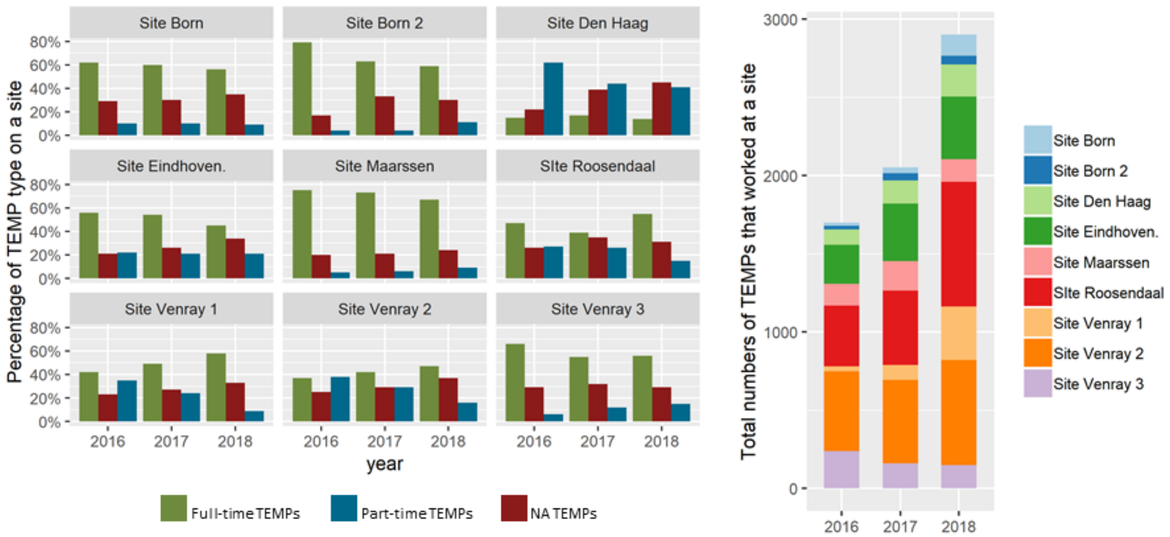


Figure 2.4: Left: the ratio between the different TEMP types per site per year. Right: the total number of TEMPs on each site per year.

2.2 No aligned strategy towards capacity planning of TEMPs

The capacity planning of TEMPs is part of the tactical workforce planning. It determines the size of the pool of TEMPs based on the needed amount of workforce. The pool of TEMPs must always be bigger than the amount of needed workforce, otherwise overtime occurs. The difference between the pool size of TEMPs and the amount of needed workforce within a certain month is called overcapacity. A lot of overcapacity results in high costs, since more TEMPs are employed. On the other hand, a lot of overcapacity gives a warehouse more flexibility and safety since more TEMPs are available when needed. The amount of overcapacity differs per site, this can be seen in Figure 2.5. Sites like Den Haag, Venray 1-2-3 have relatively a bigger blue area, thus a bigger pool of available TEMPs than needed.
It is desirable to minimize the overcapacity, since it is likely that a lot of overcapacity causes a TEMP to work less than desired. The constraint is that there must be enough flexibility within the workforce pool to, for example, replace the TEMPS that are ill [4]. The value of the lowest overcapacity ratio possible is estimated by the following assumptions:

1. A TEMP takes on average 25 days per year off.
2. A TEMP is on average ill for 12.5 days per year.
3. Adding those values gives the total amount of days per year that a TEMP needs a replacement TEMP, this results in 37.5 days.

There are 313 days per year that a CEVA warehouse is open, thus given that there are 37.5 days per year where another TEMP is needed to replace another, at least 12% additional workforce is needed. All sites seem to have always an overcapacity ratio of at least 12%, except for some periods with high demand like autumn 20108. However the overcapacity ratio changes per site. The question to be answered is: what should be the optimal strategy towards the ratio of overcapacity? A high overcapacity ratio creates more

[4] TEMPs are also used to replace fixed blue collars when they are ill, but that value is incorporated in the actual needed amount of TEMPs.

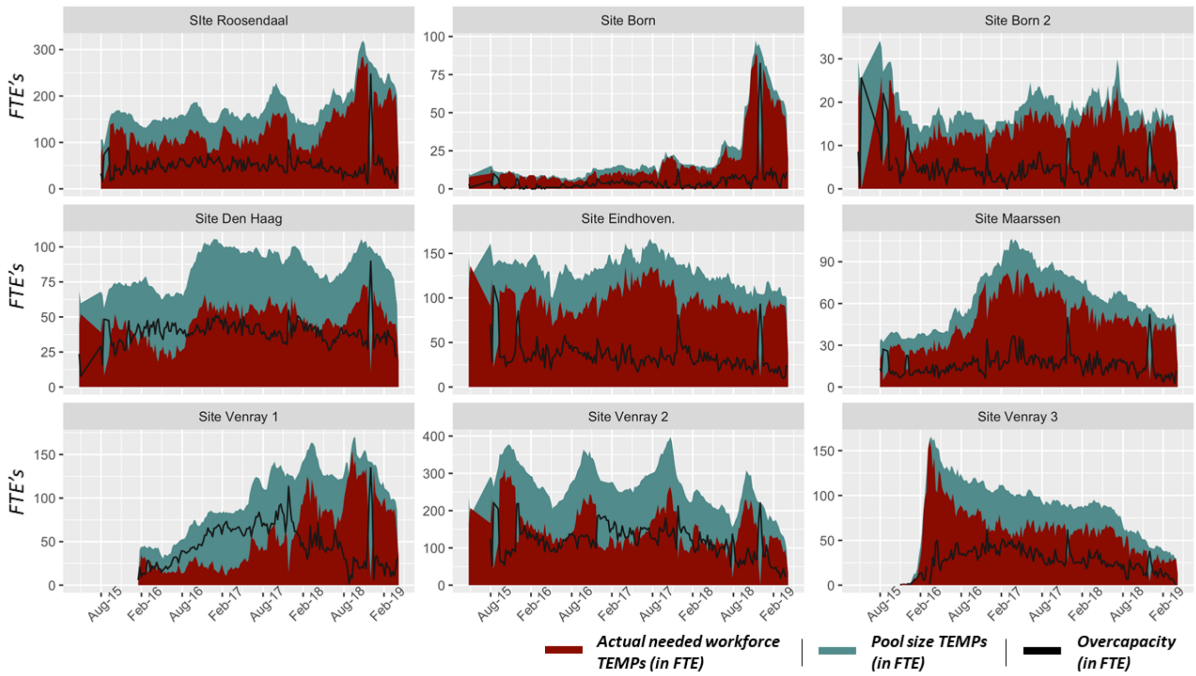


Figure 2.5: An overview of the size of the pool of TEMPs and the actual needed TEMPs together with the overcapacity for the CEVA warehouses.

flexibility and safety, but it is likely that a lot of TEMPs quit if they cannot work that much. On the other hand, a low overcapacity ratio is cost efficient only when demand is met. This requires a perfect forecasting of demand and perfect planning. The next section elaborates more on the outflow rate of TEMPs, since that was one of the action problems as identified in section 1.2.3.

2.3 High inflow and outflow rate of TEMPs

This section quantifies the inflow and outflow rate of TEMPs. The rate differs per site since different strategies are used and a seasonality has also some impact to the inflow and outflow rate. It is likely that the a high outflow rate causes a high inflow rate. Or the other way around, a high inflow rate causes a TEMP to receive less work which could also be a reason to leave. Therefore the result of a survey that was held during the outboarding process gives insight in the different reasons of leaving a warehouse. This section ends with describing the cost impact of a high inflow and outflow rate.

2.3.1 Inflow and outflow rates

This sections answers research question 2a: *How many TEMPs flow out on a monthly base?*

As mentioned in section 1.2.3, there is a feeling that the number of TEMPs who quitting and starting at CEVA warehouses increases. That feeling is confirmed by Figure 2.6, over there the number of inflows as well as the number of outflows increased over the past few years. Logically speaking when a warehouse wants to expand, the number of inflows increases. In this case, the inflow rate is higher than the outflow rate, so in general the warehouses grow in size but both the number of inflows and the number of outflows increases. Thus, Figure 2.6 gives an confirmation that there is problem concerning the high outflow rate of TEMPs.

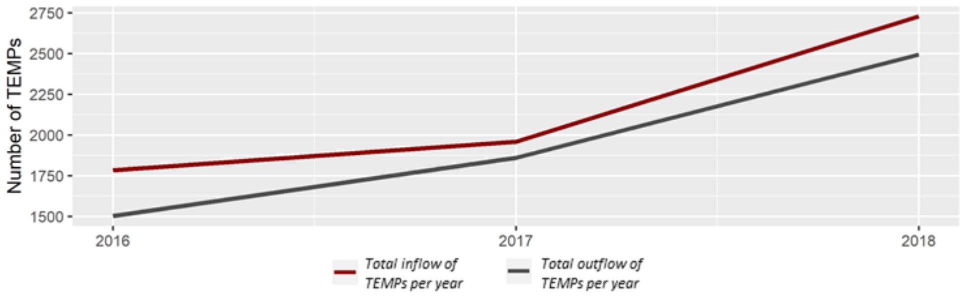


Figure 2.6: This figure shows that the outflow rate of TEMPs did increase over the past couple of years.

In an ideal situation, the pool of TEMPs move along with the fluctuations of the demand. If the demand increases more TEMPs needs to be hired and if the demand decreases the pool of TEMPs must decrease. In practice this is often not the case. The actual inflow and outflow numbers over a period starting from 05-2018 til 05-2019 are given in Figure 2.7 (mind that the y-axis values change per row of graphs). Over there it is clearly not the case that TEMPs only flow in or out of the pool.

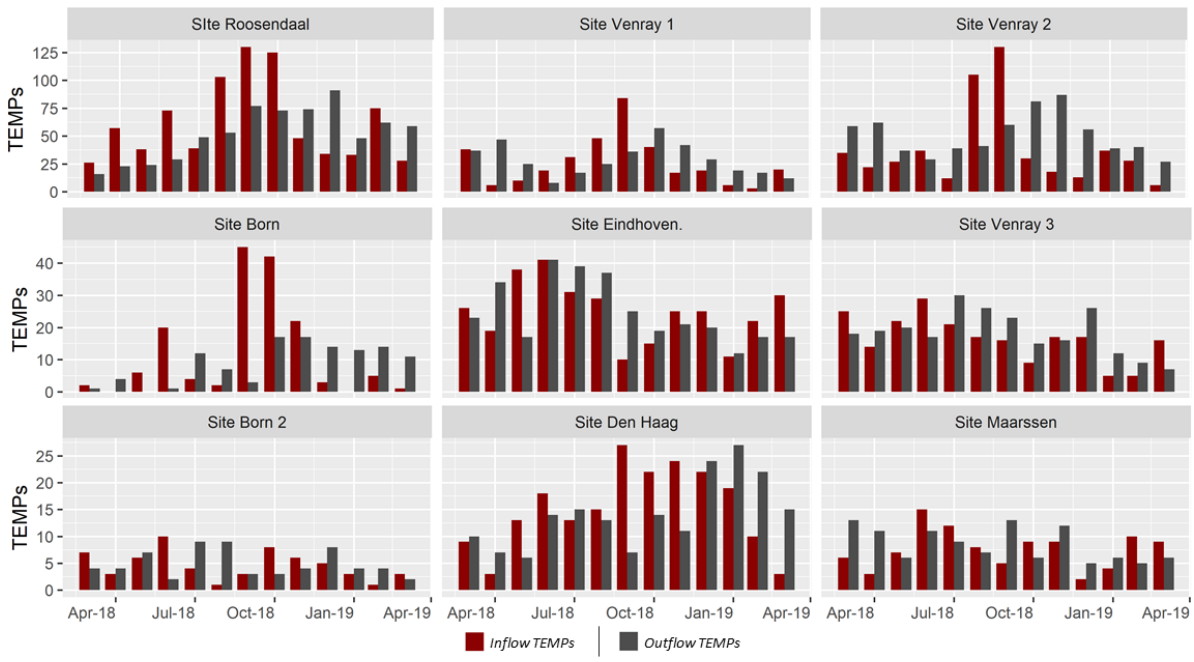


Figure 2.7: The rate of inflow and outflow of TEMPs per warehouse

Anyway, TEMPs do flow out during the year. The reason for that might be the ending of the temporary contract, a TEMP that want to work elsewhere or a TEMP that becomes ill for a long period. All reasons are independent of the size of the pool of TEMPs, so independent of the inflow rate. Although, there are cases that might be conflicting in terms of the inflow and outflow rate. An example of that can be seen in Figure 2.8. Initially, one would expect that if demand increases, the inflow rate of TEMP must also increase and the outflow rate decreases since more workforce is needed. The black square within that figure indicates that there are situations where the inflow rate increases while the outflow rate increases as well. This case might be dependent on the size of the pool of TEMPs, more about that will be discussed in section 2.4.

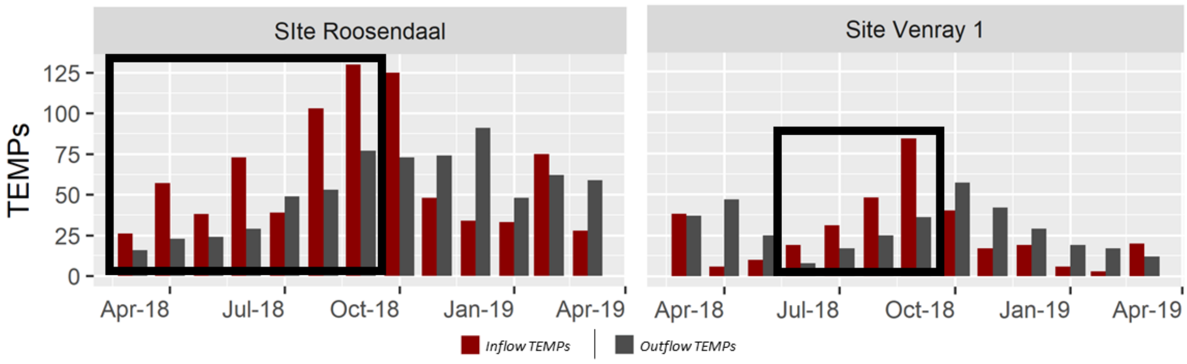


Figure 2.8: A highlight of a case where the inflow of TEMPs increases as well as the outflow of TEMPs.

The exact inflow and outflow rate over the period 05-2018 and 05-2019 is given in Table 2.2. First the average inflow and outflow of the nine sites is calculated, followed by the total inflow and outflow of those nine sites. The inflow rate is slightly bigger than the outflow rate, so in general the warehouses needed more workforce within that period. In order to calculate the ratio of the pool that is replaced by new TEMPs, the outflow rate is divided by the average pool size. The inflow rate is bigger than the outflow rate, so in an optimal situation, every outflow is unnecessary. Therefore is outflow rate is used in stead of the inflow rate in order to calculate the ratio of the pool that is replaced by new TEMPs. Interesting to notice is that every month, almost 25% of the entire pool of TEMPs is renewed. This result in a replacement of the entire pool of TEMPs around three times a week. The inflow and outflow rates for all nine sites are listed in Table B.2. The next section elaborates on the possible reasons why TEMPs leave, this might give an indication of the causes of the high inflow and outflow rate.

Table 2.2: The inflow and outflow rates of TEMPs during 05-2018 till 05-2019

	Inflow *(monthly TEMPs)*	**Outflow** *(monthly TEMPs)*	**Average pool size** *(TEMPs)*	**Ratio of pool replaced** *(per month)*	**Pool replaced** *(per year)*
Average	23.9	23.7	100	24%	2.9
9 sites	215	213	905	24%	2.9

2.3.2 Causes of outflow

This sections answers research question 2b: *What are the causes that a TEMP flows out of the organization?*

There are various causes why a TEMP leaves a warehouse. In general an outflow can be caused by the preference of CEVA or by the preference of a TEMP. From the perspective of CEVA, the TEMPS are the first ones to exclude from the workforce pool when demand decreases due to the easy firing process with negligible costs. From a perspective of a TEMP, a TEMP can leave the company quite easily due to the zero hour contract with the employer when another company offers better primary or secondary working conditions. The list below summarizes likely causes of the possible outflow of a TEMP [5].

Outflow of a TEMP by a decision of CEVA:

- The TEMP cannot meet the desired productivity.
- A TEMP was unable to meet the standard requirements of CEVA, for example showing up on time and working in a safe way.
- There is a decrease of demand, thus the workforce pool must decrease as well.
- A TEMP is promoted with a fixed contract [6].

[5]This has been verified with the HR coordinator responsible for the outflow of employees.

[6]The promotion to a fixed contract means that the TEMP is hired by CEVA directly, in stead of an employment agency. This can happen within two years of employment.

Outflow of a TEMP by the decision of that TEMP:

- A TEMP was looking for short-term employment.
- A TEMP came from abroad, like Poland or Portugal, and want to work for only one period of time.
- A TEMP can receive a higher wage elsewhere.
- A TEMP is offered to work more hours elsewhere.

Since July 2018 till the start of 2019 a survey was held every time a TEMP was excluded from the workforce pool, so for both cases when a TEMP left on own initiative or when a TEMP left on the initiative of CEVA. This survey provides the company some insights about the most important reasons why a TEMP left the company. Important to mention is that CEVA does not fire TEMPs directly, CEVA just does not use a TEMP anymore since CEVA is not obliged to provide hours to a TEMP. Regarding this thesis, it would be interesting to identify the reasons of outflow that occur frequently and that can be influenced by the workforce capacity planning. There are around 1300 respondents which worked for at least two weeks at a site. The result of this survey is listed in Table 2.3.

Table 2.3: A survey of the reason of outflow during the outboarding process of TEMPs between mid 2018 and the start of 2019 over all Benelux sites.

Reason of outflow	**Ratio**	**Outflow initiated by:**
Attitude and behaviour	20%	Company
Received CEVA fixed contract	9%	Company
Productivity low	8%	Company
No zero hour contract possible anymore	4%	Company
Illness	2%	Company
Total ratio of reasons initiated by the company:	**43%**	
Private reason	14%	TEMP
Too few hours	9%	TEMP
Other job	9%	TEMP
Other	8%	TEMP
Back to country of birth	7%	TEMP
Back to school	5%	TEMP
Working environment	3%	TEMP
Low salary	2%	TEMP
Total ratio of reasons initiated by the TEMPs:	**57%**	

The observation in general about this survey is that TEMPs leave due to the initiative of CEVA or by their own initiative. There are maybe many more possible reasons but a survey provides a list of the most important ones. The survey was held every time a TEMP left CEVA. Around 40% of the TEMPs left due to the initiative of CEVA and 60% of the TEMPs left due to their own initiative. The capacity planning of TEMPs cannot influence the decisions of CEVA since they are independent of the size of the workforce pool. The capacity planning can influence the decision made by the TEMPs since the most frequent reason, working less hours than desired, is based on the amount of overcapacity. Therefore, this thesis continues to research more about the relationship between working less hours than desired and the outflow rate. The next section elaborates on the cost aspect of the high inflow and outflow rates.

2.3.3 Cost of outflow

This sections answers research question 2c: *What are the estimated costs of outflow and what are the potential savings regarding an improvement of the capacity planning strategy?*

As mentioned in section 2.3.1, per month around 213 TEMPs leave a warehouse. Since the rate of inflow was higher in that period, the assumption is that all those 213 TEMPs needed to be replaced by a new TEMP. The costs of sourcing those new TEMPs are made by the employment agencies, but are out of scope of this thesis. Other costs that are involved are costs made during the onboarding and outboarding process. The onboarding process includes administrative tasks, training and a loss of productivity. The outboarding process includes only administrative tasks. An overview of the costs that are involved when hiring a new TEMP is given in Table 2.4.

The costs of training is certain, but the costs of lost time due to productivity losses are estimates by the warehouses. The costs of a lower productivity could also be incorporated in the need for extra workforce capacity during the start of a TEMP. In that case, the costs of hiring a TEMP is estimated at a value between €400 and €600. The extra capacity must be covered by overtime or by hiring more TEMPs. To conclude, this thesis regards the costs of hiring a TEMP as described in Table 2.4, which is estimated at a value between €800 and €1200 per TEMP. The exact hourly tariff of a TEMP remains a company secret, therefore a range is indicated as the costs of hiring a new TEMP.

Table 2.4: A breakdown of the costs of a new inflow of a TEMP.

Hours spend	**Type of loss**	**Reason of loss**
22.00h	Lost time	Estimate productivity loss in hours due to start
00.50h	Administration	Distribution of company clothing
01.25h	Introduction	Onboarding process, presentation
01.50h	Review moment	By supervisor on day 1, 5 and 20
08.00h	Training	First day
01.00h	Training	5Ss
01.00h	Training	Safety
02.00h	Training	AFS *(Airfreight Security)*, 4 hours of training for 50% of the employees
01.00h	Administration	Put new employee in systems (facturation, protime, creating account etc.)
02.00h	Training	Extra safety and quality training due to inexperience
04.00h	Lost hours	Productivity loss due to lack of motivation of replacement
01.00h	Administration	Exit interview, hand-in company clothing, final administration
€xx	Hourly tariff TEMP *(Company secret)*	
45.25h	A summation of the total hours invested per new TEMP	
€800-€1200	Range of total costs that is invested per new TEMP	

In general there are 213 TEMPs per month that are leaving a CEVA warehouse and needs to be replaced by new TEMPs. In terms of costs this means that the whole pool of TEMPs needs to be replaced and trained 2.9 times a year, which costs between €2.000.000 and €3.100.000 per year. Not every site has the same size of their pool of TEMPs, but on average that means that a site spends per year between €220.000 and €340.000. If the monthly rate of outflow could be reduced with 25% by optimizing the capacity planning of TEMPs, a total of 600 new TEMPs do not need to be hired. This results in a potential cost savings of €500.000 to €700.000 per year.

2.4 Proposed solution towards improving the capacity planning of TEMPs

This sections answers research question 2d and 3a: *2d-How can the relation between the size of the pool of TEMPs and the outflow rate be modelled?* and *3a- How does the current long-term forecasting method perform?*

The problem cluster identified four core problems of which two can be tackled by this research. The absence of dedicated forecasting software results in a lot of uncertainty, therefore the resource capacity level is a lot of times higher than needed. The conclusion is that given a strategy that is not aligned over all sites, it can happen that the needed resource capacity is not aligned with the available capacity at a certain moment. In addition to that, a high rate of outflow and inflow of TEMPs is noticed. The outflow rate of 213 TEMPs per month costs on a yearly base between €2.000.000 to €3.100.000. It's likely that the cause of the high outflow rate is due to the overcapacity of the pool of TEMPs. When TEMPs get less hours offered than they usually receive, it is imaginable that they leave the organisation. If the capacity planning op TEMPs can be improved by reducing the outflow of TEMPs by 25%, a cost saving of €500.000 to €600.000 can be accomplished per year. The improvement of the capacity planning consist of three topics, which are listed below. The purpose is that the first two topics serve as input for the third topic.

1. Model: Estimation of the outflow rate of TEMPs when receiving less work.
2. Model: Long-term forecasting with time series data.
3. Strategy: How must the pool of TEMPs behave when demand changes.

The first topic verifies the assumption that receiving less work is one of the causes that a TEMP leaves. Due to seasonality or after a period of a maximum of two years employment it is inevitable to have some outflow of TEMPs, but still a large portion of outflow could be caused by receiving less work. Another purpose of the the estimation of the outflow rate model is that the size of pool of TEMPs can be adjusted when this estimation is known. However, this assumes that future demand is known. Therefore, the long-term forecasting model is made to known to what extent future demand can be predicted.

The forecasting model uses time series data to predict monthly demand. The purpose of this model is to use the best forecasting methods, these are determined in the literature section, for monthly time series data to get an estimate of the likely forecast error. Currently, the average forecast error for a three month ahead forecast is unknown. Some site don't receive a demand forecast of their clients, some client only provide a yearly forecast and some clients deliver a very inaccurate forecast. At the moment, the warehouses use the yearly forecast to anticipate towards seasonal fluctuations and determine the workforce capacity on a weekly base. Clearly, it would be valuable if the workforce capacity can be determined on a monthly base since it takes a couple of weeks to source new TEMPs. In order to use the insights of the outflow rate model, future demand needs to be known. the time series forecast model will conclude if the monthly time series data is good enough to get a reasonably accurate forecast. Otherwise, other input data variables or data cleaning methods must be used.

The analysis of the outflow rate provides an advice about the strategy towards the ideal pool size of TEMPs when demand changes. The forecast model indicates if it is possible to predict monthly demand with a reasonable accuracy, so this model indicates if is is feasible to use insights of the outflow rate model in practice.

A lot of variables are involved when determining the capacity of the pool of TEMPs. These variables can say something about the lead time to hire a TEMP, the productivity level, the ratio between fixed employees and temporary employees and many more. If a reasonable forecast can be generated for a couple of months ahead, a very complex planning problem exists. This planning problem can be solved by an MILP, Mixed Integer Linear Programming, problem. The outcome of such a model result in the exact amount of TEMPs that needs to be hired or excluded to and from the current pool of TEMPs while the cost of hiring is minimized. Due to the outcome of the outflow rate model and the situation that many of those variables are fixed assumptions or out of scope regarding this thesis, no MILP model is created. Some useful literature about a MILP model that solves a workforce capacity planning problem is added. This is valuable for the recommendations section to provide some guidance how further research can improve the capacity planning even more.

The next chapter elaborates on the theoretical aspects that is used for the two models, the first section is dedicated for the forecasting model. After discussing the literature, the way how the outflow rate model and time series forecast model are build is explained. The solution of improving the capacity planning of TEMPs is given in section 6.1, over there the results of both models are merged into one sentence that provides an answer to the main research question.

3 | Literature review

3.1 Forecasting

This sections answers research question 3c: *Which forecasting method or methods are capable to deliver the best results according to the literature?*

Within any logistic operations it is vital to have insights in what is going to happen, otherwise processes cannot be aligned and therefore efficiencies will drop. Forecasting can have a significant impact to generate future insights. Companies typically perform a forecast by extracting historical patterns and apply those to forthcoming periods. One of the most cited researchers within this topic are Box et al. [9]. They provide knowledge about the forecasting of time series data. It means that the available observations of a times series at time t can be used to forecast its value at some future time $t+l$. Those forecasts can be used for economic and business planning, production planning, inventory and production control and optimization of industrial processes.

The question that a lot of people asking is how well are we able to perform a forecasts. The answer to that depends on the forecasting technique used, the data that is used and external variables. A set of forecasting techniques will be discussed in more depth later on. There are three external variables identified by Hyndman and Athanasopoulos [10] that indicate the predictability of events:

1. How well are the parameters that contribute to the forecasts understood;
2. How much data is available;
3. Can the forecast effect the thing where the forecast is performed over.

These three major challenges can be tackled if the right forecasting procedures are executed. Several authors defined methods to give a structured approach regarding forecasting, but the two most mentioned are listed in *"Forecasting: principles and practice."* by Hyndman and Athanasopoulos [10] and *"Introduction to time series and forecasting."* by Brockwell et al. [11]. They provide the following steps in a forecasting task and they will be discussed within the following subsections.

1. Problem definition;
2. Gathering information;
3. Preliminary (exploratory) analysis;
4. Choosing and fitting models;
5. Evaluating a forecasting model;
6. Using the model.

3.1.1 Problem definition

The most difficult part of forecasting is the first phase of the problem definition. This stage requires a deep understanding what the purpose of the forecasts is, who requires the forecast and how does the forecasting process fit within the organisation. Especially the last point is very important, since it considers data gathering and data management. Those processes are often involved with high investment costs.

3.1.2 Gathering information

The forecasting process can use two kinds of information: statistical data and accumulated expertise of field experts. In case of a lack of historical data, a forecast model can be build by a judgemental method.

These judgemental methods are often integrated to adjust the forecasts in case of unique events. Although it's done often, literature that is recently written about a judgemental method is missing.

The judgemental forecasting method has the strongest link with aspects from the cognitive psychological literature, a review about this topic has been done by Hogarth and Makridakis [12]. Their conclusion is that people have limited ability to process information and people remain adaptive. In addition to that, they provide an overview of all the biases caused by human judgement related to the forecasting process. It seems that this overview is still valid today, but the need for human judgment did decrease since the introduction of data sampling techniques [13]. The basic idea is that the statistics of a population can be modelled by re-sampling from a limited chunk of data. As of the introduction of an improved data sampling technique called bootstrapping in 1991, the need to implement human judgemental methods to adjust forecasts decreased [14]. The data sampling techniques are accurate enough to cope with a lack of historical data.

The statistical data consist of a series of observations in time. A good forecast model uses old data to handle evolutionary changes in the organization and uses more recent data to implement more structural changes in a forecast. It is important to know the structure of the time series data, since outliers or unique events can be present and must be removed from the data. There is no fixed minimum number of observations needed since that amount heavily depends on the occurrence of random variation according to Hyndman et al. [2]. Despite, Hyndman and Athanasopoulos provides a guideline of a minimum amount of observations needed for three common forecasting methods. These can also be applicable for other methods, but extra attention regarding this topic is needed. The result can be found in Table 3.1, where m_t is the amount of periods in a year for t is equal to a quarter, month or week. These common forecasting methods will be discussed in chapter 3.1.4.

Table 3.1: Minimum requirements for common forecasting methods [2].

Forecasting Method	**Parameters (Par)**	**Minimum Periods Required**	**Quarter**	**Month**	**Week**
Simple Regression	1	$m_t + Par + 1$	6	14	54
Holt-Winters	3	$m_t + Par + 2$	9	17	57
ARIMA, *example of* $(1,1,1)(1,1,1)$	6	$m_t + Par + 1$	10	18	58

3.1.3 Preliminary (exploratory) analysis

Most forecasting methods work for a set of data with the same characteristics. In the next section, 3.1.4, these aspects are connected to a number of forecasting models. However, first these characteristics must be made visible by graphing the data and look for consistent patterns, significant trends and the presence of seasonality. Outliers need to be explained and excluded. Then the strength of the relationships between variables can be researched. These steps are needed as a final preparation in order to choose the right forecasting model.

3.1.4 Choosing and fitting models

This sections answers research question 1c and 1d: *(1c) - To what extent can the forecast be improved by using traditional forecasting techniques? (1d) - To what extent can the forecast be improved by using modern forecasting techniques?*

The best model to use depends on the availability of historical data, the strength of relationships between the forecast variable and any explanatory variables and the way in which the forecast is going to be used. It could be useful to compare multiple models and studies, since it is quite easy to create ideal circumstances where an improved forecast model outperforms others. In addition to that, there is not a lot of literature available regarding the relative performance of models as a standard forecasting tool. This makes it hard to select the best model according to Hyndman and Koehler [15]. An overview about the findings of this paper is listed below.

1. The conclusions of improved forecasting methods are based on a few time series data. This raises questions about the statistical significance of the results and the generalizations.
2. Often, the improved forecasting methods are evaluated for short-term horizons, so one-step-ahead, instead of considering medium to long-term periods.
3. When using a machine learning forecasting model, often a benchmark lacks with statistical learning forecast models.

It is common to compare two or three potential models [3]. Nowadays there are a lot of forecasting models available which each excel in a specific data set. The best general method is hard to define, since that depends heavily on the environment to forecast on. Since those settings have external influences, it's hard to control and often very time consuming. Therefore there is a need for a more general approach regarding forecasting. Luckily, there are two studies which compare models that are used in international forecasting competitions. Based on that, some generalisation of good performing forecasting methods can be derived. More about the competitions is told in section 3.1.7. The following Table 3.2 shows a list of the best performing models, based on the studies of Makridakis et al. [3] and Crone et al. [4]. The results are ranked on descending order. The purpose of those forecasting competitions is to develop a model which delivers an accurate forecast for over 3.000 different time series data (from industry, finance sector, socio-demographic etc.) based on lowest sMAPE.

Table 3.2: Comparison of forecasting model performance by different studies [3], [4].

Forecasting		**Best reference**		**Ranked by *sMAPE***	
Method	Type[a]	Referred Author	Year	Makridakis (2018)	Crone (2011)
ETS *Exponential Smooting*	SL	R. Hyndman	2002	1	-
ARIMA *Autoregressive Integrated Moving Average*	SL	R. Hyndman	2007	2	6
Damped *Exponential smoothing*	SL	E. Gardner	1985	3	2
Comb *(ETS, ARIMA, Theta)*	SL	R. Andrawis	2011	4	3
Theta	SL	V. Assimakopoulos	2000	5	1
SES *Single Exponential Smoothing*	SL	E. Gardner	1985	6	4
Holt	SL	P. Kalekar	2004	7	5
BNN *Bayesian Neural Network*	ML	D. Foresee	1997	8	10
MLP *Multi-layer Perceptron*	ML	C. Bergmeir	2012	9	8
Naïve	RW	R. Hyndman	2006	10	-
SVR *Support Vector Machine*	ML	L Cao	2001	11	9
RNN *Recurrent Neural Network*	ML	K Lee	1992	12	-
KNN *K-Nearest Neighbor Regression*	ML	J Arroyo	2009	13	7
AANN *Automated Artificial Neural Network*	ML	S. Makridakis	2000	-	-

[a] The types are listed with abbreviations, the meaning of these are SL = Statistical learning, ML = Machine Learning and RW = Random Walk

The purpose of Table 3.2 is to create a good intuitive feeling about which methods have a good general performance. As mentioned before, an accurate forecast depends heavily on the data to forecast on. Therefore the competitions uses a large set of different time series data (more than 3.000 sets). These sets consists of yearly, quarterly, monthly or weekly observations, no daily time series data is included. Based on Table 3.2, the methods that are likely to give a good forecast result and that are useful to implement during this thesis are the first four of the list. These methods are ETS, ARIMA, Theta and Comb, the explanation of these models is given from section 3.1.4 till section 3.1.4.

The damped exponential smoothing is not implemented since this methods shares a lot of properties with the ETS method and the ETS method performes better. Besides, the advanced machine learning models are lacking performance compared with the statistical learning models. There are multiple reasons why that happens, but the main difference between those two types is that the machine learning models don't use the property of time series data in which the last observation is one of the most valuable ones. The implementation of the three chosen methods will be discussed in chapter 4, but first the principles of these methods are explained in this section.

ETS method

The ETS method is an abbreviation of Error, Trend and Seasonal and it is based on a set of exponential smoothing models. This method is developed by Hyndman et al. [16] to automatically choose a good forecast model, based on the evaluation of a set of exponential smoothing methods.

The ETS method includes an error component, a trend component or a seasonal component. The error component can be additive or multiplicative. In case of an additive component, the error component has a constant impact. In case of a multiplicative component the errors can increase or decrease in time when performing the forecast. The same holds for the trend and seasonal component, the can be additive or multiplicative. In addition to that, they can be excluded from the model. To summarize this information, Table 3.3 is made. Over there the conclusion is that 30 different forecast models *(2 error {Additive, Multiplicative} times 5 trend {none, additive (damped), multiplicative (damped) } times 3 seasonal components {none, additive, multiplicative})* can be made with the ETS method.

Some of these models have more familiar names in the field of forecasting, these are listed below. Basically there are three base models which are also listed, with their abbreviation, in Table 3.3. These models will be explained in more detail.

- *N,N* Simple Exponential smoothing *(SES)*
- $A_{(d)}$,*N* or $M_{(d)}$,*N* Holt's linear method *(Holt)*
- $\{A/M, A\}$ or $\{A/M, M\}$ Holt-Winters' method *(HW)*

Table 3.3: The exponential smoothing methods.

Trend Component		**Seasonal Component** *N* *None*		*A* *Additive*		*M* *Multiplicative*	
N	*None*	N, N	*(SES)*	N, A	*(HW)*	N, M	*(HW)*
A	*Additive*	A, N	*(Holt)*	A, A	*(HW)*	A, M	*(HW)*
A_d	*Additive damped*	A_d, N	*(Holt)*	A_d, A	*(HW)*	A_d, M	*(HW)*
M	*Multiplicative*	M, N	*(Holt)*	M, A	*(HW)*	M, M	*(HW)*
M_d	*Multiplicative damped*	M_d, N	*(Holt)*	M_d, A	*(HW)*	M_d, M	*(HW)*

As mentioned before, a more detailed look to the ETS method is given. First the method distinguishes two types of errors, additive errors and multiplicative errors. An additive error is calculated by the difference between the forecast value and the actual value. A multiplicative error is calculated by the difference between the forecast value and the actual value, divided by the forecast value. These two error influence the level, base and season values and therefore the forecast as well. The two error types are listed below.

- *Additive:* $\varepsilon_t = y_t - \hat{y}_t$
- *Multiplicative:* $\varepsilon_t = \frac{y_t - \hat{y}_t}{\hat{y}_t}$

The performance of an ETS model depends on the use of variables. Table 3.4 gives the equations to determine the forecast value at a certain time for a specific model, the abbreviations are listed below.

- $\hat{y}_t$ *The value of the forecast at time t.*
- l_t *The value of the level at time t.*
- b_t *The value of the base (trend factor) at time t.*
- s_{t-m} *The value of the seasonal factor at the time t minus the seasonal period m.*
- ϕ *A smoothing factor {0,1} to adjust the trend factor.*

Table 3.4: An overview how to determine the forecast value of each of the ETS models.

Trend	**Seasonal**		
	N	A	M
N	$\hat{y}_t = l_{t-1}$	$\hat{y}_t = l_{t-1} + s_{t-m}$	$\hat{y}_t = l_{t-1} * s_{t-m}$
A	$\hat{y}_t = l_{t-1} + b_{t-1}$	$\hat{y}_t = l_{t-1} + b_{t-1} + s_{t-m}$	$\hat{y}_t = (l_{t-1} + b_{t-1}) * s_{t-m}$
A_d	$\hat{y}_t = l_{t-1} + \phi * b_{t-1}$	$\hat{y}_t = l_{t-1} + \phi * b_{t-1} + s_{t-m}$	$\hat{y}_t = (l_{t-1} + \phi * b_{t-1}) * s_{t-m}$
M	$\hat{y}_t = l_{t-1} * b_{t-1}$	$\hat{y}_t = l_{t-1} * b_{t-1} + s_{t-m}$	$\hat{y}_t = l_{t-1} * b_{t-1} * s_{t-m}$
M_d	$\hat{y}_t = l_{t-1} * b^{\phi}_{t-1}$	$\hat{y}_t = l_{t-1} * b^{\phi}_{t-1} + s_{t-m}$	$\hat{y}_t = l_{t-1} * b^{\phi}_{t-1} * s_{t-m}$

ARIMA method

The ARIMA method is an abbreviation of Auto Regressive Integrated Moving Average. It includes six parameters that determine the behaviour of the model, they are linked to parts of the name of the method which can be found in Table 3.5 [17]. The notation of this model is $ARIMA(p, d, q, P, D, Q)$, a mathematical breakdown of the model is listed in Table 3.6.

Table 3.5: The parameters of the ARIMA model.

Technique	**Abbreviation**	**Non-seasonal parameter**	**Seasonal parameter**
Auto regressive	AR	p	P_m
Integrated	I	d	D_m
Moving Average	MA	q	Q_m

The auto regressive component determines how many past values are included in the regression model, thus parameter p indicates how may lags of the forecasted values are included in the model. A high number of p results in a forecast value that does not change much when performing a one-step-ahead forecast. A low number of p results in a forecast value that quickly converges to it's mean. The integrated component is used to stabilize a time series, thus parameter d indicates the degree of differencing. A high number of d results in a stable time series, but observations will be lost. The moving average component indicates how many lags of the error terms are included in the model. A high value of q results in a forecast model that does not change very much if a new observation, thus the most recent error term, is available. As mentioned before, the mathematical model is described in Table 3.6. Over there the variables that determine the forecast value are displayed per set of parameters. The non seasonal parameters can range from zero to three, a value higher than three is very unlikely since a lot of data is lost. The seasonal parameters are zero or one, since there is a seasonality or not. The total amount of combinations that are possible are: $(p * d * q)(P * D * Q) = (4 * 4 * 4)(2 * 2 * 2) = 512$ The abbreviations used are:

$\hat{y}_t$	The forecast value at time t	e_t	Error variable, the difference between $\hat{y}_t$ and y_t
μ	The base value of the forecast, a constant	y_{t-1}	The actual time series value at time $t-1$
θ	A coefficient for the AR terms	s	The seasonality variable
ϕ	A coefficient for the MA terms		

Table 3.6: A mathematical breakdown of the ARIMA model.

Parameters (p,d,q)(P,D,Q)	**Forecast formula's**
(p,0,0)	$\hat{y}_t = \mu + \phi_1 * y_{t-1} + \ldots + \phi_p * y_{t-p}$
(p,0,0)(1,0,0)	$\hat{y}_t = \mu + \phi_1 * y_{t-1} + \ldots + \phi_p * y_{t-p} + \phi_s * y_{t-s}$
(0,d,0)	$\hat{y}_t = (y_t - y_{t-1}) - \ldots - (y_{t-d} - y_{t-(d+1)})$
(0,d,0)(0,1,0)	$\hat{y}_t = (y_t - y_{t-1}) - \ldots - (y_{t-d} - y_{t-(d+1)}) - (y_{t-s} - y_{t-s-1})$
(0,0,q)	$\hat{y}_t = \mu - \theta_q * e_{t-1} - \ldots - \theta_q * e_{t-q}$
(0,0,q)(0,0,1)	$\hat{y}_t = \mu - \theta_q * e_{t-1} - \ldots - \theta_q * e_{t-q} - \theta_s * e_{t-s}$

The ARIMA method rely on past values and work best on long and stable series. The set of parameters is chosen according to the lowest AIC estimator *(Akaike Information Criterion)*. Although the AIC estimator will choose the best model from a set, it won't say anything about the quality of the best model since it is a relative measure. The estimator is based on choosing the model with the highest likelihood of the fit of the model, but penalises the use of many variables. It handles the trade-off between the underfitting and overfitting of a model[1]. The AIC can be calculated in two ways, which is stated in equation (3.1) till (3.2) and their result is the same value.

$$AIC = 2K - ln(\hat{L}) \tag{3.1}$$

$$or$$

$$AIC = N * Log(\frac{RSS}{N}) + 2K \tag{3.2}$$

Where:

- N Number of observations
- K Number of parameters + 1
- L The maximum likelihood of obtaining a low error measure
- RSS Residual Sum of Squares

Theta method

The Theta model is developed by Assimakopoulos and Nikolopoulos [18] and the idea is to break one stream of time series data down into several series that include individual components such as the trend cycle, seasonality and an error component. This is called a decomposition approach. For each of the decomposed series, a simple exponential smoothing forecast is calculated. The final forecast value is determined by the average of the simple exponetial smoothing forecasts. An example of the decomposed series can be found in Figure 3.1.

The decomposed series are called "Theta lines". These are calculated by the trend line value where the difference is added between the trend line and the original demand is multiplied by the theta parameter value. This is shown in equation (3.3).

$$\begin{aligned} Original\ demand =& Y_t \\ Decomposed\ line =& (l_t * b_t) + \theta * ((l_t * b_t) - Y_t) \\ where: & \ 0 \leq \theta \\ Trend\ line =& l_t * b_t \end{aligned} \tag{3.3}$$

Figure 3.1 shows two decomposed series with a theta value of $\theta = 0$ and $\theta = 2$. A value of $(0 \leq \theta \leq 1)$ results in a smoothed line in order to capture the long term features, where values of $(1 \leq \theta)$ results in a more erratic theta line in order to capture the short-term behavior. The number of "Theta lines" and the theta parameter values is not fixed, so a Theta forecast can be optimized by changing the amount of decomposed series and changing

[1]The terms underfitting and overfitting are explained in chapter 3.4.1.

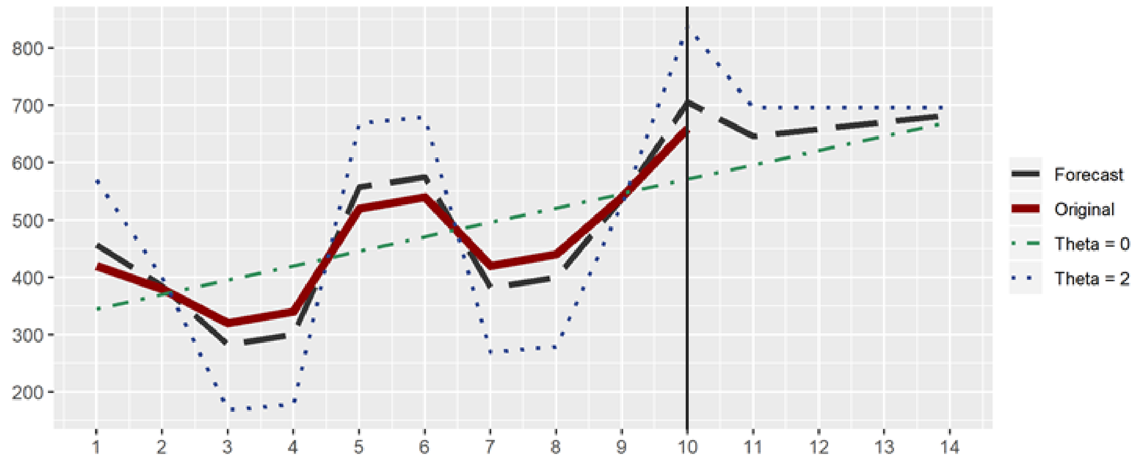


Figure 3.1: An example of a Theta-model forecast and the decomposed series for theta is equal to zero and two. A forecast is provided from time is equal to 10.

Comb method

The Comb forecasting method is an abbreviation for the word combination, so it includes multiple forecasts models. It uses the weighted average performance of the ETS, ARIMA and Theta method. The weights are equally distributed among the three models which is used in Table 3.2. The ratio between the weights can differ and selected on the lowest forecast error, as long as the sum of the weights are equal to one. The formula for the Comb forecasting method is listed in formula *(3.7)*, .

$$\hat{Y}_t = a * \hat{Y}_{ETS} + b * \hat{Y}_{ARIMA} + c * \hat{Y}_{Theta} \tag{3.4}$$

$$where$$

$$a + b + c = 1 \tag{3.5}$$

The reason why a weighted average of multiple forecast models is used, is that it's unlikely that one model performs best within a whole period. Therefore the use of multiple models makes sure that the average performance of the model increases. But in case one of the models performs good for a given data set, then the Comb method will make the forecast worse by taking the weighted average of multiple forecasts. Lastly the overall performance is good, since it ended up high at the forecasting competitions, therefore it could be a useful model to implement when performing a forecast.

3.1.5 Evaluating the quality of a forecasting model

When the set of forecasting methods is chosen, the question rises which one performs the best? To answer that question, multiple data sets are needed to get the best general impression. After the forecasts are made and data about the actual performance over that forecasting period becomes available, the result can be evaluated. An evaluation can be generated by the differences between the forecast values and the actual values, but these can be calculated in multiple ways. Again there is a discussion which accuracy measure should be used. The difference can be that one measure is more sensitive to outliers than others, therefore good theoretical argumentation is needed. This section will elaborate which type of accuracy measures are available and what is recommended from a theoretical perspective.

A typical forecast error can be defined as $e_t = Y_t - F_t$ where Y_t is the observation at time t and F_t is the forecasted value on time t. Hyndman and Koehler [15] mentioned three different type of error measures, an enumeration of these measures are listed in the next sections.

Scale-dependent error measures

These measures are helpful when comparing different methods applied to the same set of data, but cannot be used when the data sets have a different scale, thus have a different length [19]. The most use scale-depend error measures are listed below, along with their mathematical expression.

1. Mean Squared Error (MSE) = $mean(e_t^2)$
2. Root Mean Squared Error (RMSE) = $\sqrt{MSE}$
3. Mean Absolute Error (MAE) = $mean(\mid e_t \mid)$
4. Median Absolute Error (MdAE) = $median(\mid e_t \mid)$
5. Mean Absolute Scaled Error (MASE) = $mean(\mid e_t \mid /(Y_t - Y_{t-1}))$

Percentage error measures

To overcome the scale dependency as mentioned in previous section, a percentage error measurement could be used. This measure is given by $p_t = 100 * (e_t/Y_t)$ and this ratio is independent of the scale. The most used measures of this type are listed below, along with their mathematical expression.

1. Mean Absolute Percentage Error (MAPE) = $mean(\mid (p_t) \mid)$
2. Symmetric Mean Absolute Percentage Error (sMAPE) = $mean(200 \mid Y_t - F_t \mid /(Y_t + F_t)$
3. Median Absolute Percentage Error (MdAPE) = $median(\mid (p_t) \mid$
4. Symmetric Median Absolute Percentage Error (sMdAPE) = $median(200 \mid Y_t - F_t \mid /(Y_t + F_t)$
5. Root Mean Square Percentage Error (RMSPE) = $\sqrt{mean(p_t^2)}$
6. Root Median Square Percentage Error (RMdSPE) = $\sqrt{median(p_t^2)}$

A big disadvantage of the percentage error measures is the use of a ratio. If Y_t is small or equal to zero, thus there is little to no demand observed at time t, than the ratio $p_t = 100 * (e_t/Y_t)$ will go to infinity. Forecasts over intermittent demand cannot be evaluated using these measures. In addition to that, forecasts over a temperature scale are also excluded when using this measure, due to the possible zero value of the observed demand.

The MAPE and MdAPE have the disadvantage that they put a heavier penalty on positive errors than on negative error, the sMAPE and aMdAPE are able to overcome this non-symmetry. Unfortunately the sMAPE and sMdAPE have another disadvantages, of penalizing low value forecasts more than high value forecasts. The percentage errors are often highly skewed, but therefore well suited for algorithms to make them more stable [20].

Relative error measures

This method divides a forecasts error measure with another forecasts error measure, this is called the relative error and is expressed as $r_t = e_t/e_t^*$. The other forecasts error measure is obtained by a benchmark forecasting method in order to compare the performance of a new model with existing ones. The most use measures of this type are listed below, most of them are already mentioned in the subsections.

1. Mean Relative Absolute Error (MRAE) = $mean(\mid r_t \mid)$
2. Median Relative Absolute Error (MdRAE) = $median(\mid r_t \mid)$
3. Geometric Mean Relative Absolute Error (GMRAE) = $gmean(\mid r_t \mid)$

Again since this measure is a ratio, there is a probability that the rate takes extreme values. The method is more complex and requires a benchmark forecast. It could be useful if the performance of one forecast is compared to multiple ones.

Conclusion error measures

Three types of forecast error measures can be distinguished. The scale-dependent error measures are simple to implement, but to compare them along multiple time series, the length of the time series must correspond with each other. A more complex approach could be to include a relative error measure in case a benchmark forecast is available. Given that the length of the time series differ, a percentage error measure is best to apply. For both of the relative error measures and percentage error measures hold that the evaluation is expressed in a ratio, so some caution is needed since it could be sensible for extreme values. To conclude, the forecast error measure that is going to be used depends on the characteristics of time series data or the presence of benchmark forecasts. This will be investigated in the modelling section 4.

3.1.6 Using the model

There are also organisational issues in using and acting on the forecasts. A brief discussion of some of these issues is given at the beginning of this chapter regarding data gathering. The conclusion is that enough data must be available, but when using a forecasting model in practice, numerous practical issues arise such as how to handle missing values and outliers. An example of how to cope with that in practice is given in chapter 4. Nowadays the best performing forecast models require a lot of human effort, since the performance increases with an increase in the level of detail. Therefore there could be a discussion between how much human input is needed to have a sufficiently accurate forecast and to what extent automated forecasting delivers a result that is satisfied by their users.

3.1.7 Forecasting competitions to select best performing method

Most users of forecast models want to know which methods produce good forecasts. Unfortunately authors of new forecasting models only compare an improved model with its predecessor, thus no answer can be given how a new forecasting model performs in general. In addition to that, most users work with different time series data. So from a literature perspective it's very difficult to conclude which models produce good forecasts. Luckily forecasting competitions provide better insights, since the goal is often to build a forecasting model that has a good performance based on many different time series data. The biggest forecasting competition is the Makridakis competition, also called the *"M-Competition"*. The history and some properties of this competition is listed in Table 3.7. This competition is found

Table 3.7: An overview of the Makridakis competitions.

	Year	**Number of time series used**	**Number of methods tested**	**Competition characterized by**
M	1982	1001	15	First forecasting competition worldwide [21].
M2	1993	29	29	Better simulation of real-world forecasting, therefore less data sets and opportunaty to talk with companies [22].
M3	2000	3003	24	Replicate and extent the features of the M and M2 competition to more times series. Since 2000 every proposed forecasting method must be competitive against the original M3 methods, otherwise the International Journal of Forecasting (IJF) won't publish a new article[23].
M4	2018	100.000	248	Replication and extension of the features of the M, M2 and M3 competition on more data sets. All major methods including traditional statistical learning (SL) ones and machine learning (ML) models were part of the competition. Outcome of the competition is that ML models lack performance compared to the traditional SL methods [24].

by Spyros Makridakis, a professor in decision sciences and active in the field of forecasting. There are in total four competition held, started in 1982. A big advantage of these competitions is that models are empirically tested on a diverse data set and that the organisers require that the creators of those models must write an article about it, so the information about good and bad forecasting models become publicly available. In addition to that, the models created during the latest M4-competition are made in Python or R and some of those models are published by their creators for academic purposes. Table 3.7 is also a good representation of historical performance of forecasting models, since every competition figures as a benchmark.

With respect to this thesis, the results of the M3 and M4 competitions are the most relevant. The conclusion, also mentioned in Table 3.2, is that as of today the statistical learning models outperform the machine learning models. This has two reasons and one remark. The two reasons why machine learning models might not perform that good is due to the lack of computational power and the complexity of a good working model in practice. A lack of computational power results in longer waiting times or a trade-off based on shorter waiting times and a worse results occurs. The complexity of a machine learning model increases when a lot of factors are taken into account that influence the forecast. For every factor, a good estimation of the impact must be determined. This complexity increases when the time series have different factors, thus more estimations of factors have to be made. The condition is that the machine learning model needs this set of variables that have explanatory value of the behavior of the time series data.

Since the start of the M3 competition, multiple forecasting competitions are organised such as the *Global Energy Forecasting Competition (GEFCom)* by Hong et al. [25]. This open competition will allow researchers to share their models in a community to strengthen their ideas, all of this will contribute to the development of advanced forecasting models.

3.2 Resource capacity planning

Resource capacity planning methodologies are designed to translate demand forecasts into a blueprint for planning staffing for the firm over a predetermined planning horizon [26]. This is only of the many definitions regarding a capacity planning. In general it consists of a certain methodology and LP model. The methodology elaborates on how the strategy copes with uncertainty of a demand forecast. The MILP, *Mixed Integer Linear Programming*, model explains which parameters, variables, constrains and goal function are included. In addition to that, the way to solve such a MILP model is explained.

3.2.1 Planning methodology

The capacity planning depends on a forecast, therefore the capacity planning must deal with the uncertainty of the forecast. There are four types of uncertainty identified by DE MEYER et al. [27].

- Variation, for example variability of customers demand.
- Foreseen uncertainty, for example the risk of illness of employee, productivity loss due to breakdown of equipment or a labor strike.
- Unforeseen uncertainty, this are the risks that could not be predicted or that the probability of occurrence is too low. Examples are a natural disaster or a trade blockade due to politics.
- Chaos, this is unforeseen uncertainty, but the event also affects the core business of a company. An example is that a natural disaster can cause a companies motivation to shift from profit oriented to a more socially responsible one.

This thesis only deals with variation and foreseen uncertainty, the other types involves more strategic level decisions. The planning strategies that are dealing with variation and foreseen uncertainty are buffering, pooling or contingency planning. The buffering strategy implies that there is an excess of resources. The pooling strategy collects multiple small buffers, therefore the variability decreases as well. The contingency planning contains a preset course of action for an anticipated scenario. Related to this thesis, it can involve a backup pool of employees during a high peak season. In general there is no best strategy, this depends too much on the input data of the forecasts and the given productivity of TEMPs.

3.2.2 MILP model

The capacity planning problem can be solved near optimal by solving a MILP model formulation of the problem. These MILP models can deal with a specific goal function which is bound to a certain set of variables and constraints. Therefore this literature section will deliver a generic model, that is created by a combination of Nahmias and Olsen [26] and Silver et al. [28], which will provide guidelines to solve the capacity planning problem for a certain set of variables and constraints. An example of such a model can be find below, first the equations are given then a section elaborates on the purpose of the equations. In addition to that, some extra variables are proposed to create a more realistic model of the capacity planning problem.

Additions to the MILP formulation from the literature that solves the capacity planning problem

- Defining the cost of undertime as the expected outflow rate according to the outflow rate model.
- Using a factor to convert one FTE to a certain number of TEMPs, this is the ratio between full-time and part-time TEMPs.

Parameters

C_H		Cost of hiring one TEMP
C_F		Cost of firing one TEMP
C_O		Cost of overtime per FTE
C_U		Cost of undertime (expected outflow rate) per FTE expressed as a formula
FTE		The factor to convert one FTE to X number of TEMPs
K		Productivity rate: the number of orderlines per FTE
$W_{t=0}$		Initial workforce level at $t = 0$ in FTE
D_t	$\forall t \in T$	The forecasted demand for TEMPs at period t in orderlines

Variables

H_t	$\forall t \in T$	The amount of TEMPs to hire in period t
F_t	$\forall t \in T$	The amount of TEMPs to fire in period t
O_t	$\forall t \in T$	The overtime in period t in FTE
U_t	$\forall t \in T$	The undertime in period t in FTE
W_t	$\forall t \in T$	The workforce level at $t = 0$ in FTE
M_t	$\forall t \in T$	The variable that determine if there is over-capacity or under-capacity in period t

Objective

$$\min \quad \sum_{t=1}^{T}(C_H * H_t + C_F * F_t + C_O * O_t + C_U * U_t * C_H) \tag{3.1}$$

Constraints

$$D_t \leq K * W_t * +K * O_t * M_t \qquad \forall t \in T \tag{3.2}$$
$$U_t = (1 - M_t) * (K * W_t - K * D_t) \qquad \forall t \in T \tag{3.3}$$
$$W_t = W_{t-1} + (H_t - F_t) * \frac{1}{FTE} \qquad \forall t \in T \tag{3.4}$$
$$W_t, O_t, U_t \geq 0 \qquad \forall t \in T \tag{3.5}$$
$$H_t, F_t \geq 0 \qquad \forall t \in T \tag{3.6}$$
$$W_t, H_t, F_t : integer \qquad \forall t \in T \tag{3.7}$$
$$M_t : binary \qquad \forall t \in T \tag{3.8}$$

The objective function and constraints are explained below:

(3.1)	The objective function minimizes the sum of hiring, firing, undertime and overtime costs.
(3.2)	Constraint that makes sure that demand is met every period.
(3.3)	Constraint that determines the amount of estimated outflow when TEMPs receive less work (undertime).
(3.4)	Constraint that determines the workforce level every period in FTE.
(3.5)	Constraint that defines the lower bound for the workforce level, overtime and undertime hours.
(3.6)	Constraint that defines that the amount of TEMPs that should be hired or fired must be bigger than zero.
(3.7)	Constraint that defines that the workforce level and the amount of TEMPs to hire or fire should be integer numbers.
(3.8)	Constraint that defines that either undercapacity or overcapacity could occur.

3.3 Data analytics

Data analytics is becoming increasingly more important within companies. All companies generate data and additional revenue or lower costs can be generated by exploring this data. The purpose is to identify to what extent CEVA is performing based on the effort to integrate data analytics into their processes. This section will elaborate more on the current degree in which data analytics can be applied, it also gives a clear definition of big data and a description of some key methods to estimate the relation between two variables.

3.3.1 Data analytics framework

One of the approaches of this report is to verify assumptions based on data analytics and to generate new insights by data analysis. A framework is useful to indicate what the current level of data analysis is, then on an organisational level it will be possible to set a target which degree of data analysis is desired in the near future. The following overview in Table 3.8 is made, it indicates multiple stages of data analysis. Currently CEVA is able to reflect on past events regarding resource planning, but they are lacking to know the demand for the next month. Therefore the level of data analytics of the organisation is diagnostic. In order to level up to the predictive phase, CEVA must create better insights in future demand and have a better understanding how multiple variables influence each other which is part of the sensitivity analysis. An example of the latter one is how the capacity planning is related to the inflow and outflow of TEMPs. The prescriptive and cognitive level are for now out of scope since first the predictive phase must be reached.

Table 3.8: Analytics maturity framework [5].

Level	**Decision Automation Level**	**Question**	**Examples**
Descriptive	Lowest	What happend?	• Reports and dashboards • Pattern-based attributes
Diagnostic	Low	Why did it happen?	• Root Cause Analaysis • Segmentation
Predictive	Medium	What will happen?	• Simulation • What if analysis • Forecasting • Sensitivity analysis
Prescriptive	High	What should I do?	• Deterministic optimization • Stochastic optimization
Cognitive	Highest	Which new data driven techniques tell me what to do?	• Statistical learning • Machine learning • Reinforced learning

3.3.2 A definition of Big data

Within an organisation that is able to collect lots of data, the need to analyse data is big. Big data is often used as a buzz word within industries. Therefore to be clear, it is helpful to know which stage the company currently is in. Furthermore it could help to create support within the company to address the need for a data driven approach to solve problems, since the more data is available the bigger the need to take advantage of that.

To start with a statement, there is not one worldwide accepted definition of big data. But two of them provide sufficient insight. The Gartner research group defines four dimensions to characterize big data, these elements are Volume, Variety, Velocity and Value [29]. Another definition is defined by Mckinsey. *Big data considers datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse* [30].

The last mentioned definition seems to be an robust one since our hardware became more advanced over time. The advanced computers around the 1980s were able to store data in term of Gigabytes, nowadays that level of storage fits within our pockets in the form a mobile phone. Therefore the quantitative description of big data will change over time, while the qualitative description of Mckinsey remains constant over time. A brief quantitative description of big data is collected by Hu et al. [6]. Over there the development of the size of a big data database is mentioned and can be found in Table 3.9. Currently the global CEVA Logistics organisation owns around five petabyte of data. By the standards of today, the global business does not posses big data, still most computers are unable to analyse this quantity of information. Although it increases the importance to start looking at how data can be used to improve decision making.

Table 3.9: The development of the size of a database which is recognized as big data [6].

Year	**Step From**	**Step To**	**Equivalent *(in GB)***
1970 - 1980	Megabyte	Gigabyte	10^0
1980 - 1990	Gigabyte	Terabyte	10^3
1990 - 2000	Terabyte	Petabyte	10^6
2010 - current	Petabyte	Exabyte	10^9

3.4 Regression analysis

This sections answers research question 2e: *What are the tools from the literature to interpret the results of the proposed outflow rate model?*

Regression analysis is a set of techniques that can help to make a generalization of observations among variables. Data can be classified as supervised or unsupervised data. A regression model with supervised data involves building a statistical model for predicting or estimating an output based on one or more inputs. Constructing a regression model with unsupervised data includes input variables but no output variables, so only relationships and structures between those inputs can be learned. In this section only the supervised models are listed, since that is aligned with the scope of this thesis. The knowledge is gathered from the book written by James et al. [31].

- Quantitative prediction problems
  - Linear regression
  - Polynomial regression
  - Ridge regression[2]
  - Lasso regression[2]
  - ElasticNet regression[2]
- Qualitative prediction problems
  - Logistic regression analysis
  - Linear Discriminant analysis

The purpose of this section is to introduce some popular methods out of the statistical learning area, since there is no single best approach to handle a correlation analysis. One of the mean issues are how to fit a model in such a way a model is not underfitted or overfitted. In addition to that, a couple of performance measurements are explained to evaluate a statistical learning model.

[2]only applicable in case multiple predictors are available

3.4.1 Quantitative prediction problems

Linear regression
Linear regression is used to model the relationship between a response variable and one or more predictors. This relationship is based on a linear function and a standard model with two predictors looks like: $Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \epsilon$. Where Y is the response, X_i the predictors, the β_i are scalars and ϵ is an error term. Given this model, a correlation matrix is calculated. This indicates how much influence the predictors have over the response.

The linear regression model has some disadvantage, namely that if the response value has three or more values, the differences between those values must be equal. In addition to that, a linear regression model has difficulties to handle qualitative responses, even if they are converted into quantitative responses. Furthermore the model could be subjected to underfitting or overfitting, a visual example of the underfitting and overfitting problem can be found in Figure 3.2 and Figure 3.3. An underfitted model is a too general representation of the data and an overfitted model is a too specific representation of the data. The following models provide basic techniques that can cope with underfitting and overfitting.

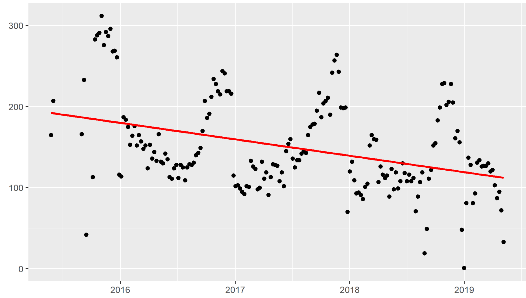


Figure 3.2: An example of underfitting.

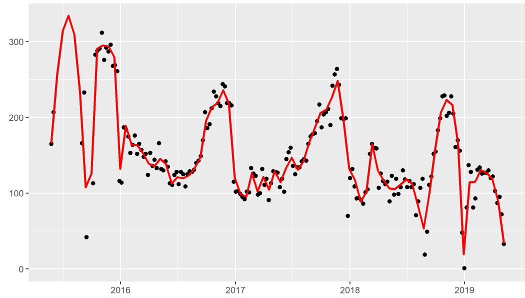


Figure 3.3: An example of overfitting

Overcome underfitting by Polynomial Regression
The polynomial regression is based on the linear regression model, but now non-linearity is taken into account. The model approximates the value of y as the n^{th} degree polynomial and looks like:

$$Y = \beta_0 + \beta_1 * X + \beta_2 * X^2 + ... + \beta_n * X^n + \epsilon$$

Overcome overfitting by Ridge Regression
The standard approach for linear regression is to fit the model based on the residual sum of squares, Residual Sum of Squares, which can be find below.

$$RSS = \sum_{i=1}^{n} (\varepsilon_i)^2 = \sum_{i=1}^{n} (y_i - (\alpha + \beta x_i))^2$$

Using this RSS comes with some challenges, since the slope of the regression line influences the impact of the weights (β), therefore overfitting occurs. To overcome this problem, regularization techniques are needed like ridge regression. This technique simplifies the model by penalizing large weights ($\lambda * \sum \beta^2$). The model is trained on minimizing a loss function that is shown in the following example:

$$L = RSS + \lambda * \sum \beta^2$$

Overcome overfitting by Lasso Regression
The ridge regression has one disadvantage and that is uses all the predictors that are included in the model, since ($\lambda * \sum \beta^2$) can shrink the coefficients towards zero, but it is unable to set them exactly to zero. Lasso regressions overcomes that problem by changing the weight penalty to ($\lambda * \sum |\beta_j|$). The result of this model is easier to interpret since the selection of variables by the lasso method. The models looks like:

$$L = RSS + \lambda * \sum |\beta_j|$$

Overcome overfitting by ElasticNet Regression
To summarize the previous two methods, when you know that all variables are useful and want to prevent overfitting, you use ridge regression. When not all variables are useful and overfitting is an issue you use lasso regression. But in case of a lot of variables, it is maybe not clear which variables are useful. In that case ElasticNet regression is helpful. It combines both methods, by adding parameter α. The loss function looks as follow:

$$L = \frac{RSS}{2n} + \lambda * ((\frac{1-a}{2}) * \sum \beta_j^2 + \alpha * \sum |\beta_j|)$$

3.4.2 Qualitative prediction problems

Logistic Regression
A logistic regression model determines the probability that Y belong to a particular category given one or multiple variables. In this case the calculation of the output must be between 0 and 1 for all values of X. The logistic function offers a good approximation and can be found below. The output of a logistic regression model follows a S-shape with the rate of occurrence.

$$p(X) = \frac{e^{\beta_0 + \beta_1 X + \ldots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X + \ldots + \beta_p X_p}}$$

The coefficients, or weights, are determined based on a maximum likelihood method. For example to estimate β_0 and β_1, the likelihood function becomes:

$$l(\beta_0, \beta_1) = \prod_{i:y_i=1} p(x_i) \prod_{i':y_{i'}=0} (1 - p(x_{i'}))$$

Linear Discriminant Analysis
There are a couple of situation where logistic regression lacks performance.

1. If the classes are well-separated, the parameter estimate becomes unstable in case of logistic regression.
2. If n is small and the predictors are normally distributed, the linear discriminant model performs better than logistic regression.
3. In case of more than two response classes, linear discriminant analysis performs better.

The linear discriminant analysis models the distribution of the predictors separately in each of the response classes, the probabilities are determined by Bayes' theorem. What it basically does is project the responses in such a way that the distances between the means are maximized and the variation of each is minimized. This created a good distinction between variables and a better estimation of the classification process. The formula of the LDA is not relevant for this thesis, since the many variations when the amount of responses classes vary.

3.4.3 Conclusion regression analysis

A good regression model finds a balance between the underfitting and overfitting of a model. Several techniques are based to minimize the Residual Sum of Squares with some other variables. Ridge regression penalizes large weights, lasso regression has the ability to exclude variables and ElasticNet is a combination of both with the drawback that in case of many variables prioritizing them becomes hard. The condition is that these three regression methods require multiple predictors. In case of a classification problem, logistic regression gives a probability of belonging to a certain type. The method of logistic regression to use depends on the spread of the observations, the number of observations and the amount of response classes.

3.5 Literature conclusion

This chapter proposes several forecasting techniques and discusses which forecasting method delivers in general the best forecasts. Subsequently, two forecasting competitions recognized three forecast methods to generate accurate forecasts in 100.000 cases. The three selected methods are ETS, ARIMA and Theta. It is expected that these methods develop the best forecasts when only historical data is given. Moreover, the mathematical properties of these methods and different error measures are given. The type of error measure must be able to compare forecasts with the same forecast horizon and the type of error measure must be easy to interpreted. Given these points, the MASE measure is used to compare different forecast methods for one time series data. The MAPE measure is used to compare the performance the selected forecast methods for multiple time series data.

On the subject of regression analysis, multiple techniques in case of multiple situations are discussed. The right regression technique depends on the type of variables that are used. Linear regression and polynomial regression is used in case of a quantitative prediction and logistics regression is used in case of a qualitative prediction. Lastly, a good regression model consists always of the trade-off between underfitting and overfitting of the data by a model. At last, the difficulties of an capacity planning, the contents of an MILP model and a framework for data analysis is presented from a literature perspective.

4 | Model Explanation

The previous chapters described the problem situation and gave an overview of the current situation at the different warehouses and introduced useful literature. This chapter combines that knowledge in order to propose a solution for the main research question, which is "How can the capacity planning of TEMPs at the CEVA Benelux warehouses be improved and how does forecasting and the use of analytics help this process?". The following models are explained in this section:

- A model to gain insights about long-term forecasting.
- A model to determine the likeliness to leave when a TEMP works less than desired.

As mentioned in the problem identification section 1.2.3 there are two core problems that were identified. The first one is that there is a lot of uncertainty in demand forecasting for the sites, this results in a high workforce capacity level. TEMPs cannot work 40 hours a week and will leave the organisation soon, the high outflow rate of TEMPs support this assumption. To lower the amount of uncertainty, a forecast model is proposed that uses time-series data without using external variables for each client. The use of the forecast model should be quite simple, but this model is mainly used to give insights to the following questions:

Forecast model

- For which type of client delivers the forecast model a good result?
- For which type of warehouse activity delivers the forecast model a good result?
- Which type of forecast method delivers a good result and which do not?

The second core problem is formulated as every site performs their own analysis regarding workforce planning which leads to inconsistency among sites. The question which strategy is best, is hard to answer. There is only a limited number of sites that use data analysis to support their resource planning decisions. The bottom line is that a site wants to have as many TEMPs as possible, since this generates flexibility. But this will also result in a high outflow rate since TEMPs cannot work as much as they want to do. Therefore it is important to known at what rate TEMPs will leave to organisation to make a trade-off between flexibility and costs. Given this reason, a model is built to determine the outflow rate when TEMPs work less than desired. The questions that the outflow rate model answers is given below:

Outflow rate model

- If a TEMP receives less work for a given period, what is the likeliness of outflow?
- How should the insights of this model be used in practice?
- What are the potential cost savings?

The two models are introduced to solve the core problems, the next step is to combine the findings of both models. To illustrate this, Figure 4.1 is added. Over there, the input, the purpose, how it works and the deliverables of the models are briefly mentioned. Besides the two models introduced earlier, a MILP model may be added to determine the optimal workforce pool policy based on minimizing costs and multiple variables. The decision is to not include a MILP model since the result of the outflow ratio model is relatively easy to interpret and there are some hard restrictions that limit the possibilities for a MILP model. That means that with the current restrictions, the (local) optimal pool size can be calculated by hand , given the capacity planning strategy as determined by this research. More about the MILP model will be discussed in chapter 5 and 6.2.

A more detailed view towards the forecast model and the outflow rate model is discussed in the upcoming sections. The results and evaluation of the models are given in chapter 5, the final conclusions in section 6.1 and the recommendations towards the company in section 6.2.

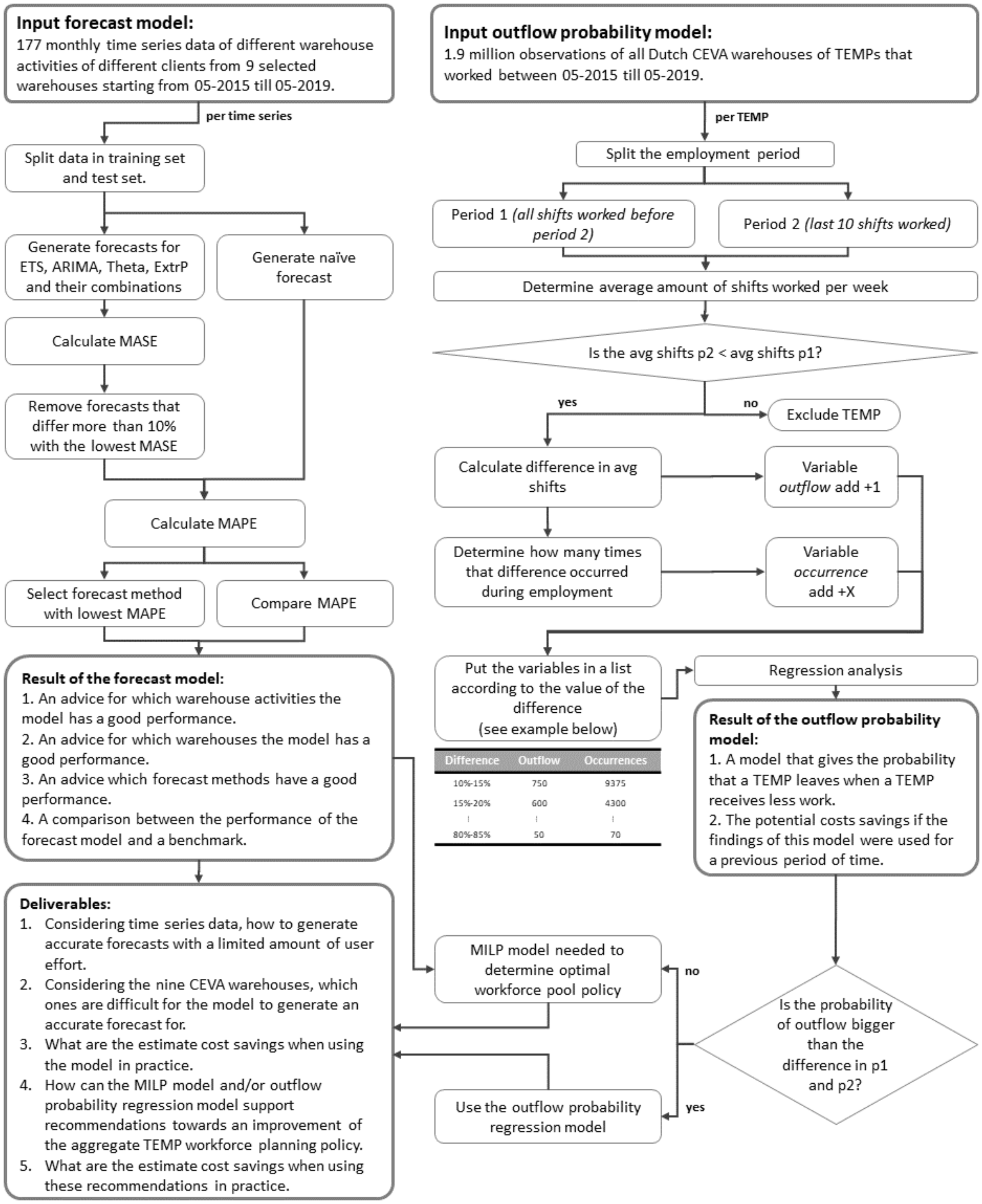


Figure 4.1: An overview of the outlines of the forecast model and outflow rate model, together with the deliverables of the model.

4.1 Forecasting model

This sections answers research question 3d: *How can the best forecasting methods or method from the literature be put into a model to find out what the best possible forecast accuracy is, given the current input data?*

The purpose of this section is to model a forecast procedure that works with limited human input, but is accurate enough to use within the business. The reason why it has to work with a limited amount of human input is, as defined by the problem cluster Figure 1.2.3, that there is no analytics team at the sites who can clean data, adjust forecast parameters or improve forecast models. This model evaluates a set of forecasting ideas that is based on literature section 3.1. The conclusion of that section is to use the best performing models from two international forecasting competitions. Per client the best fit with a forecast method is determined, the aggregate forecasts of all clients per site determines the future demand at a site. This chapter describes the how the forecast models works, chapter 5 gives the result how the forecast models performs given a naive forecast and discusses the findings.

An overview of the forecast model is given in Figure 4.2. Over here, the input data, calculations and the deliverables of the models are listed. It shows the outlines of the forecast model. The model can be split into three sections which are listed below. The explanation of the forecasting model is done according to these sections.

1. Convert warehouse data to time series data
2. Forecasting model selection
3. Check forecast model robustness

Convert warehouse data to time series data.
This section explains how the warehouse data is converted to time series data. The time series data consists of monthly data, since there is a limited availability of daily data. Daily data consists of client specific information, so it has to comply with the General Data Protection Regulation and therefore can only be available for at most 90 days. The assumption is that aggregated monthly data is accurate enough as long-term measure for the demand of a warehouse.

Forecasting model selection.
This section explains how the model selects a good forecast method per time series data. Three existing methods *(ETS, ARIMA, Theta)* are evaluated and an own method *(ExtrP)* is proposed to improve the forecasting process given the characteristics of the companies warehouses. The performance of the forecasting model is evaluated by summarizing the error measures of the best forecast method per time series data.

Check forecast model robustness.
The performance of the forecast model is tested on a large data set, but that does not guarantee a good performance in the future. Therefore the robustness of the forecast model is checked by an analysis to overfitting and a sensitivity analysis.

The purpose of the forecast model is to deliver insights about which sectors and operations are suited for the given forecasting techniques and formulates an advice on how the forecasting model can contribute to predict long-term demand under different circumstances. The series of sectors and operations that are forecasted by the model and the set of forecast methods are described below.

Sector of client:

- Retail
- Technology
- Healthcare
- Industrial

Warehouse activities

- Units received
- Picking units
- Picking orderlines
- Shipping units
- Shipping total
- Shipping orders

- Picking pallets
- Inbound trucks
- Outbound trucks
- Shipping orderlines
- Items returned

Forecast methods:
With and without the ExtrP-parameter

• ETS	(-ExtrP)
• ARIMA	(-ExtrP)
• Theta	(-ExtrP)
• ETS-ARIMA	(-ExtrP)
• ETS-Theta	(-ExtrP)
• ARIMA-Theta	(-ExtrP)
• ETS-ARIMA-Theta	(-ExtrP)

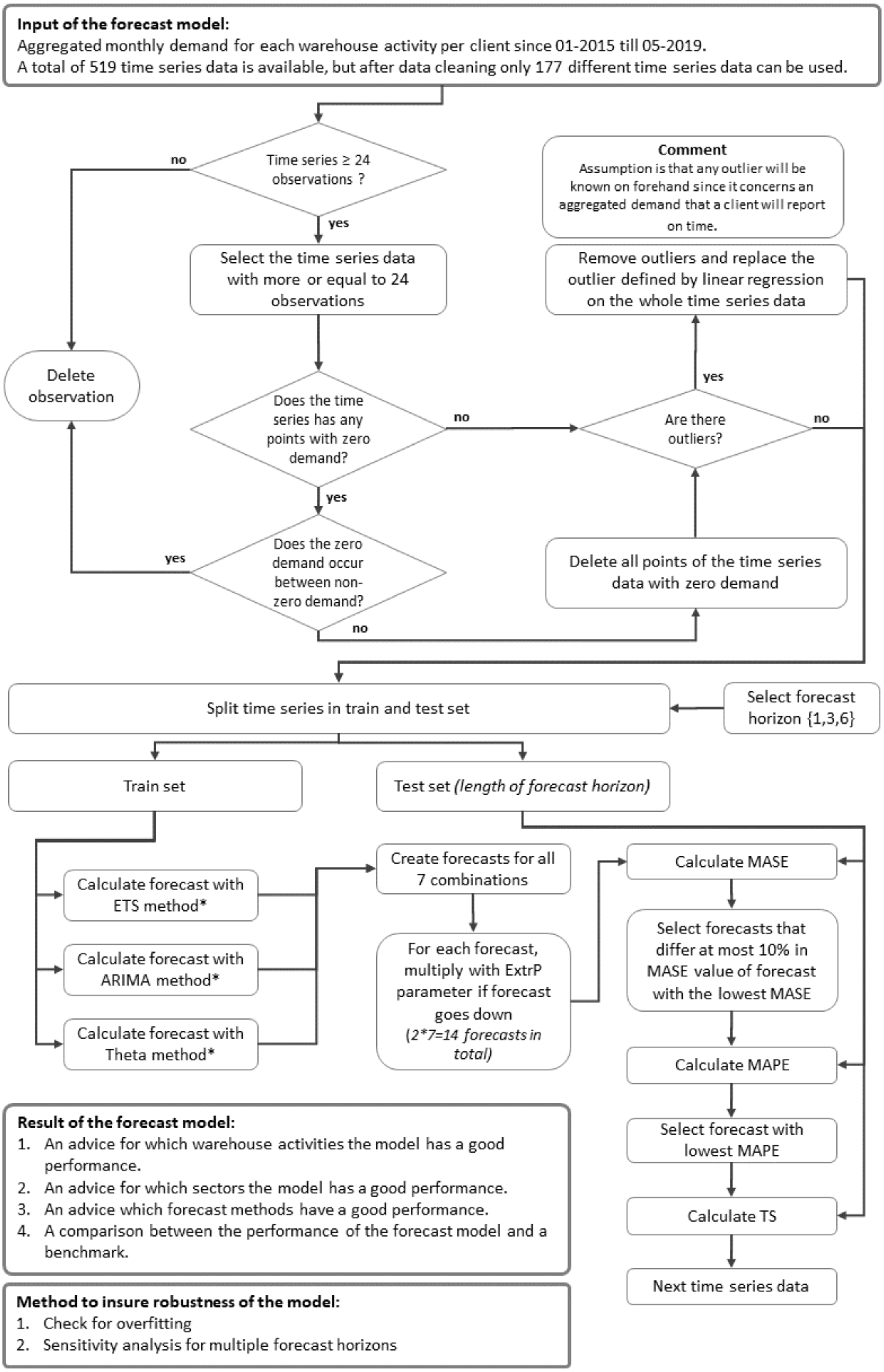


Figure 4.2: An detailed overview of the contents of the forecast model.

4.1.1 Convert warehouse data to time series data

The first step consists of the conversion of data from the Warehouse Management System (WMS data) to time series data. It is preferred to use time series data that have many observations, since seasonal patterns can be better distinguished. Literature section 3.1.2 mentioned that at least 18 observations are needed when performing a monthly forecast. Still this includes only one observation in case of a yearly seasonality, thus a minimum of 24 observations would be better in theory. Therefore a minimum of 24 observations per time series data can be used, on the condition that enough time series data remain available. This trade-off will be discussed in chapter 5. The conversion of warehouse data to time series data is listed in Figure 4.3.

The data gathering from the WMS is described in section 2.1.3. Unfortunately there are too many different warehouse data management systems active. A new model must be made per different WMS, this makes it very time consuming to withdrawal data from every database. A solution is to gather data about the warehouse activities from somewhere else that is less time consuming.

The data that is used as input for the forecasting model is gathered from monthly reports in which the aggregated results per warehouse activity per client are listed. These reports are acceptable, since monthly data is sufficient enough for the forecast model but it is not recommended since it requires a lot of manual labor and a lot of people within the organisation are involved. In case weekly or daily data is needed, the method as described in section 2.1.3 must be used.

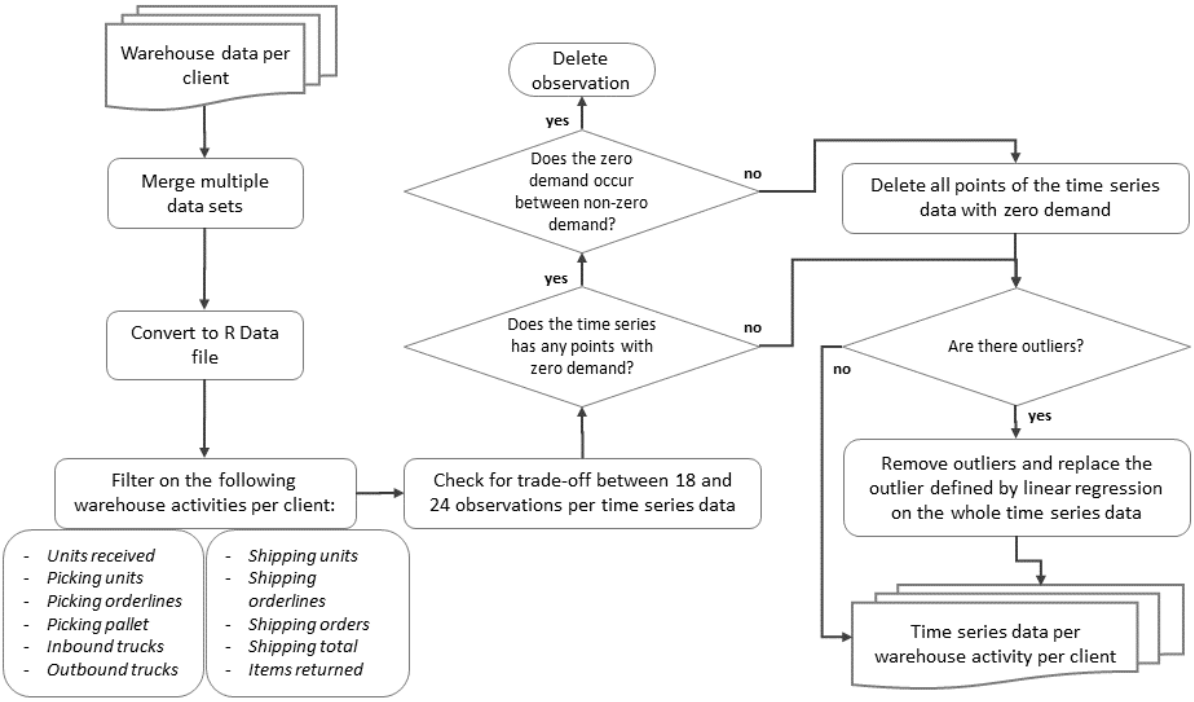


Figure 4.3: Convert warehouse data to a monthly time series per warehouse activity per client per site.

4.1.2 Selection of method

As mentioned in the literature chapter about forecasting, choosing the best model heavily depends on the characteristics of a data set. This could potentially be very labor intensive. Therefore there is a need to see how an forecasting model performs that evaluated multiple methods. In this case, the literature section selected a set of potential good performing forecasting methods. In addition to that an extra parameter is added to the set of forecasting methods. It is assumed that the extra parameter will improve the performance of forecast method, since it is designed to handle a specific type of demand behaviour. More about the extra parameter is explained in section 4.1.2.

The procedure to select the best forecasting method is already described in figure 4.2. however a more detailed description is given as pseudo-code in Appendix A algorithm 6. The best forecast method is selected based on two criteria, the MASE and MAPE values. The MASE criteria is used to compare different methods on the same data set. The MASE value of forecast models must be low, but the best method is selected on the lowest MAPE value. The reason for that the MAPE value of methods on different dataset can be compared with each other.

Among the set of forecasting methods, a combination of multiple forecasting method is possible. In that case, the forecast value is the average of multiple forecast values. Chapter 3.1.4 explains that combining the ETS, ARIMA and Theta methods results in a combination which is referred in the literature as "Comb". By including the ExtrP method to the "comb" method, a new combination called "Combe" is created. Previously, the literature section explained how the single forecast methods work. The upcoming sections explain how these methods work in practice.

Forecast ETS

As mentioned in the literature section, the ETS method consists of an error, trend and seasonal parameter. A total of 30 different forecast models are evaluated including 2 single exponential smoothing model, 8 Holt models and 20 Holt-Winters models. The best model is chosen based on the lowest AIC. The pseudo-code can be found in algorithm 1.

Algorithm 1 Pseudo-code: ETS forecasting method

```
Input: Time series data
Output: The forecast values of the ETS method

error ← parameter that is estimated by model
trend ← parameter that is estimated by model
season ← parameter that is estimated by model
damped ← parameter that is estimated by model

Make combinations of within the method        ▷ N = "none", A = "additive", M = "multiplicative"
for all error ∈ error types {A,M} do
    for all trend ∈ trend types {N,A,M} do
        for all season ∈ season types {N,A,M} do
            if (error = A AND (trend = M OR season = M)) then
                Exclude non existing model
            end if

            if (trend = N AND season = N) then
                forecast ← Single Exponential Smoothing (SES) forecast on training data
            end if
            if (trend = {A,M} AND season = N) then
                forecast ← Holt forecast on training data
            end if
            if (trend = {A,M} AND season = {A,M}) then
                forecast ← Holt Winters forecast on training data
            end if

            AIC_local ← −2log(likelihood) + 2p                ▷ Determine AIC of model
            if (AIC_local < AIC_global) then
                Store model and parameters as best global model
            end if
        end for
    end for
end for
Return: Method parameters and the values of the MASE and MAPE.
```

Forecast ARIMA

The auto-regressive integrated moving average method uses four parameters that determine the behaviour of the model. The auto-regressive component determines how many past values to include in the regression model. The integrated component is used to stabilize the time series. The moving average component indicates how many lags of the error terms are included in the model. The best model is chosen on the lowest AIC. The pseudo-code can be found in algorithm 2.

Algorithm 2 Pseudo-code: ARIMA forecasting method

Input: Time series data
Output: The forecast values of the ARIMA method

{p} ← *{0,4} variable that indicated the number of autoregressive lags.*
{d} ← *{0,4} variable that indicated the number of nonseasonal differences.*
{q} ← *{0,4} variable that indicated the number of moving-average terms.*
{P} ← *{0,1} variable that indicated the number of seasonal autoregressive lags.*
{D} ← *{0,1} variable that indicated the number of seasonal differences.*
{Q} ← *{0,1} variable that indicated the number of seasonal moving-average terms.*
Capital letters are the variables when seasonality is involved.

Check on seasonality by differencing
Determine the amount of model configurations
for all configurations **do**
    Select sequentially a set of parameters.
    forecast ← ARIMA(training data,p,d,q,P,D,Q)
    $AIC_{local} \leftarrow -2log(likelihood) + 2p$
    if $(AIC_{local} < AIC_{global})$ **then**
        Store configuration and the parameters
    end if
end for
Return: *ARIMA configuration with lowest AIC*

Forecast THETA

The Theta model decomposes the time series data into multiple time series data. For each stream of time series data a simple exponential smoothing forecast is made. The final forecast consists of the average values of the simple exponential smoothing forecasts. The pseudo-code can be found in algorithm 3.

Algorithm 3 Pseudo-code: Theta forecasting method

Input: Time series data
Output: The forecast values of the Theta method
Variable: A set of theta values

Determine frequency value, these are the number of "theta lines". *Frequency value is determined by the the lag value, this is a function in R*
Decompose the data into the number of theta lines, calculated by the theta values

for all Theta lines **do**
    $forecast_i$ ← single exponential smoothing forecast
end for
Final forecast is the average of the sum of all $forecast_i$.
Return: Theta configuration and the forecast values.

ExtrP parameter

This sections answers research question 3e: *Is there a way to improve some proposed forecasting methods out of the literature, by adding parameters to deal with specific demand behavior?*

The extra parameter, ExtrP, is implemented to improve the performance of current forecast methods. The main motivation behind this method is a frequently mentioned phrase out of the literature that says "the performance of a forecast model depends heavily on the characteristics of its input data". One of the characteristics of the input data, so the characteristics of the demand at warehouses, is that the demand at the start of a high season increase a bit, but during the end of a high season the demand suddenly drops. The occurrence of this increase in demand and suddenly drop can be seen in Figure 4.4.

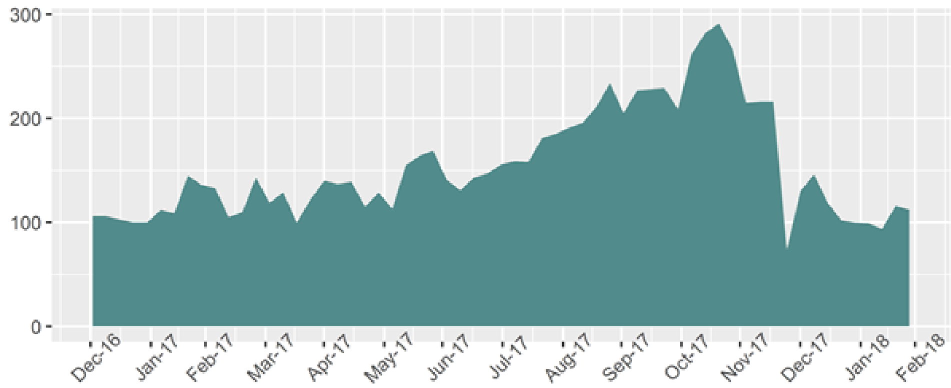


Figure 4.4: The demand of a client where demand increases and suddenly drops.

The reason why that happens can be explained by an example from an electronic goods client. Their high season period starts around August and end around January, this has a lot to do with events like Black Friday, Christmas and Saint Nicholas [1]. During the months August, September and October a CEVA warehouse is replenished with goods from Asia until they almost reach their maximum storage capacity, a lot of inbound activities happen at this time. During the months October, November and December the local warehouses of clients or the physical stores clients are replenished with goods, so a lot of outbound activities happen around that time. In addition to that, the e-commerce activities starts to increase in November and December, this increases the workload since picking goods for single customers is more labor intensive than picking goods to replenish a store. At the end of December or in January some goods are returned by a store or online customer, but then demand drops since the market is saturated with presents.

This sudden decrease in demand takes place somewhere in the months December, January and February. The reason why a forecast method that incorporates a seasonality factor cannot capture this sudden decrease, is because the moment when this happens is not the same every year. Therefore it might be reasonable that the training data consist of observations where there is a sudden demand drop at December and the next year in January, a forecast method will smooth this demand drop. The ExtrP parameter adjusts this smoothing and therefore supports a forecast method to generate a more accurate forecast.

The ExtrP parameter that adjust the forecasts values of other forecasting methods. If the forecast indicates that demand decreases, the ExtrP parameter decreases the forecast even more. The reason behind this, is that the seasonality factor of a forecast method is smoothed. Since we know that the event described in Figure 4.4 definitely happens at some clients, it may be worth to experiment if this addition is successful. The pseudo-code can be found in algorithm 4.

[1] Saint Nicholas is a Dutch feast where gifts are bought for young children.

Algorithm 4 Pseudo-code: ExtrP method

```
Input: A forecast that is made by the ETS, ARIMA, Theta or a combination of those methods.
Output: The adjusted forecast values
Variable: The ExtrP parameter value (default = 0.96)

if (Forecast horizon (or length of forecast values) > 1) then
    for all Forecast values do
        if forecast went down compared to the previous observation then
            forecast_value = forecast_value * ExtrP
        end if
    end for
else if (Forecast horizon = 1) then
    if forecast went down compared to the previous observation then
        forecast_value = forecast_value * ExtrP
    end if
end if

Return: the adjusted forecast values
```

4.1.3 Robustness check of the model

There are two ways to verify if the forecast model is able to generate a robust result. That means that the forecast model delivers approximately the same result under different conditions. Examples of different conditions are varying length of the training and test data set.

In case the length of the training set differs, the forecast should generate an approximately same result, because most of the observations of the training data is still the same. If the forecast accuracy drops when the length of the training set differs, then it is likely that the forecast overfitted the initial training data set.

In case the length of the test set differs, it is expected that the forecast accuracy decreases with a constant rate. Otherwise it can be concluded that the forecast is too sensitive for different forecast horizons.

As previously stated, the forecast model is robust enough if the model delivers approximately the same results as the initial situation. A test on overfitting determines if the forecast model is robust enough when the length of the training data differs. A sensitivity analysis to different forecast horizons determines if the forecast model is robust enough when the length of the test data differs. First the test on overfitting is described, after that a section elaborates on the sensitivity analysis.

Test on overfitting by cross-validation

A good forecast model is supposed to learn from historical data and extract repetitive behaviour of demand in order to say something useful of future demand. A forecast model can extract repetitive behaviour in a simple way, such that estimations of future demand are quite general. This is underfitting and results in a high forecast error. The other way around is that a forecast model captures every repetitive behaviour of historical demand, this includes random errors as well and results in a too complex model. The difference with overfitting and underfitting is that the problem of underfitting is solved by the model since that results in a high error rate, but overfitting is hard to notice. An overfitted forecast model may result in a low error rate, but the model is not robust enough for future changes in the training data. Therefore it is important to focus on potentially overfitted forecast models in order to ensure that the forecast method is robust enough.

A way to identify overfitting is to do to cross-validation. Normally cross-validation excludes a certain subset of the data to generate a new data set, but this is not very common for time series data since the observations are dependent of each other. Therefore the way to cross-validate time series data is to evaluate a forecast with a rolling origin Tashman [32]. The condition is that sufficient observations must be available.

The rolling origin is applied by using a forecast horizon of three months as the base forecast. Every step of the rolling origin decreases the training set length with one month, but the test data set continues to consists of three months. To clarify the rolling origin, Figure 4.5 is added in case there are 30 observations available. The white cells represent the training data and the gray cells represent the test data. The purpose is to test to what extent a forecast method is fitted to the training data. There is an indication of overfitting if it occurs that the forecast error rapidly increases when the step value of the rolling origin changes. If the forecast model is able to produce more or less the same forecast result with less training data, there is no indication of overfitting.

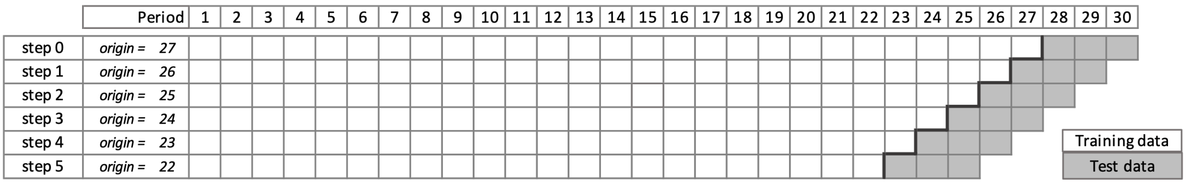


Figure 4.5: An example of cross-validation for time series data when using a rolling horizon.

Sensitivity analysis for multiple forecast horizons

It is logical to assume that if the forecast horizon increases, the forecast accuracy decreases due to the higher amount of uncertainty. Therefore the forecast error may increase when the forecast horizon increases, but the errors cannot increase rapidly. Ideally the errors increase with a constant rate, an example can be found in Table 4.1.

Table 4.1: An example of a sensitive forecast model for multiple forecast horizons.

Forecast horizon	**1**	**2**	**3**	**4**	**5**	**6**	**Sensitive for different forecast horizons**
Error rate per horizon	5%	10%	15%	20%	25%	30%	No
Average error rate	5%	8%	10%	13%	15%	18%	
Error rate per horizon	3%	7%	14%	16%	35%	45%	Yes
Average error rate	3%	5%	8%	10%	15%	20%	

Over there, the forecast that is not sensitive to different horizons has an error rate that increases with 5% per period. In case of six forecast horizons, the error rate on period six is equal to 30%. The average error rate for a forecast over six period is 18%, which is as expected lower than the error rate on period six. The other forecast, which is sensitive to different forecast horizons has error rates that do not increase with a constant value.

The reason why this sensitivity reason is important can be seen when the average error rates and the error rate per horizon are compared. It seems that the average error rates of both forecasts are quite equal, so based on that one could conclude that the performance of both models is rather similar. But the sensitive forecast performs good, until period 5 and 6. In this case, the performance of both forecasts look different now and the forecast that is not sensitive is preferred over the sensitive forecast.

To conclude, a forecast can be evaluated by the average error rate. A problem occurs when a forecast model has a large variation between the error rates per forecast horizon. This causes an irregular performance which is not desired. A sensitivity analysis of the error rates per horizon must determine to what extent the performance of a forecast is robust enough.

4.2 Outflow rate model

This sections answers research question 2d: *How can the relation between the size of the pool of TEMPs and the outflow rate be modelled?*

In order to improve the tactical resource planning, some characteristics of TEMPs must be analyzed, since the problem cluster 1.2.3 identifies that the high outflow rate of TEMPs is one of the visible problems that is already identified within the company. The root-cause for this problem can be formulated as the absence of dedicated forecasting software and the fact that each site has their own strategy regarding workforce planning. The first problem of the absence of dedicated forecasting software is tackled by the previously proposed model. This section proposes a model that supports strategy making regarding the workforce planning of TEMPs.

There is one major decisions involved when determining the workforce pool strategy. For a certain point in time, how big should the workforce pool be. It is obvious that a deficit of the pool of TEMPs must be avoided, since the company must meet the demand. In addition to that, a surplus of the pool of TEMPs results in many negative consequences such as high training costs of TEMPs, a possible lower productivity since TEMPs work irregular and TEMPs that decide to leave to company since they cannot work the amount of hours as desired.

To support strategic decision making, it can be helpful to perform a research to the negative consequences of a surplus of the pool of TEMPs since these are not quantified. This section focuses on the case that there is a surplus of TEMPs in the workforce pool and TEMPs don't get the opportunity to work the amount of hours that they desire to work. The result of this event is that the TEMPs are more likely to leave to company. A high outflow rate of TEMPs occur and this affects the strategy regarding the workforce planning.

The question that this model solves is:
"If a TEMP cannot work the desired amount of hours a week, what is the likeliness of leaving?"

Since the start of 2018 some sites keep track of the reason why a TEMP leaves by making sure that they fill in a survey during the out-boarding process. Unfortunately the results of this survey are not 100% reliable since most of the TEMPs state that a personal reason is the main factor of leaving. A personal reason could mean that a TEMP wanted to work more, but that cannot be verified as more interpretations are possible. Therefore there is a need to model the likeliness of outflow. In addition to that, chapter 5.2.4 discusses the result of the survey and the relevance for the outflow rate model. The structure to answer the question of this section is as follow. First, general overview of the contents of the model is given in Figure 4.6. The code of some important section is given in Figure C.3, C.4 and C.5. This is followed by the model approach and main assumptions, then the data cleaning procedure, followed by the data analysis part. The results of the outflow rate model are listed in chapter 5.2.

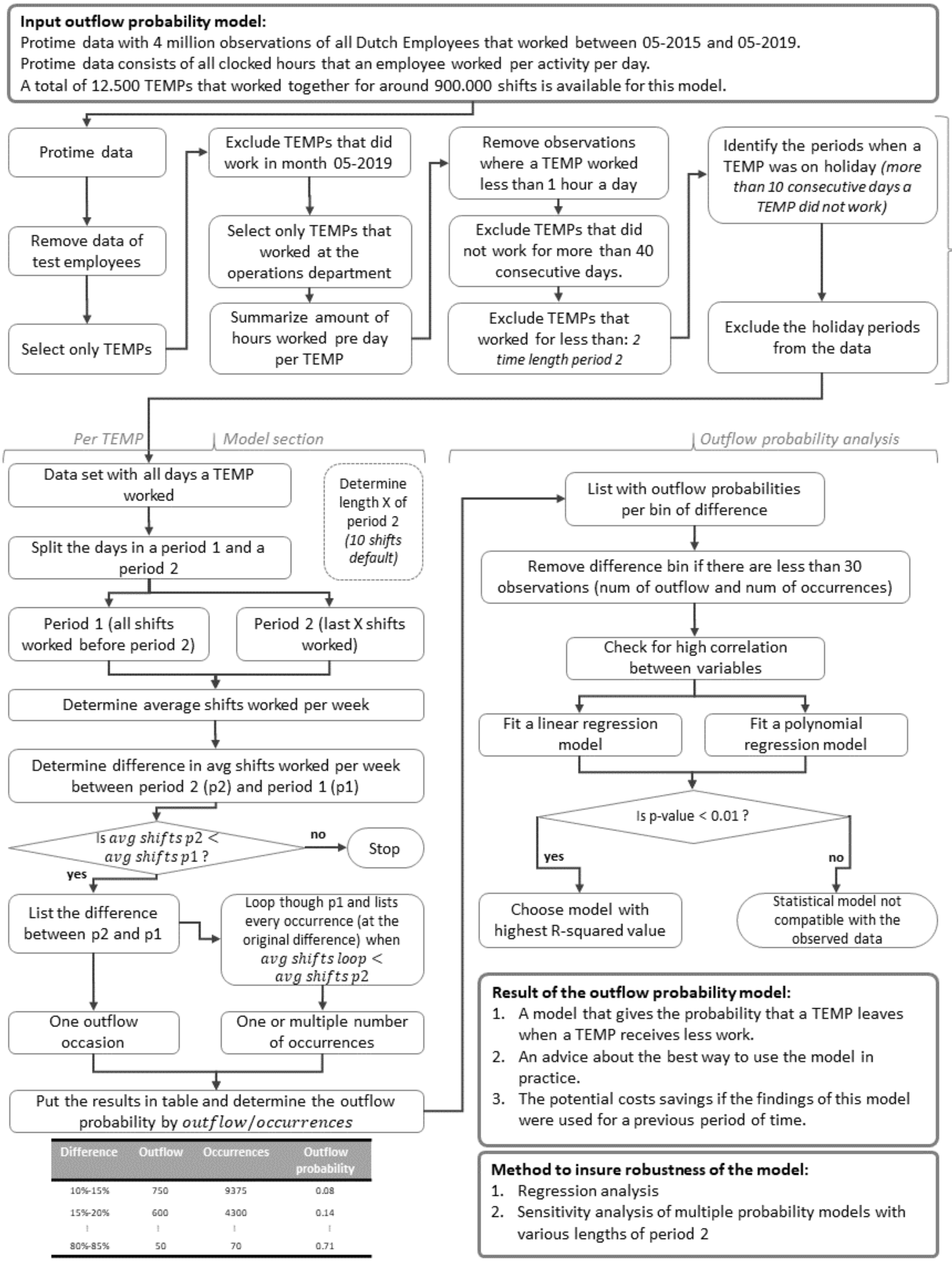


Figure 4.6: An detailed overview of the contents of the outflow rate model.

4.2.1 Approach and main assumptions

TEMPs leave if they work less then the amount they desire to work. This assumption is true for sure, since TEMPs are very dependent of their income. To get that estimation of outflow, the desired amount of work (expressed in shifts) must be known for each TEMP. Then for some period, if the actual amount of work is less than the desired amount of work and the TEMP has decided to quit, it can be marked as an outflow due to less work. The approach is to look at all the circumstances where the actual amount of work was less than the desired amount of work and sum all the occasions where a TEMP left or not. This procedure is repeated for multiple value of the differences between the actual and desired amount of work. The result is an overview with the outflow rates, the main assumptions are listed below:

- The protime data consists of all employees, but only observations of TEMPs are used.
- No distinction is made per warehouse location or warehouse activity.
- This analysis considers shifts as observations. The duration of a shift has a range from 5 till 10 hours, but most shifts have a span of around 7.8 hours (first quartile 7.7 hours and third quartile 8.0 hours).
- A TEMP does not determine to leave the company after one day not working, there must be a certain period that a TEMP worked less than desired in order to make the decision to leave the company. The desired amount of work is determined by splitting the time a TEMP worked at CEVA in period 1 and a period 2. An overview of the definition of period 1 and period 2 is given by Figure 4.7.
- Period 1 can be called the base period and consist of the all shifts a TEMP worked before the review period, so before the last 10 shifts worked.
- Period 2 can be called the review period, which consist of the last 10 times a TEMP worked.
- To analyze the outflow behavior, we compare the average number of shifts worked in the base period and the review period. If a TEMP worked considerably less in the review period, than there is an indication that a TEMP left due to receiving less work.
- This procedure is an estimation of the ratio of outflow. It is less likely that a small overcapacity rate results in outflow. Therefore the outflow ratio's for a small overcapacity number is considered to have other causes than a small overcapacity rate.
- It can happen that there are observations in which a TEMP worked more in period 2 than in period 1. These observations are left out.
- The data analysis part returns a list of outflow rates given a set of percentages of differences between actual and desired working hours. The assumption is that a regression model provides a good generalisation of estimated outflow rate given a certain decrease in work.
- The TEMPs that are hired at the beginning of a high season and flow out at the end of that high season are likely to have little effect on the data analysis, since these TEMPs are likely to be the first ones to leave. The assumption is that they suddenly receive no more work in stead of slowly decreasing the amount of work.

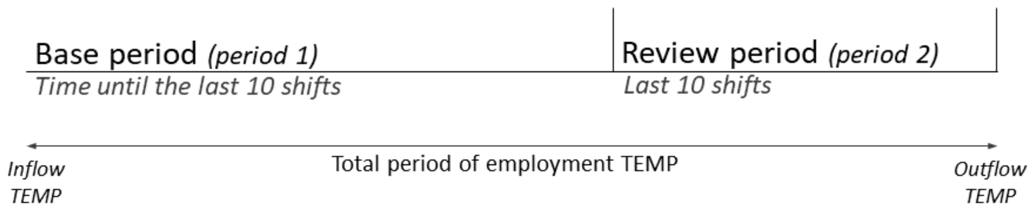


Figure 4.7: The average amount of shifts per week from period 1 (base period) is compared with that of period 2 (review period), right before a TEMP leaves the company.

4.2.2 Data cleaning

The analysis starts with data cleaning, since not all of the observations are useful. Without data cleaning the result could be a mismatch with the actual situation. The assumptions of the data cleaning process are listed below. Some assumptions need a further explanation, these will be discussed separately.

- The observations where TEMPs worked less than one hour a day are excluded, since that is considered as a mistake by the TEMP or supervisor to work on that day.
- On average a TEMP must have worked between 5 till 10 hours per shift.
- Per TEMP a minimum of 40 observations is required, thus a TEMP must have worked at least 40 times in order to estimate the desired amount of work.
- All the TEMPs that were working in the last full month of the protime data are excluded, in this case that is April 2019.

- The periods where a TEMP is considered to be on holiday are removed from the data set. A holiday is considered to be a period between 10 and 40 days of not showing up.
- If a TEMP does not show up after 40 days, all of the observations of that TEMP are removed. Since it could happen that a TEMP starts working again after half a year, but this makes is very hard to determine the desired amount of work.

Holiday periods are removed.
The period of time that a TEMP is not working due to a holiday influences the average number of shifts per week for period 1 (base period) and period 2 (review period). Therefore the time that a TEMP has a holiday must be excluded from the data. All the observations that took place after the holiday are moved to the time just after the holiday started. This procedure is made visually in Figure 4.8. The line on top are all the moments a TEMP worked in the year 2017. In the months Mars and July the TEMP took a holiday and all observations after that holiday are moved in front, this results in the most bottom line.

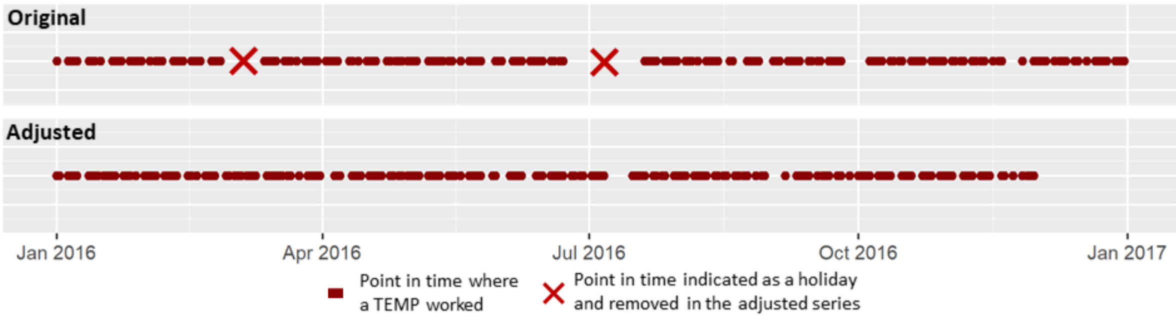


Figure 4.8: The holiday cleaning procedure of a TEMP in order to determine their usual workload

4.2.3 Data analysis

This section elaborates on how to process the data. First, the number of outflows and the number of occurrences per bin are calculated. These are the observations that are used as input to determine a regression model. At last, a sensitivity analysis must determine if the default variables are robust enough.

Determine the outflow rates

To determine the outflow rate when receiving less work, we have to know if a TEMP left when the TEMP received less work and in addition to that, were there moments where a TEMP received less work, but decided to stay. This determines the outflow rate, it provides an answer to the situation when a pool of TEMPs receive less work, what is the estimated rate in which the TEMPs leave.

First a list with bins is made. The bins consist of the differences between the average amount of shifts worked per week between period 1 (base period) and period 2 (review period), in this case the bins start from 2.5% and end at 100% with steps of 2.5%. Per TEMP the difference between the base and review period is determined, which is equal to the overcapacity rate at that moment. The next step is to determine the number of moments where a TEMP had the same or more difference in average shifts per week the TEMP usually does over the whole period of time the TEMP worked at the company. The outflow rate is calculated by dividing the number of outflows that belongs to a certain bin by the number of occurrences that a TEMP experienced the same or more difference of that bin for a period of time. This process is explained in procedure 5.

Algorithm 5 Determine the outflow rate

```
procedure OUTFLOWPROBABILITY
    Load protimeData
    Remove observations if:
        A TEMP worked ≤ 1 hour per shift
    Exclude TEMP from data set if:
        A TEMP worked ≤ 5 hours or ≥ 10 hours on average per shift
        A TEMP worked ≤ 40 shift in total
        The gap between two shifts ≥ 40 days
        A TEMP worked in the last full month of the data set
    bin ← sequence of 0.025 till 1.000 with stepsize 0.025
    for all TEMP ∈ protimeData do
        period_1 ← determine average shifts per week for the base period (period 1)
        period_2 ← determine average shifts per week for review period (period 2)
        binValue ← reviewperiod/baseperiod
    end for
    numberOfOutflow ← sum all outflows per bin
    numberOfPeriods ← Based on the number of shifts worked, determine how many period to review
        of 10 shifts (70 shifts worked in total becomes 6 periods to review).
    for all bin value do
        for all TEMP ∈ protimeData do
            for all numberOfPeriods do                                    ▷ Of each TEMP
                difference ← determine the difference of value of the base period and this period
                if difference ≥ bin value then
                    numberOfOccurence += 1
                end if
            end for
        end for
        Store all numberOfOccurences per bin
    end for
    outflowProbability ← Number of outflows/Number of occurences ∀bins
end procedure
```

Regression analysis

After the outflow rates are determined for a set of values for the review period, a regression analysis is performed. The purpose of the regression analysis is to estimate the relationship between receiving less work and the outflow rate. The steps of this analysis can be found in Figure 4.6. The first step is to delete the observations that were determined with less than 30 occurrences, in order to exclude unreliable observations. The check for correlation indicates only if a regression model can deliver promising results. A high correlation between the variable mean that if one variable increases, the other one increases as well, or if one variables decreases, the other one decreases as well.

A linear and polynomial regression model are fitted on the data, since the data consists of quantitative variables. As mentioned in literature section 3.4, the linear regression model can have one term in case of two variables. Therefore there is only model with a certain set of parameters that maximizes the R-squared. The polynomial regression model can have multiple terms in case of two variables. A high number of terms (X_1^n) results in a model that is likely to overfit the data. Therefore only a second term and a third term are evaluated to maximize the R-squared. A threshold of a p-value less than 1% is applied to the selection of the regression model, since that indicates that the changes of the predictor or predictors of the model are related to the changes in the response variable. Eventually the model with the highest R-squared value is chosen.

Sensitivity analysis

Section 4.2.1 mentioned that the model compares the average shifts worked per week over the last 10 shifts (review period) with the average shifts over the period before those last 10 shifts (base period). Figure 4.6 defines the last 10 shifts as the default value, but the length of period 2 can differ since this value is based on logical reasoning. The outcome of the outflow rate model could differ when the length of period 2 changes from 10 shifts to, for example, 15 shifts. Therefore a sensitivity analysis is needed in order to see those changes and determine the impact of the length of period 2 on the result of the regression model.

Hence, the sensitivity analysis is done by running the outflow rate model for multiple lengths of period 2, followed by a regression analysis. These values are 7, 15 and 20 shifts. The results are plotted in one graph in order to see the differences and to be able to discuss the outcome. All results are listed in chapter 5.2.

4.3 Strategy towards improving the capacity planning of TEMPs

The previous models figure as input for the capacity planning strategy. The outflow rate model estimates how many TEMPs are likely to leave when they are offered less work. This provides knowledge to make a decision about what to do with the capacity of TEMPs, in other words the pool of TEMPs, when the demand changes. In case demand decreases, there is the question if the pool of TEMPs must scale down entirely, a bit or must remain the same. This question can be answered when the estimated number of TEMPs that are leaving due to less work is known.

The outflow rate model provides knowledge about what to do with the capacity planning of TEMPs when demand changes, but this model can only be used if the changes in demand can be predicted with an acceptable accuracy rate. Otherwise, the capacity planning decisions are done too late. The forecast model provides an estimate of the forecast accuracy for the demand of the clients within a sector. The purpose is that based on the accuracy of the forecast model per sector, it is determined if the outflow rate model can be used as input for the capacity planning of TEMPs for that sector. Another purpose is to provide knowledge about which input data of the forecast model is necessary. The forecast model uses time series data and the best time series forecasting methods, as provided in the literature section 3.1.4, are implemented. In case the accuracy of the forecast model is sufficient, than the effort to determine a forecast is kept to a minimum. In case the accuracy of the forecast model is insufficient, more effort may be put in data cleaning or including more variables that are likely to influence demand.

Ultimately, the needed amount of TEMPs can be calculated if three conditions are met. The first condition is that there is an accurate demand forecast, the second condition is that the strategy towards the capacity planning must be clear. The last one is that the productivity rates should be known. As mentioned in section 1.5, the assumption is that the productivity parameters are constant. Currently the capacity planning uses fixed productivity rates per client. The items of every client are different, that means they differ in weight and size so the productivity rates differ per client. In addition to that, the productivity rates also changes when the demand changes due to the economies of scale. Figure C.1 in chapter C supports these statements. The reason why the productivity rate is mentioned, is because it is an important aspect in order to determine how many TEMPs needs to be hired or excluded from the pool. Unfortunately, a research towards a better estimation of the productivity rate given a certain demand rate and external influences is a thesis on it's own. Therefore, within this thesis it is assumed that the productivity rates are known.

As mentioned previously, the outflow rate model estimates how many TEMPs are likely to leave when they are offered less work. This provides knowledge about how the pool of TEMPs must behave when the demand changes. It could be the case that the outflow rate is not the leading variable that determines how the pool of TEMPs should change. Therefore a MILP model as proposed in literature section 3.2.2 could be useful. However, this is formulated as an advice towards the company, since a MILP model is out of scope due to constraints that are applied because of strategical reasons. An example of these strategical reasons are a predetermined ratio between fixed blue collars and TEMPs, further research must provide enough support to see this ratio as a variable that can change over time.

To conclude, there is a high outflow of TEMPs which costs a lot of money. It is likely that an improvement towards the capacity planning can reduce that outflow rate. Two models are proposed in order to develop a set of recommendations that will help to improve the capacity planning. The first model explores the relationship between the size of the pool of TEMPs and likeliness that TEMPs leave the pool. The model provides the capacity planning with advice how the pool of TEMPs should change when demand changes in order to reduce unwanted outflow of TEMPs. The second model looks into the demand forecast and advises how accurate the forecasts can be made using only monthly time series data. The sectors that have acceptable demand forecast are able to use the advice of the outflow rate model. Otherwise, the sectors need a different forecast model that requires different input data or extensive data cleaning.

5 Model results

Two models are made in order to improve the workforce capacity planning of TEMPs. The purpose of this chapter is to present the results of the outflow rate model and the time series forecasting model. The result of the two models together provides an answer how the capacity planning of TEMPs can be improved which results in a lower outflow rate.

First the performance of the forecasting model is presented and the robustness of this model is evaluated followed by the conclusions. Second, the the outflow rate model is presented and a sensitivity analysis provides the confidence that this model is robust enough. An overview of the number of outflows due to receiving less work over previous years, as determined by the model, indicates the economic relevance of the model. Third, a section describes how the capacity planning of TEMPs can be improved, using these two models. The final conclusion and recommendations can be find in respectively section 6.1 and section 6.2.

5.1 Forecasting model

This sections answers research question 3f: *How well does the proposed forecasting model perform?*

The purpose of the forecast model is to obtain reasonably accurate forecasts given a limited input of a user. The forecast model delivers insights about which sectors and operations are suited for the given forecasting techniques and give an advice how the forecasting model can contribute to predict long-term demand under different circumstances.

The data cleaning process could be very time consuming, due to the filtering of unique events. This forecast model did not exclude unique events, only when a unique event results in zero demand. The accuracy of the forecast models for a set of different sectors and warehouse activities are compared to a naive model as the benchmark. The naive forecast consist of an average of the past three observations. Eventually this section summarizes the findings about the extent how these forecasts can be used to improve long-term demand prediction, which contributes to the improvement of the tactical workforce planning of TEMPs.

5.1.1 Input data

The aggregated volumes per month of different warehouse activities per client are used as input for the forecast model. The reason is that using more data results in a better validation of the performance of the forecast, as shown in literature section 3.1.7. The most recent forecasting competition uses up to 100.000 different time series data to validate their models. In this case, that amount is not available. Table 5.1 lists the available different time series data per warehouse activity for two minimum number of observations. As mentioned in literature section 3.1.2 Table 3.1, the minimum amount of required monthly observations is 18 in case of the ARIMA model. Therefore Table 5.1 lists the amount of available different time series in case of the required minimum of 18 and a minimum of 24 observations. The minimum of 24 observations is used to see if a desirable amount of different time series data remains.

The maximum number of different time series data that the forecast can use is equal to 219 sets in case of a minimum of 18 observations per data set. It is preferred to use more observations if that is possible, since a model can extract seasonal patterns better. In case a minimum of 24 observations is used, at least 2 reference values are available given a yearly seasonality. Therefore a minimum of 24 observations

Table 5.1: The number of available time series data per warehouse activity for two minimum amount of observations per data set.

Number of different time series data sets available		
Activity	**Min 18 observations**	**Min 24 observations**
Units received	25	20
Picking units	25	20
Picking orderlines	22	18
Picking pallet	8	6
Inbound trucks	19	14
Outbound trucks	18	15
Shipping units	13	10
Shipping orderlines	31	26
Shipping orders	19	17
Shipping total	29	22
Items returned	10	9
Total	**219**	**177**

is desired. There are 42 different time series less when setting the criteria of the minimum amount of observations per set to 24. This is quite a difference, but the assumption that more observations per data set is better is leading in this case. So further forecasting results are based on time series data with a minimum of 24 observations. To conclude, the forecast model evaluates monthly time series demand data of 177 different clients and warehouse activities, each time series consist of a minimum of 24 observations.

5.1.2 Results

The overall results are listed per sector, per warehouse activity and per method. The results are benchmarked with a naive forecast model, since no actual forecast values for those 177 time series data exists. The naive forecast model uses the mean value of the last three observations as forecast.

The error measure that is used to evaluate the performance of both models is the MAPE *(Mean Absolute Percentage Error).* This measure is easy to interpret and therefore good to use from a company perspective. There are some situations where the MAPE is not a good measure. The MAPE cannot be calculated when demand is zero. If the forecast is considerable higher than the actual value, the MAPE value will be bigger than one. To overcome this last issue, a selection of forecast models with a reasonable MASE value is chosen. From that list, the forecast with the lowest MAPE is selected. If that MAPE is higher than one, that forecast will be penalized since it will unnecessary effects the overall performance. A check is included in the forecast model to discard any time series with zero demand, but this should not be necessary since it is expected that there is always demand within a warehouse for the given activities.

Forecast performance per sector

There are four sectors in which the clients of CEVA Benelux are categorized. Figure 5.1 shows the result of the forecasting model per sector for a forecasting horizon of three months. Overall, the forecast model performs better than the naive forecast. An summary of the findings of the figure is given below.

- The MAPE values of the forecast model with a forecasting horizon of three months ranges between 14% and 19%.
- The MAPE values of the naive forecast with a forecasting horizon of three month ranges between 18% and 25%.
- The model has more difficulties to predict demand for the industrial sector, since the accuracy of the naive forecast corresponds with the ones of the retail and technology sector.
- The model has the same performance for the healthcare, retail and technology sector, but the healthcare sector does not show the same rate of improvement compared the retail and technology sectors.
- Based on improvement, the model shows the best result for the retail and technology sector.
- Based on MAPE, the model has a low MAPE for the healthcare, retail and technology sectors.

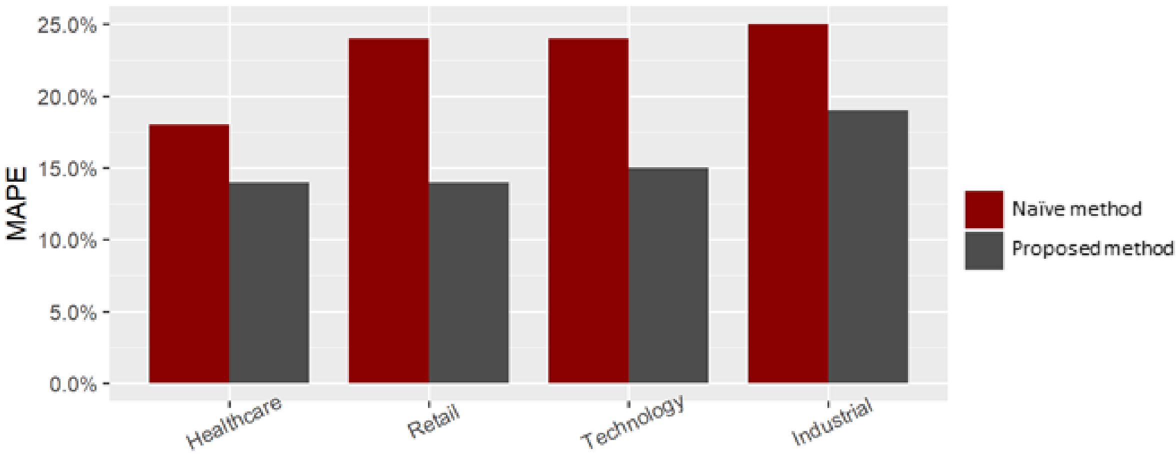


Figure 5.1: The result of the forecast model per sector.

Forecast performance per warehouse activity
As mentioned before, it may be useful to evaluate the performance of the forecast on the individual warehouse activities. It can be a very valuable insight if it appears that certain warehouse activities are good to predict by the model so the amount of labor needed could be predicted with a relative high accuracy according to the need of that activity. In case it appears that it is very difficult to forecast a certain activity, the recommendation should be that this specific activity should receive more attention.

The forecast performance per activity is listed in Figure 5.2. Overall, the model performs better than the naive forecast. An summary of the findings of the figure is given below.

- The MAPE values of the forecast model with a forecasting horizon of three months ranges between 9% and 25%.
- The MAPE values of the naive forecast with a forecasting horizon of three month ranges between 12% and 33%.
- The model performs better when predicting aggregated demand such as orders, orderlines and pallets. Individual demand, such as single units seems harder to predict.
- The demand of outbound trucks can be predicted with the highest accuracy, but this is quite obvious since an outbound truck consists of aggregated demand and often an outbound truck has fixed pick-up times, even if the truck is fully loaded or not.
- The demand of inbound trucks can not be predicted with a high accuracy. An explanation for this, could be that the replenishment of the warehouses for an upcoming season have no fixed month. So for example a fashion retailer can ship it's cloths from Asia to Europe during July and November to prepare for the upcoming winter season.
- The intensity of returned items are hard to predict. But the MAPE of the naive forecast is also high, therefore the stream of returned items must fluctuate a lot without a certain pattern.
- Based on improvement, the shipped units and items returned show the biggest improvement (around 10%) between the model and the naive forecast.
- Based on improvement, the number of outbound trucks and shipping total show the smallest improvement (around 2%) between the model and the naive forecast.

The activities where the forecast model performs good, depends on a low MAPE (lower than 15%) and a significant improvement compared with the naive forecast (improvement bigger than 5%). The activities that score good on both criteria are listed below:

- Shipping orderlines
- Picking orderlines
- Picking pallets

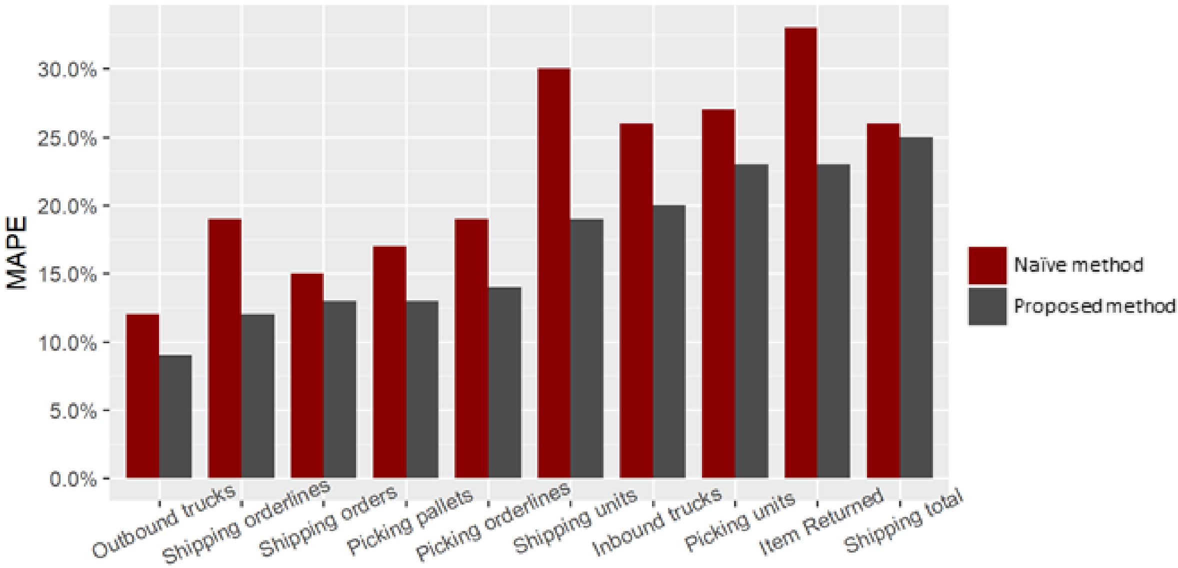


Figure 5.2: The result of the forecast model per warehouse activity.

The activities where the forecast model improve the benchmark method significantly (more than 10%), but does not have a low MAPE value are:

- Shipping units
- Items returned

The activities where the forecast model cannot improve the benchmark method significantly (less than 3%) are listed below. The number outbound trucks do not fluctuate a lot since there are agreements about the frequency a truck leaves a warehouse, fully loaded or partial full loaded. That is the reasons forecast model cannot improve the benchmark a lot. The number of total units shipped does fluctuate a lot over time, without a distinct demand pattern. Over here, more aggregated demand should be used as input for the forecast model.

- Outbound trucks
- Shipping orders
- Shipping total

Forecast performance per method
The forecast model evaluates different settings for all of the 14 different forecast methods and combination of forecast methods. A group of good performing methods are chosen by having a low MASE value and the best method is selected to have the lowest MAPE value of that set of methods per time series data. In order to know which method or combination of methods are performing good given the 177 different times series data sets, Figure 5.3 is made.

According to Figure 5.3, the Theta models selected quite often and the addition of the Extra-P parameter seems to be working in most cases. Altogether, both methods are used for around 30% of all the time series data sets. Below, more insights are about the frequency of best selected methods are given:

- The abbreviations of the methods are as follow: ETS = E, ARIMA = A, Theta = T.
- All the methods are selected at least once, that indicates that the behaviour of the time series data is quite diverse.
- The literature section suggested that a combination of methods can outperform single methods. Based on this figure, it cannot be concluded that this occurs for this data set, since the MAPE values are missing. But the single methods are selected more often (70%) than a combination of methods (30%).
- The ExtrP model seems to be a good addition, since it is selected 96 out of the 177 times (55%).
- The combe method (ETS, ARIMA, Theta and ExtrP) is selected for only 3%, so it is likely that this method works only for a specific situations.

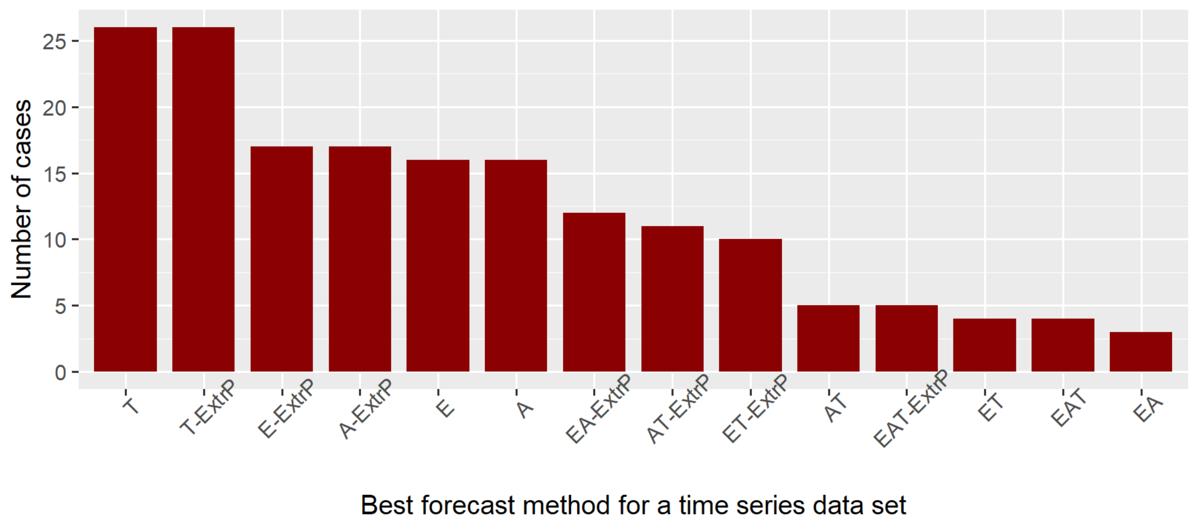


Figure 5.3: The amount of time a forecast method was the best of all the methods used in the forecast model in case a forecast horizon of 3 months is used.

5.1.3 Robustness analysis

The previous section described the performance of the forecast model. One way to guaranty the accuracy of the model is by using lots of time series data. Other methods to ensure the accuracy of the model given different situations are performing an analysis to overfitting and sensitivity. First the addition of the ExtrP forecast method is evaluated, then the results of the sensitivity and overfitting analysis are shown.

Evaluation of ExtrP method

The ExtrP method, the Extra Parameter, is a method to cope with a specific demand pattern that occurs for some clients of the company. This pattern can be recognized by a slowly increase of demand for four or five of months, when suddenly the demand drops within one or two months. The ExtrP method adds a multiplicative factor that decreases the forecast more heavier when the forecast identifies that the forecast goes down.

Figure 5.4 evaluates the effectiveness of the ExtrP method, by comparing the performance of the original method and the performance of the original method combined with the ExtrP method. The evaluation is done by using the 177 time series data as input, but not every time series data is used. A small difference between two forecasts with a high error rate has less impact than a small difference between two forecasts with a low error rate. Therefore, only the methods that produce a forecast with a reasonable error rate are included.

The result is that in three out of the seven methods, the ExtrP method is a useful addition. It seems that the ExtrP method does not work with the methods where multiple forecasting models are combined. To conclude, the ExtrP method does improve the performance of the ETS, ARIMA and Theta models. Although a large set of data is used and the method does result in a lower forecast error, there is no proof that overfitting of the data does not occur.

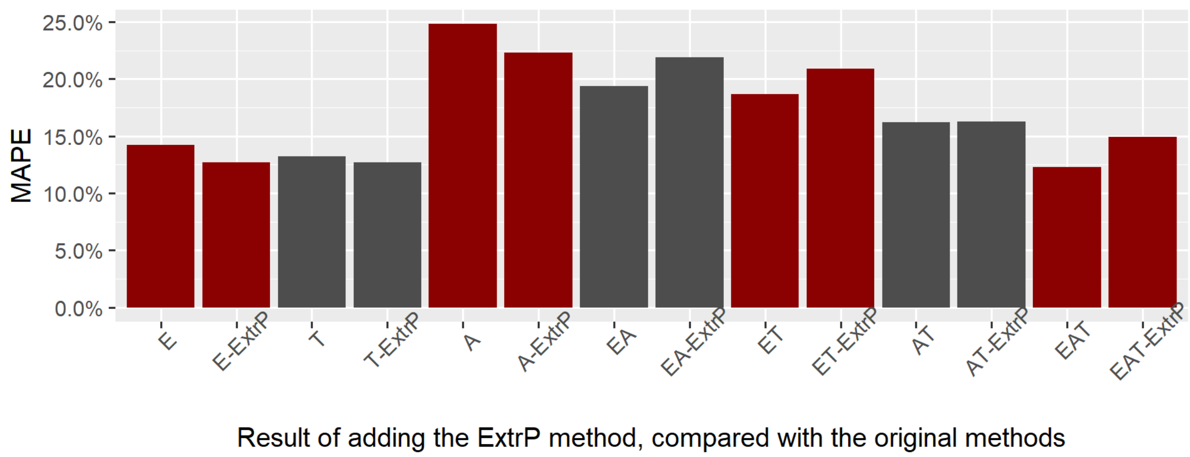


Figure 5.4: An evaluation of the effectiveness of the ExtrP method compared with the original forecast method.

Overfitting analysis by rolling origin

A good forecast model is supposed to learn from historical data and extract repetitive behaviour of demand in order to say something useful of future demand. A forecast model can extract repetitive behaviour in a simple way, such that estimations of future demand are quite general. This is underfitting and results in a high forecast error. The other way around is that a forecast model captures every repetitive behaviour of historical demand, this includes random errors as well and results in a too complex model. The difference with overfitting and underfitting is that the problem of underfitting is solved by the model since that results in a high error rate, but overfitting is hard to notice. An overfitted forecast model may result in a low error rate, but the model is not robust enough for future changes in the training data. Therefore it is important to focus on potentially overfitted forecast models in order to ensure that the forecast method is robust enough.

The rolling origin is applied by using a forecast horizon of three months as the base forecast. Every step of the rolling origin decreases the training set length with one month, but the test data set continues to consists of three months. There is an indication of overfitting if it occurs that the forecast error rapidly increases when the step value of the rolling origin changes. The forecast method has a different performance when small changes are applied to the training data, therefore the forecast is initially too good fitted or adjusted to the training data.

The rolling origin cross-validation method is applied to every forecast of the 177 different time series data. The results are averaged per forecast method to indicate which methods are prone to overfitting, these can be find in Figure 5.5. The headers *"overfitting occurs"* and *"extreme overfitting occurs"* include the methods that are likely to overfit the data. The headers *"a bit of overfitting occurs"* and *"robust forecast methods"* include the methods that have little to no motives to overfit the data. This can be identified as method who have a steady performance, so no fluctuating errors, for different forecast origins. All methods that may have overfitted the training data and who are likely to not have overfitted the data are listed in Table 5.2. A total of 50 out of 177 different time series data use one of these methods. It must be mentioned that the methods that show signs of overfitting are selected on a subjective base. That means the methods without a steady performance are marked as overfitted.

To conclude, forecasting with a rolling origin is a method to check if a forecasting method overfits the training data. This is the only method to cross-validate time series data. For all forecasting methods that came up as best method for the 177 different time series data, a forecast using a rolling origin of five steps is applied. The result is that 47 out of the 177 time series data are likely to overfit the training data. In addition to that, 4 out of the 7 methods where the ExtrP variable is included overfit the data. This does not mean that the ExtrP variable is not good to use, since there are methods where the variable does work. Extra caution is needed, since the ExtrP method may lower a forecast error, but often overfitting occurs.

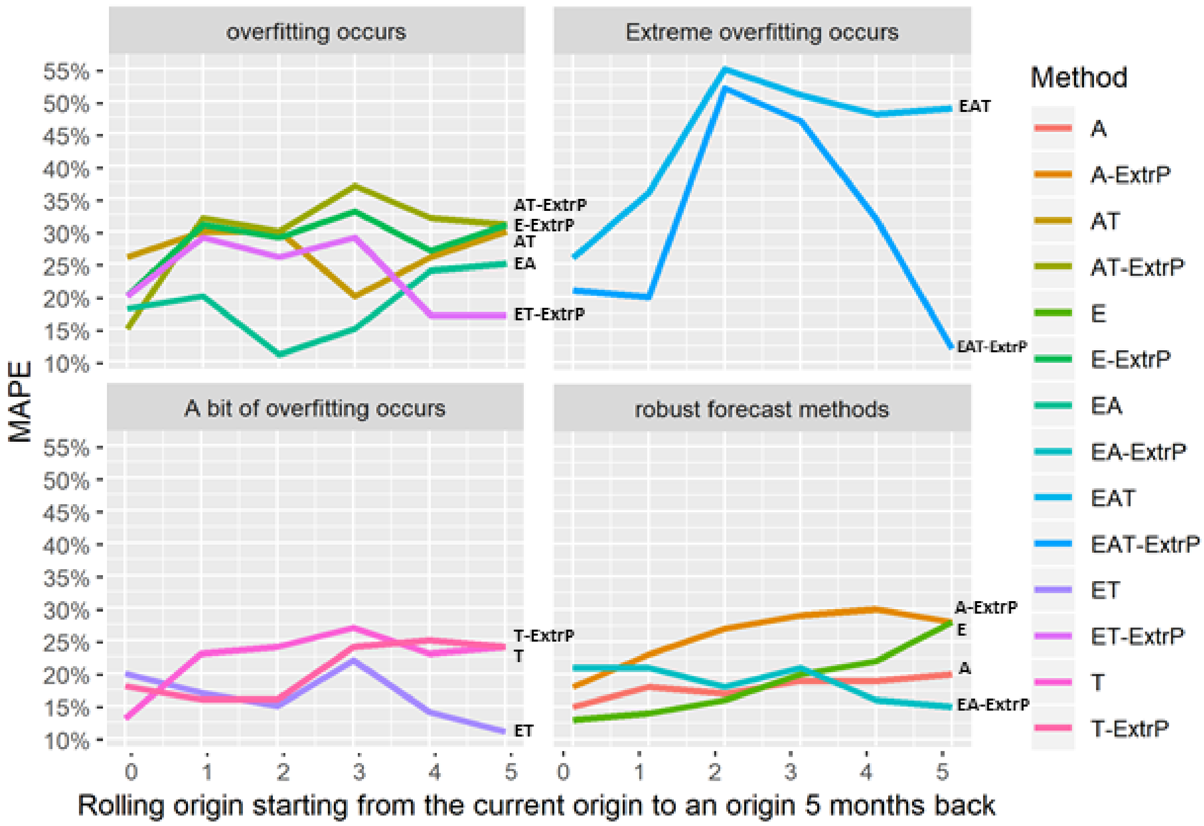


Figure 5.5: An analysis which of the forecasting methods are prone to overfitting, a forecast horizon of three months is applied.

Sensitivity analysis by multiple forecast horizons

As mentioned in section 4.1.3, it's logical to assume that the forecast error increase when the forecast horizon increases since the amount of uncertainty rises. A forecast is sensitive to different forecast horizons if that increase is not linear. In other words, a forecast is sensitive if there is a large variation between the error rate of multiple forecast horizons.

In order to test the forecast method if they are sensitive to multiple forecast horizon, Figure 5.6 is made. Over there the best forecast methods for the 177 different time series data are selected, initially they had to compose a forecast with a horizon of three months. This figure includes the same method on the same data set, but for a forecast horizon ranging from 1 month to six months. The methods are categorized in four groups:

- Not sensitive, the forecast errors increase linearly with the forecast horizon.
- Not sensitive, the forecast errors have a constant value over the forecast horizons.
- Sensitive, since large variations of an increase or decrease occurs.
- Sensitive, since small variations of an increase or decrease occurs.

The result is that 7 of the 14 methods are not likely to be sensitive to multiple forecast horizons. There are two methods that show a very large variation in forecast errors like the EAT-ExtrP and EAT. When a one month ahead forecast is performed, the method show an average error of 10%. When that method has to forecast six months ahead, the average forecast error is equal to 50%. The one month ahead forecast could be acceptable, but the rapid increase of errors when the horizon increases is less acceptable. Other sensitive methods are ET-ExtrP, E-ExtrP, A-ExtrP, E and AT. Over there the errors increase and decrease, so if the horizon increases the errors may decrease like the case of the ET-ExtrP method. This is not desirable, since it seems like the forecast depends too much on the test data set.

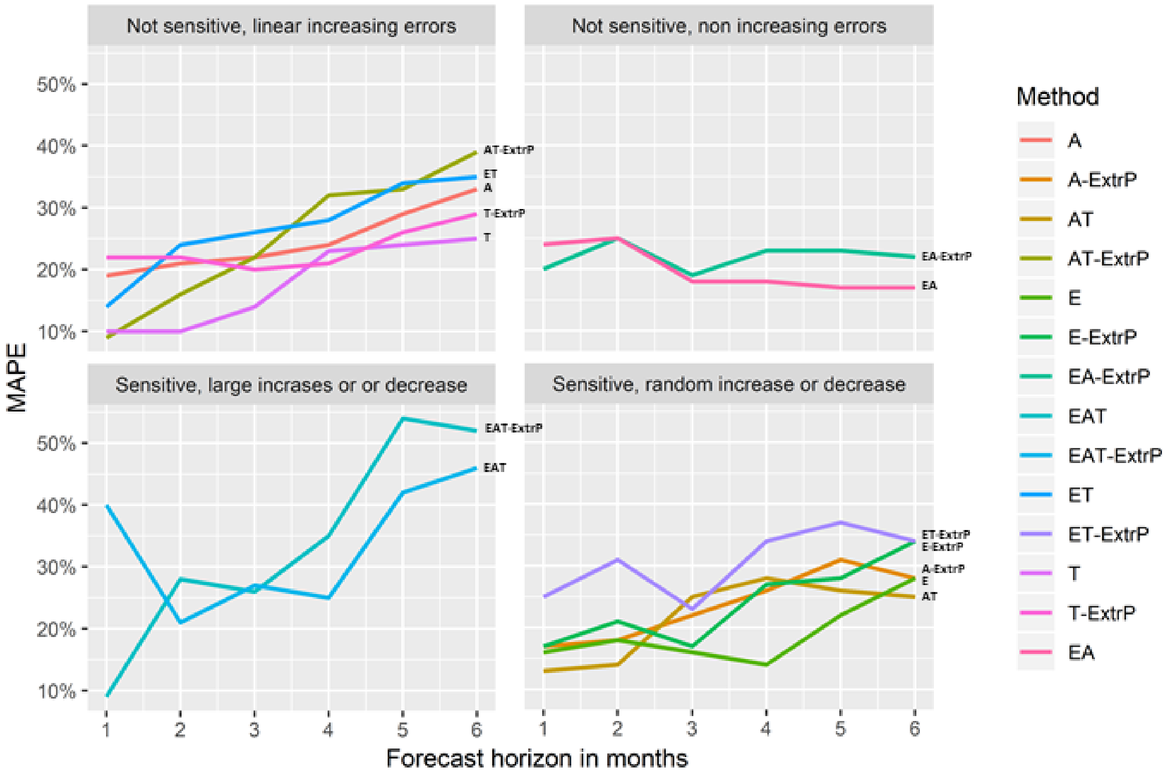


Figure 5.6: A sensitivity analysis of the forecast methods by multiple forecast horizons.

To conclude, a forecast can be evaluated by the average error rate but it is important that the errors rates increase with a constant value when the forecast horizon increases. Otherwise, the result of a forecast depends too much on a certain set of test data. An overview is listed, after the next section, which summarizes the methods that are likely to be or not be robust.

Forecast performance after robustness analysis

Some forecast methods have a good performance for a certain set of data and a certain forecast horizon. It may happen that the performance of the forecast method fluctuates when the forecast horizon or the data set slightly changes. In this case, using this forecast method is not appreciated. The previous sections identified which methods are likely to overfit the data and which methods are highly sensitive to multiple forecast horizons. Table 5.2 summarizes the results of the test on overfitting (section 5.1.3) and the sensitivity test on multiple forecast horizons (section 5.1.3).

A total of 5 of the 14 forecast methods are robust enough to use. This means that 88 out of the 177 forecasts were run with forecast methods that were not robust enough. Therefore, these forecasts are run for a second time with only the robust forecast methods. It is expected that the forecast error increases, since the first time only the method with the lowest error was chosen. The question is, to what extent does the forecasting error increase when only the robust forecasting models can be chosen. If the forecast error increased a lot over initial situation and the robust methods, than the either the time series data is hard to predict or the methods are still not good enough. Per activity the average increase of the forecast error is equal to 4%, so that might not be that much.

Table 5.2: The result of the robustness analysis of the forecast methods.

Method	Method performance		Method robustness	
	Times used	MAPE	Sensitivity	Overfit
A	16	25%	✓	✓
T	26	13%	✓	✓
T-ExtrP	26	12%	✓	✓
ET	4	21%	✓	✓
EA-ExtrP	12	22%	✓	✓
EA	3	19%	✓	×
AT-ExtrP	11	16%	✓	×
A-ExtrP	17	23%	×	✓
E	16	14%	×	✓
E-ExtrP	17	12%	×	×
ET-ExtrP	10	21%	×	×
AT	5	16%	×	×
EAT	4	12%	×	×
EAT-ExtrP	5	15%	×	×

The result per sector does change a lot, since the purpose is to predict the demand at a warehouse in order to estimate the needed amount of workforce. Therefore, only the activities that are good to predict are included in the demand forecast per client. The result of the expected forecasting error per activity is given in Figure 5.7. The activities with a relative low forecasting error are listed below. These activities have the ability to contribute to a good estimation of needed workforce if they are used as input for the forecasting model.

- Picking orderlines
- Picking pallets
- Shipping orderlines
- Shipping orders

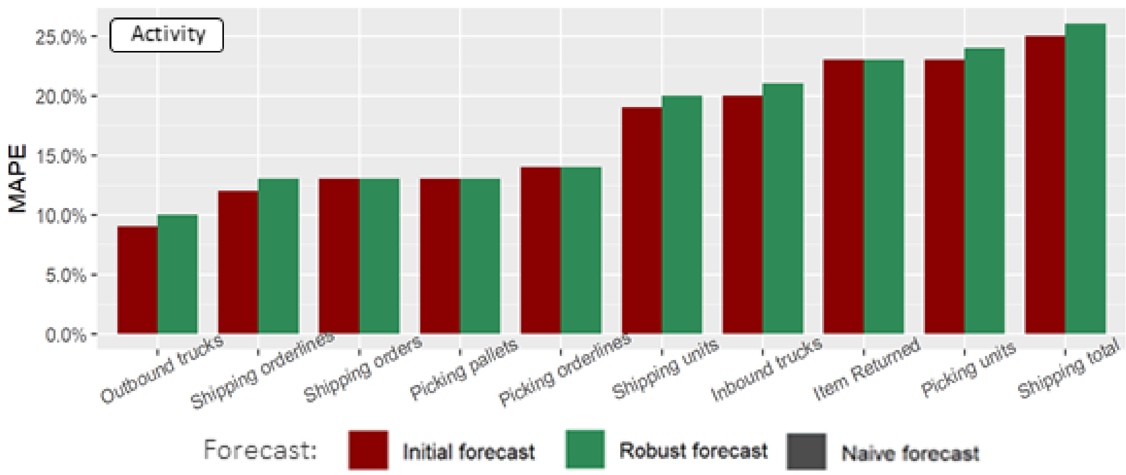


Figure 5.7: The result of the forecast model (3 months ahead) when only the robust methods are included for all activities.

The forecast per sector is made using only time series data of the activities as described above and only with the five robust methods. The result can be found in Figure 5.8. The result is that the ratio between the times that the methods were used as best forecast changed.

The initial forecast showed that the most used methods were the Theta and Theta-ExtrP. Still the Theta method remains the most used method, but after that the ARIMA method is the second most used method. The reason for that is the MASE criteria, this creates a set of feasible forecast methods based on the method with the lowest MASE. Since some methods are excluded from these forecasts, a new set of feasible forecasts is created. Therefore another method may have a lower MAPE, which is the case for the ARIMA method.

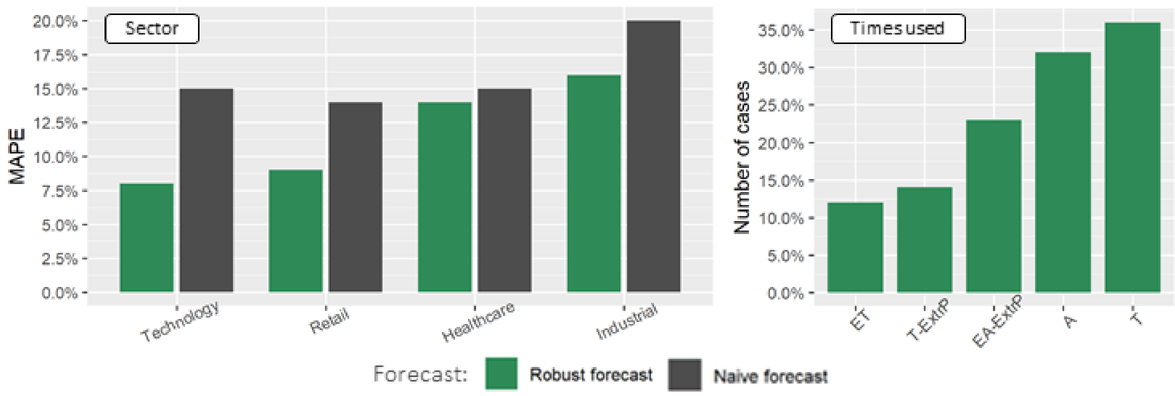


Figure 5.8: The result of the forecast model (3 months ahead) with only robust forecast methods and 4 realistic activities included.

5.1.4 Conclusion of the forecast model

The purpose of the forecast model is to obtain reasonably accurate forecasts given a limited input of a user. The model delivers insights about how accurate the sectors and warehouse operations can be predicted, in addition to that various forecasting methods and an improvement for those methods are evaluated. The accuracy of these methods are compared to a benchmark method, this naive forecast consist of an average of the past three observations.

The input of the model is chosen based on a trade-off between a minimum of 24 observations and a minimum of 18 observations as proposed by Hyndman et al. [2]. A minimum of 24 observations, 2 years of data, is preferred if enough time series data remain left. Since this is the case, 177 monthly time series data sets from different clients and warehouses with a minimum length of 24 observations are selected.

Three forecasting methods are selected based on their performance at two international forecasting competitions. Over there, around 248 forecasting methods are evaluated based on the average performance on 100.000 time series data. Surprisingly, the outcome of the competitions is that the statistical forecasting methods perform better than the machine learning forecasting methods. It is likely that forecasting without using external variables such as weather conditions, product promotions, region and economic development does not use the full potential of a machine learning model. In addition to that, when performing a forecast on time series data, the last observations are always the most important one. A machine learning model does not add more value to the last couple of observations as a statistical forecast model does. So in case of a response variable with multiple predictors, a machine learning model can be the best way to predict demand. In case of time series data, a statistical forecasting methods can be the best way to predict demand.

The selected statistical forecasting methods are ETS, ARIMA and Theta. In addition to these single methods, a combination of these methods (the Comb forecast method) should also generate good forecasts. Furthermore, an own method (ExtrP) is proposed that should help to improve the forecast accuracy in a situation where demand decreases rapidly, this occurs at some clients at the end of a season. In general, a forecast method smooths out rapid changes of demand. The ExtrP method removes this smoothing element only when a forecast generated by the ETS, ARIMA or Theta indicated that demand decreases. The ExtrP method is a multiplicative parameter that must be used together with a single forecast of the ETS, ARIMA or Theta methods or with a combination of those methods.

The results of the model are focused on a three months ahead forecast. First the robustness of the methods is evaluated, this includes a test on overfitting and a sensitivity test to multiple lengths of the forecast horizon. A rolling origin, ranging between the current origin to 5 months back, is applied as test on overfitting. A forecast method is overfitted when the errors fluctuate when less training data is used. Figure 5.5 indicates that seven out of the fourteen forecast methods are likely to overfit the data. Regarding the sensitivity test, the same training data is used for multiple test sets. It is expected that the errors of not sensitive methods increases when the test set expands in length, but does not fluctuate. Figure 5.6 identified that seven out of the fourteen forecasts methods are likely to be sensitive. The final result is that five of the fourteen methods are robust enough to use, their results are listed in Figure 5.8. A summation with brief conclusions is given below per topic.

Warehouse activity

- The activities where demand is aggregated can be better predicted.
- The activities with the lowest error thus are best suited to forecast on are:
  - Picking orderlines
  - Picking pallets
  - Shipping orderlines
  - Shipping orders
  - Outbound trucks
- Range of activities with low errors ranges between 10% and 14%
- Range of activities with high errors ranges between 21% and 23%.
- The activities outbound trucks and returned items have one of the highest error rates. This is not really a problem for the outbound trucks since a site knows that much better in a couple of weeks in advance and this activity does not tell much about the needed workforce. The returned item can be better predicted on a less aggregated level.

Sector

- The forecast error with an forecast horizon of three months ranges between 8% and 16%.
- The forecast error with a one month ahead horizon ranges between 6% and 16%, as indicated in Table B.1.
- The technology (8%) and retail (9%) sectors are the best predictable sectors, it is likely that the are good to predict since they have a clear seasonality. A high demand season for the technology sector occurs around the end of the year and the high demand seasons of the retail sector move along with the winter and summer clothing seasons.
- The clients within the healthcare and industrial sector have a forecast error of respectively 14% and 16%.
- The forecast model improves the result of the naive forecast the most at the retail and technology sector.

Method

- The most used forecasting methods are Theta *(35%)* and ARIMA *(25%)*
- A total of five methods came out to be robust enough to use for this dataset: Theta, ARIMA, Theta-ExtrP, ETS-Theta and ETS-ARIMA-ExtrP
- As mentioned in the literature, it is useful to combine different methods into a forecast since the Theta-ExtrP, ETS-Theta and ETS-ARIMA-ExtrP outformed the single method forecasts together in 38% of the times.
- Even dough, the Comb method (ETS-ARIMA-Theta) performed well in the forecasting competition. Tough, the Comb method was not selected very often as best method and did not succeed the test on overfitting and sensitivity to multiple forecast horizons. So to conclude, in general the Comb method may perform well, but when multiple methods are used as benchmark, it is the case that one of those single methods outperform the Comb method. Only in case a forecasting model wants to include one method, the Comb method might an option.
- The addition of the ExtrP method is rewarding since it improved the result of the Theta model 25% of the time. However, the ExtrP variable in combination with 5 of the 7 other methods results in a model that overfits the data and is too sensitive for multiple forecast horizons.

5.2 Outflow rate model

This sections answers research question 2f: *If the relation between the size of the pool of TEMPs and the outflow rate is known, how much could potentially be saved in the past when anticipating on this relationship?*

There is a high rate in which TEMPs leave the company. One of the causes could be that TEMPs leave due to receiving less work than desired. Surveys that were held during the outbound process do not provide the support of a certain assumption about the chance of leaving due to receiving less work than expected. By analyzing data about the behaviour of TEMPs, it is expected that some relation can be found between offering less hours and the outflow rate. The steps towards this analysis are written in chapter 4.2 in which also the psuedo-code (5) is given, in this part the results are listed. The first thing to present are the settings of the model, followed by the raw outcomes of the model. Next, the results are analyzed and the way to interpret these results is given. Furthermore a section is dedicated to sensitivity analysis and a validation of the results. Finally the impact of the outflow rate is determined for existing operations in terms of how many TEMPs left due to receiving less work than wanted. The amount of money that is lost due to this outflow rate is determine in section 5.2.6, over there the possible savings are determines when the resource planning is improved.

5.2.1 Input data

The data that is used as input for the model consists of all the TEMPs that worked at the Dutch warehouses of the company. This includes also the TEMPs that worked at different sites than mentioned in chapter 2. These different sites are relatively small, but the trustworthiness of this analysis increases when more TEMPs are used as observations. The behavior of 12.273 TEMPs in total are analyzed over a period between the year 2015 and 2019. As mentioned at the description of the model in chapter 4.2, the outflow rate of a TEMP can only be analyzed when that TEMP worked for more than 20 shifts at the company. Otherwise it is unclear how many hours a TEMP usually work and how many hours a TEMP did work during the period right before leaving the company. The pool of TEMPs is reduced from 12.273 TEMPs to 7.491 TEMPs, but part of this group is still active during the time of the analysis. In order to determine the behaviour of a TEMP during their last couple of shifts, a TEMPs cannot be active anymore. When applying this filter to the TEMPs, a pool of 6.286 TEMPs is left to analyze.

5.2.2 Initial results

The model evaluated the outflow behaviour of 6.286 TEMPs. Bins that contain the percentage less worked with a step size of 5% are made. The bins indicate how much a TEMP worked less, or in other words how overcapacity is present. What the model does is for every TEMP looking at the average amount of shifts worked per week for the base period (period 1) and for the review period (period 2). If a TEMP worked on average less shifts per week in the review period compared with the base period, that TEMP is flagged. That difference is used to look trough the whole period that the flagged TEMPs worked at a site, if it occurs that within a period of 10 shifts a flagged temp worked less or equal then that difference, it is marked as an occurrence. Per bin the number of occurrences and the number of outflows are listed. The likeliness of outflow per bin is calculated by dividing the number of outflows by the number of occurrences. The total run time of the model is approximately 9.5 hours on a normal laptop, the result can be seen in Table 5.3.

A first glance at the initial results show an increasing likeliness of outflow when the a TEMP receives less work, so if the bin value increases the outflow rate increases as well. The result of Table 5.3 cannot be used as a final answer to the outflow rate. The result of the model must be analyzed in such a way that the expected outflow rate is determined. Therefore the next section will perform some analysis to convert observations to expectations.

Table 5.3: The likeliness of a TEMP leaving the organisation given a certain percentage of less work.

Less worked than usual *(%)*	**Number of occurrences**	**Number of outflows**	**Probability of outflow**
2.5-5 %	683	98	14%
5-7.5 %	1361	87	6%
7.5-10 %	744	99	13%
10-12.5 %	1291	91	7%
12.5-15 %	778	124	16%
15-17.5 %	1283	284	22%
17.5-20 %	801	125	16%
20-22.5 %	1161	216	19%
22.5-25 %	761	209	27%
25-27.5 %	858	385	45%
27.5-30 %	826	397	48%
30-32.5 %	443	212	48%
32.5-35 %	531	213	40%
35-37.5 %	237	120	51%
37.5-40 %	234	89	38%
40-42.5 %	243	60	25%
42.5-45 %	163	68	42%
45-47.5 %	70	60	86%
47.5-50 %	64	43	67%
50-52.5 %	41	9	22%
52.5-55 %	22	17	77%
55-57.5 %	28	3	11%
57.5-60 %	7	3	43%

5.2.3 Analysis of the results

As mentioned before, the number of occurrences and the number of outflows of Table 5.3 are observations. In order to use the estimated outflow rate in practice, these observations must be converted to expectations. In other words, the results must be generalized that fits in a model. That model can be used in practice in order to know the expected number of TEMPs that leave the organisation when they receive less work than desired. The section below explains the steps needed to determine that model.

Visualization of the results
First, it is useful to have a visual overview of the results. As mentioned before Table 5.3 indicates that the likeliness of outflow increases when a TEMP receives less work. Is this the case in every situation, are there any outliers or is that increase of likeliness linear or exponential? These questions may rise and more insights can be generated by Figure 5.9.

Regression model
Figure 5.9 shows that there is some indication for a relation between the outflow rate and the difference in receiving less work. If a regression model must be applied to this set of data, only a linear regression or polynomial regression are applicable (as mentioned in chapter 3.4). There is one independent variable (percentage of less shifts worked per week than usual) and one dependent variable (the outflow rate), in addition to that the variables are continuous. Therefore logistic regression cannot be used.

In order to answer the question, *"is it true that if the percentage of less shifts worked increases, the outflow rate also increases"*, the correlation between the two variables must be calculated.

$$corr(y, x) = corr(outflow_{rate}, difference) = 43\%$$

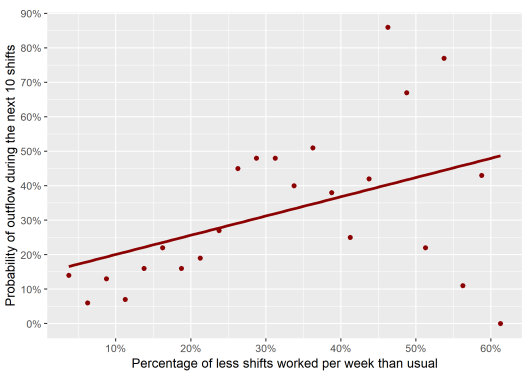
A correlation of only 43% means that four out of ten times the percentage of receiving less shifts increases, the outflow rate increases as well. This is rather low so a linear regression or polynomial regression model will not perform that good. There are two terms that indicate the performance of a regression model, the p-value and the R-squared value.

Figure 5.9: The initial result of the outflow rate of Table 5.3. *Run time = 7 hours*

The p-value can be interpreted as the value that indicates how well the changes of the independent variable are related to the changes of the dependent variable. A low p-value means that the dependent variable is a good addition for the model. The definition of the R-squared value is given by the percentage of the variation of the dependent variable that is explained by the regression model. A high R-squared value indicates that the variability of the dependent variable is well explained by the regression model. The results are listed in Table 5.4. A plot of these results can be find in Figure 5.10, the linear regression model is displayed on the left and the polynomial regression model is displayed on the right.

Table 5.4: The result of two regression models to determine the outflow rate.

Model	P-value	R-squared
Linear regression $(y = c_0 + c_1 * x)$	$x : 0.034$	0.151
Polynomial regression $(y = c_0 + c_1 * x + c_2 * x^2)$	$x : 0.019$ $x^2 : 0.014$	0.338



(a) Linear regression model

(b) Polynomial regression model

Figure 5.10: Two regression model to determine the outflow rate

As indicated by the correlation of only 43%, the results were not expected to be good. Therefore it is interesting to find ways to improve the models. In addition to that, currently the support of both models is quite low. That means that there are some values for the independent variable with only a few observations. The support can increase if those observations are left out. More about this process is explained in the next section.

Improvement of regression model

As mentioned in literature section 3.4, a good regression model deals with the trade-off between underfitting and overfitting. The polynomial regression model is included to overcome the tendency of a linear regression model to underfit the data. A drawback of a polynomial regression model is the possibility of overfitting the data, but the proposed polynomial model includes only up to a second degree polynomial. If a higher number degree polynomial was proposed, the likelihood of overfitting the data increases. Since Figure 5.10(b) does not show aspects that the data is overfitted and only up to a second degree polynomial is used, there is no need to implement models like ridge or lasso regression.

There are certain values of the input data that have a few observations. For example in Table 5.3 bin 50-52.2% has 9 number of TEMPs that left because of less work. The confidence that the corresponding outflow rate is a reliable value is low, due to the lack of observations. There is no rule of thumb to leave out data with a limited number of observations, therefore the only criteria is that the decision must be based on logical intuition. Table 5.3, column "number of outflows", provides the number of observations. The bins with less than 30 observations per bin are excluded since that is less than 1% of all the observations. The assumption is that the input data for the regression models is more reliable. Again the correlation value is calculated to know if the exclusion of observations has the potential to improve the regression model.

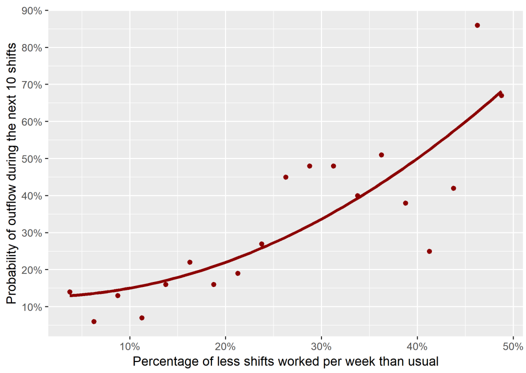
$$corr(y, x) = corr(outflow_{rate}, difference) = 83\%$$

The higher correlation indicates that 8 out of 10 times the percentage less shifts increases, the likeliness of outflow increases as well. This suggests that the linear and polynomial regression models can be improved in terms of p-value and R-squared value. The results are listed in Table 5.5 and Figure 5.11.

Table 5.5: The result of the improved regression models to determine the outflow rate.

Improved model	P-value	R-squared
Linear regression $(y = c_0 + c_1 * x)$	x : 6.67e-05	0.64
Polynomial regression $(y = c_0 + c_1 * x + c_2 * x^2)$	x : 1.14e-04 x^2 : 0.95	0.64

(a) Improved linear regression model



(b) Improved polynomial regression model

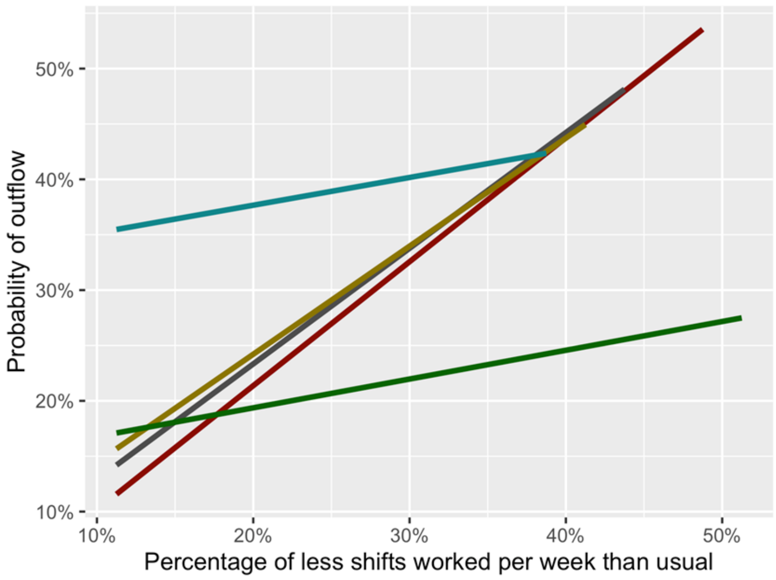
Figure 5.11: Two regression model to determine the outflow rate

Both the p-value and the R-squared values improved, except for the second term of the polynomial model. This means that the second term of the polynomial model is not a good addition, since a high p-value indicates that there is a high probability that there is no difference between the outflow rate variable and the second term if the less shifts worked per week variable. Thus, the polynomial regression model does not meet the conditions to be statically significant. The conclusion is that the linear regression model is a good generalization of the observations between the percentage less worked than usual and the outflow rate of TEMPs. From this point, all the calculations and examples are shown with the linear regression model.

5.2.4 Sensitivity analysis

As mentioned in section 4.2.3, there can be multiple lengths of the review period (period 2) in which TEMPs leave. In the case of section 5.2.3, a fixed number of 10 shifts is used as input for the model. So, a sensitivity analysis shows how and if the outflow rate model changes in case of different lengths of review period.

In theory, if the length of period 2 increases, a TEMP works less for a longer period of time. This increases the confidence that every outflow of a TEMP due to less work increases corresponds with an outflow due to less work identified by the model. The downside is that more TEMPs are excluded from the data, since the length of employment increases. The model has less observations to use. The other way around, if the length of period 2 decreases, more observations are available but the likeliness that it is just coincidence that a TEMP worked less and then leaves increases.



Length p2	p-value	R-Squared
8	0.28	0.09
10	0.00	0.54
12	0.03	0.35
14	0.01	0.45
16	0.72	-0.08

Figure 5.12: The linear regression models of the outflow rate given a set of different lengths for period 2, in addition to that the R-squared values and p-values are given. *(Run time = 35 hours)*

So the desirable length of period 2 comes down to a trade-off between the number of available observations and period 2 that is as long as possible. Therefore the outflow rate model is run for 5 different lengths which are 8,10,12,14,16. The sensitivity analysis shows to what extent this variable influences the outflow rate. This result can be found in Figure 4.2.3.

For each of the different lengths of period 2, a regression model is made. It looks like that this variable does influence the outflow rate, since the values 8,16 differ from 10,12,14. Furthermore on the right of figure 5.12, the p-values are listed. A p-value higher than 0.05 indicates that a variable has no meaning full addition to the model. Therefore only the values 10,12,14 are suited to use as input for the model. As mentioned at the beginning of the previous paragraph, if the length of period 2 increases, the less observations are left. The number of TEMPs that is used to analyse the outflow rate is 2900 in case length of p2 is 10 and 2700 in case length of p2 16. The difference of 200 TEMPs is equal to 7%, which is acceptable since it is only a small percentage of the total amount of observations. Altogether, the choice to set the length of period 2 to 10 shifts is a good one since it has the highest R-squared value.

To conclude, a sensitivity analysis is performed for various lengths of period 2. The purpose is to check if the model is robust enough for different values of the variable. This period 2 consists of the last certain number of shifts a TEMP worked before the last shift. If it occurs that the model gives a very different result per small increase or decrease of the value of period 2, than the model may not be reliable enough to use. The result of the sensitivity analysis is that the number of shifts in period 2 can change from 10 to 14 shifts without changing the result of the outflow rate model much. This supports the confidence in the model that it is able to capture multiple relationships and works for not only one value but a set of values for a variable.

5.2.5 Interpretation of the outflow rate model

Section 5.2.3 indicates that the best representation of the observations where a certain rate of TEMPs left for a given percentage of less worked than usual can be done with a linear regression model. Section 5.2.4 verified that the length of the review period (period 2) is not very sensitive to small changes, the current length of the review period can be used. The question that remains is how to interpreted the results of the outflow rate model, this is explained in this section.

First, it must be known when the outflow rate model can be applied. The result of the linear regression model is an indication of a certain percentage of TEMPs that are likely to leave when they work less for a week. The thing is that it is unlikely that the model is applicable for situations where TEMPs work a bit less than usual. Therefore, the threshold level must be known. This threshold level indicates the percentages of decrease in work which starts to have an impact to the outflow of TEMPs. To formulate this in a different way, at what percentage of less work does the number outflows of TEMPs starts to increase. The answer to that question is given in Figure 5.13.

The conclusion of Figure 5.13 is that the number of outflow show a linear increase at the less worked than usual percentage from 0% to 15%. From a less worked than usual percentages equal to 15%, the number of outflows starts to increase. Therefore the assumption is that the TEMPs starts to flow out if they receive less than 15% work than usual. This assumption implicates that the outflow rate model is applicable when the percentage less worked than usual is higher than 15%. In terms of the overcapacity, it means that number of TEMPs that are likely to flow out can be determined by the outflow rate model when the overcapacity is more than 15%.

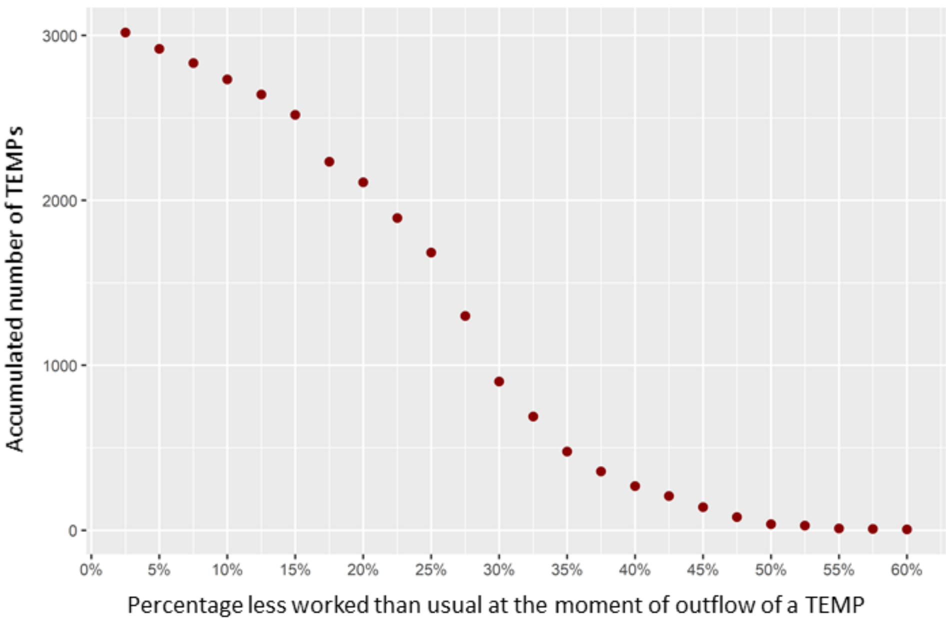


Figure 5.13: The accumulated number of outflows for a certain less worked than usual percentage.

Second, the outflow rate model provides observations of the outflow rate when TEMPs receive less work than usual. The regression model generalise those observations into estimations, so the regression mode provides the expected outflow rate for a given rate in which TEMPs work less than usual. The result is presented in Figure 5.14. Over there, the regression line determines that the estimated outflow rate increases with a factor of 1.09 if the less worked rated than usual increases. In practice, the situation might be that the pool of TEMPs suffers from an overcapacity of 20%, the expected outflow rate is determined by multiplying the overcapacity rate by 1.09. So the expected outflow rate is equal to 22%, which means that 22% of the TEMPs of the current pool are likely to leave due to receiving less work.
To conclude, it is expected that TEMPs leave from the point when they receive 15% less work. That means that the outflow rate model is only applicable when the overcapacity of TEMPs is bigger than 15%. In case this condition is met, the expected outflow rate is calculated by multiplying the overcapacity rate with the factor 1.09.

Figure 5.14: The linear regression model to determine the estimated outflow rate when a TEMP receives less work.

5.2.6 Cost impact of the outflow rate model

This section reviews the impact of the previously determined relation between the outflow rate and the period when a TEMP receives less work. The linear regression model, as determined in Figure 5.14 is used to calculate how many TEMPs left due to receiving less work. The period considered is the year 2018 and all sites are included. For each month two variables must be known:

1. The actual amount of TEMPs that is needed to perform all the warehouse activities.
2. The amount of available part-time and full-time TEMPs.

The overcapacity is calculated by dividing the number of TEMPs needed by the current pool of TEMPs, but according to section 2.2 there are at least 12% more TEMPs needed to deal with days a TEMP is ill or were on holiday. Thus the number of TEMPs needed is calculated by multiplying the actual number of TEMPs scheduled by a factor of 1.12. It is likely that outflow occurs on the condition that the overcapacity is bigger than 15%. The following formula's summarizes how the estimated outflow rate is calculated, based on the overcapacity rate.

$$
\begin{aligned}
Number\,of\,TEMPs\,needed &= Actual\,number\,of\,TEMPs\,scheduled * 1.12 \\
Overcapacity &= \frac{Number\,of\,TEMPs\,needed}{Current\,pool\,of\,TEMPs} \\
where & \\
Overcapacity &\geq 15\% \\
Estimated\,outflow\,ratio &= 1.09 * overcapacity
\end{aligned}
$$

The impact of the likeliness of outflow, given in the number of TEMPs over the year 2018, is shown in Figure 5.15. The blue line corresponds with the pool of TEMPs and the red line corresponds with the actual amount of TEMPs needed. It could be that the amount of actual amount of TEMPs needed is bigger than the amount of available TEMPs, in that case the assumption is that the part-time or full-time TEMPs did overwork. This won't affect the outcome of this analysis, since this only considers the situations where overcapacity occurs.

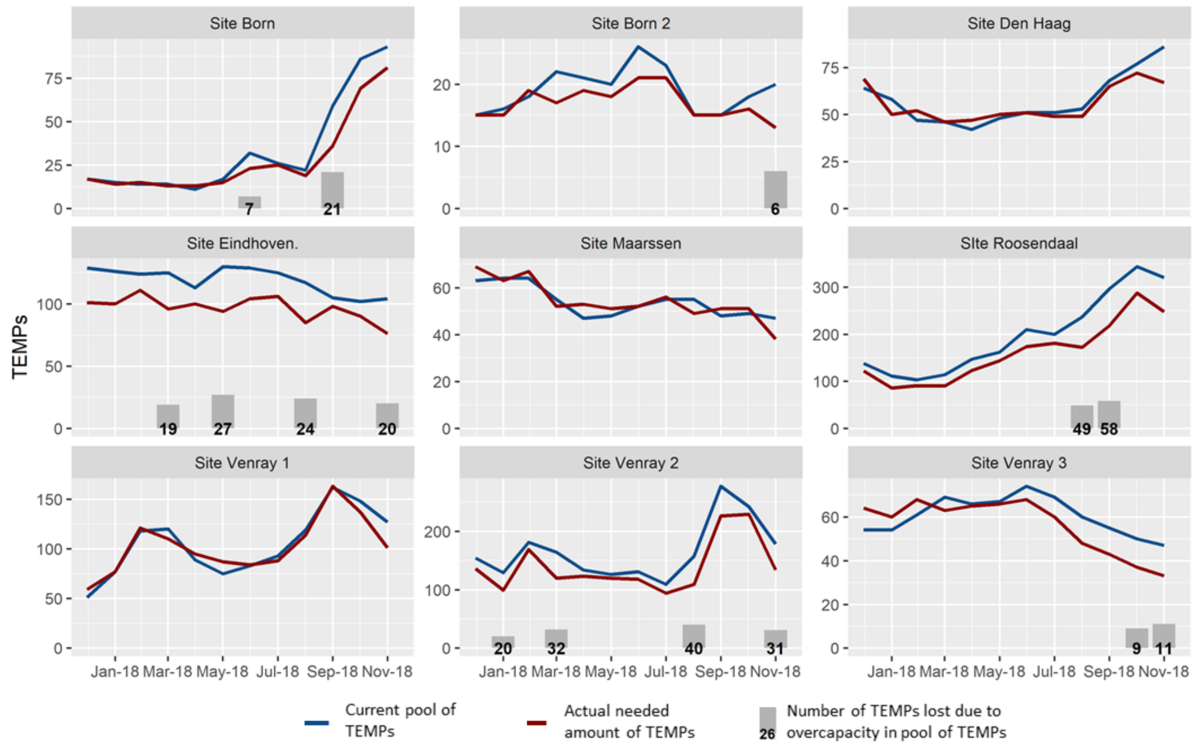


Figure 5.15: The impact of overcapacity, as determined by the outflow rate model, expressed in TEMPs lost.

Figure 5.15 shows that a total of 451 TEMPs left due to receiving less work. The total number of TEMPs that left during that period is equal to 2069 TEMPs. Therefore, the conclusion is that 21% of all TEMPs that leaving the company is caused by giving them less work than they desire. It is estimated that the outflow of TEMPs due to receiving less work costed in 2018 around €350.000-€530.000. An important comment is that these are not the total costs that could have been saved in 2018. The following section provides the possible savings over 2018. There are two cases when outflow occurs due to receiving less work:

1. *Demand increases*
   It could be the case that in order to prepare a site for a seasonality, the site expands their workforce pool too early in advance. The workforce pool increases but the amount of work per TEMP decreases.
2. *Demand decreases.*
   It could be the case that after a seasonality a site shrinks their workforce pool too slow. The demand decreases and a TEMP receives less work.

Costs savings when demand increases
Figure 5.15 shows that there are 240 TEMPs that left when the demand increased. An explanation for that is that currently some sites are facing a low unemployment rate within their area, so for them it can be hard to find new TEMPs. Therefore they hire many TEMPs in advance, but forget the negative consequences that already employed TEMPs might leave due to less work. Due to the increase in uncertainty when demand increases, the risk of having undercapacity becomes bigger. So it is not realistic to ask from sites that they have a maximum overcapacity of 15% when demand increases. Therefore the assumption is that 50% of the outflows due to an increase in demand could be saved.

Costs savings when demand decreases
Figure 5.15 shows that there are 211 TEMPs that left when the demand decreased. Since the workforce pool must decrease when the demand decreases, the outflow of TEMPs when demand drops is not entirely unwanted. The event that is undesirable is when more TEMPs leave than necessary. The outflow rate model shows that this event occurs when the overcapacity is bigger than 15%. Therefore a part of the 211 TEMPs that left is undesired. The amount can be estimated by the regression model of the outflow

rate model results, the description is given in (5.1) and the calculation is given in equation (5.2). The result is that there are 27 undesired outflow of TEMPs when demand decreases, so this amount could have been saved in 2018 by improving the capacity planning.

$$Undesired\ outflow = current\ pool * (outflow\ ratio - overcapacity\ rate) \tag{5.1}$$

$$Undesired\ outflow = pool * ((overcapacity\ rate * 1.09) - overcapacity\ rate) \tag{5.2}$$

Total costs savings in 2018
Table 5.6 summarizes the cost savings when the demand increases and decreases. In case of an increase of demand, the potential number of TEMPs that could be saved is approximated by 50% of the total outflows due to an increase in demand. In case of a decrease of demand, the potential number of TEMPs that could be saved is approximated by the undesired outflows, calculated by equation (5.1). The total potential cost savings for the year 2018 result in a range between €110.000 - €160.000.

Table 5.6: The estimated number of TEMPs that left due to receiving less work, but could potentially be retained by improving the capacity planning in 2018.

Situation 2018	Number of TEMPs left	Potential TEMPs saving	Potential costs saving
1: *Demand increases*	228	114	€91.000 - €137.000
2: *Demand decreases*	146	21	€17.000 - €25.000
Total	**374**	**135**	**€108.000 - €162.000**

Sensitivity analysis for multiple values for the maximum overcapacity rate.
The value of the maximum desired overcapacity is equal to 15% for the calculations made in Table 5.6. Figure 5.13 indicates that from 15% less work than usual, the TEMPs are likely to flow out. The result of Figure 5.13 is an assumption, so the outcome might be different for another perspective. Therefore a sensitivity analysis of this variable is needed to indicate the impact to the estimated total cost savings. The total costs savings in 2018 is again calculated when the maximum desired overcapacity is equal to 10%. So, the assumption is that outflow is likely to occur from 10% less work than usual. The result is given in Figure C.2, over there the total costs savings of the year 2018 ranges between €130.000 - €200.000. The conclusion is that a sensitivity analysis of two values for the maximum desired overcapacity does not have a big impact to the total estimated cost savings in 2018.

Validation of the cost savings by the outflow model in 2018
The previous section indicates that the outflow rate model estimates that a total of 150 undesired outflows could been saved by making sure that the overcapacity rate does not exceed 15%. The question is how likely is the case that the result of the model actually provides the correct outflow rate in case of overcapacity. In other words, is there a way to validate the cost savings by the outflow model in 2018.

A way to validate the result of the cost savings by the outflow model is by looking at the total number of outflow in 2018. By a breakdown of the potential outflow causes a certain number of outflows remain left. This number is likely to be the amount of TEMPs that left due to overcapacity, which is equal to the amount of potential savings. The result is presented in Table 5.7.

Most of the outflow cause ratio's are determined based on the survey as presented in section 2.3.2. The NA TEMPs ratio is determined by section 2.1.4, the seasonality and trend cause ratio is determined by summing all the necessary outflows if the pool of TEMPs moved perfectly along with the demand fluctuation in 2018. Since it is likely that there are no other outflow causes left, it is assumed that the remaining outflow cause is outflow due to receiving less work. As mentioned in Table 5.7, around 320 TEMPs are identified as potential savings. That means the outflow of 320 TEMPs was unnecessary.

To conclude, the model identified around 140 TEMPs that could have been saved from flowing out by keeping the overcapacity to a maximum rate of 15%. A validation of this result shows that up to 320 TEMPs left likely due to receiving less work. The validation method works with the average ratio of the outflow causes, this provides an indication if the result of the proposed outflow rate model approximates a realistic results. In this case, the result of the model is very conservative, but this increases the reliability of the model.

Table 5.7: A breakdown of the outflow causes to validate the result of the outflow rate model.

	Ratio	TEMPs per cause	Total TEMPs
Total outflow of TEMPs 2018	**100%**		**2500**
Breakdown of outflow causes TEMPs			
NA TEMPs (leave within 20 shifts worked)	30%	750	1750
Seasonality and trend (demand fluctuations)	24%	605	1145
Received fixed contract	10%	250	895
Back to country of birth	7%	175	720
Back to school	5%	125	595
Not pleased with salary or working environment	5%	125	470
End of temporary period	4%	100	370
Long-term illness	2%	50	320
Remaining outflow	**13%**		**320**
(potential savings in TEMPs by better capacity planning)			*(320)*

5.2.7 Conclusion outflow rate model

There is a high rate in which TEMPs leave the company. One of the causes could be that TEMPs leave due to receiving less work than desired. The question is how many TEMPs are likely to leave when they are offered less work. To answer this question, a model is created to determine the likeliness of outflow.

The model uses protime data as input data. The protime data consists of information about all the days a TEMP worked and the duration of each shift of a TEMP. This enables the model to calculate the average shifts worked per week during the employment period of a TEMP. The model splits the time of a TEMP at a site in two period. Period 2 consists of the last 10 shifts before a TEMP left the organisation. Period 1 consists of all the shifts worked before period 2. The model identifies an outflow due to less work if a temp worked considerable less in the review period (period 2) than in the base period (period 1). Furthermore, the model looks in the base period if the TEMP has more occasions where the TEMP worked considerably less. The likeliness of outflow is calculated by dividing the outflow by the number of occasions a TEMP worked considerably less. These steps are repeated for all the TEMPs in the protime data. The end result of the model is a regression analysis for the outflow rates. This regression model shows the relation between the percentage less work versus the outflow rate of a TEMP. A schematic overview of the outflow rate model can be found in Figure 4.6.

The reliability of the model is verified by a survey of TEMPs from 08-2018 till 02-2019, which indicates that the result of the model may be a bit too pessimistic. That means that the likeliness of outflow by the model is a bit higher than the survey suggests, but the trustworthiness of the survey is not high. The robustness of the model is tested by a sensitivity analysis for different amount of shifts in period 2. The result is that no big changes of the outcome of the model occur when period 2 consists of 10 to 14 shifts. Therefore it can be concluded that, in terms of costs, it is always better to reduce the workforce pool of TEMPs if demand decreases.

In 2018, the estimated outflow due to less work is estimated. Two situations occur: outflow when demand increases and outflow when demand decreases. The potential cost savings in case of outflow when demand increases ranges from €90.000 to €140.000. The potential cost savings in case of of outflow when demand decreases is approximately €20.000.

The conclusion is that an overcapacity of more than 15% results in TEMPs that are likely to leave. The financial aspect is that there are undesirable costs of involved of hiring new TEMPs to cover the TEMPs that left. Over the year 2018, it is estimated that a total of €110.000 - €160.000 could have been saved if the capacity planning of TEMPs was arranged in a better way.

5.3 Improvement of the capacity planning strategy of TEMPs

The purpose of this thesis is to advice how the capacity planning of TEMPs can be improved using the results of a quantitative analysis. This was previously identified as the main research question. The result of the past chapters and models help to formulate an answer to that question. The strategy towards an optimal resource capacity planning is described in this chapter. First an explanation of the perspective from a TEMP towards the current pool capacity planning is given, than an advice is given how the pool of TEMPs should react to changes in demand. This is followed to what extent a forecast can help to predict the demand in case of the conditions that apply for the company. A future perspective of how these advises could be merged into one solution based on software finalizes the content of this chapter.

5.3.1 Motivation of the behaviour of a TEMP

The first chapter identified that there is a large inflow and outflow of TEMPs. A large inflow of TEMPs means that a lot of costs are involved to train them. Chapter 2 gave the corresponding numbers and indicated that a cost saving of €160.000 to €240.000 may be feasible given an initial estimation.

It is assumed that the second most frequent reason why TEMPs leave is due to receiving less hours than they want to work [1]. This assumption is supported by the following arguments why it is important for a TEMP to work their desired hours.

- Most employment agencies won't give a guaranteed minimum of hours a TEMP can work.
- The hourly wage is just above the minimum wage determined by law.
- TEMPs receive their payment once a week. Most of them determine their budget based on their earnings per week. So if they receive less money within a couple of consecutive weeks, they are more likely to respond to that instead of determining a budget based on the earnings per month.
- A big part of the pool of TEMPs come from abroad. Their main purpose to work in the Netherlands is to make money, which takes care of their family in their home country.
- TEMPs do not know the forecasts. In case of the start of a high season, the pool of TEMPs must increase in order to prepare a warehouse for a peak of the demand. At the beginning, the TEMP cannot work that much since the pool is too big. This is demotivating since a TEMP sees new people get training while he or she does not get the opportunity to work their desired amount of hours.

5.3.2 How must a pool of TEMPs react on changes in demand?

The size of the pool of TEMPs determines to a large extent the amount of hours a TEMP can work. As mentioned in the previous part, it is very important for a TEMP to get the opportunity to work their desired amount of hours. From a business perspective, there is another important factor which is the costs of the pool of TEMPs. Besides the fact that a TEMP must work from time to time in order to keep their productivity level, a TEMP needs to be trained during the onboarding procedure which costs money. The question is how the pool of TEMPs should change when the demand changes based on a perspective from the TEMPs and a business perspective.

The business perspective wants to save money on training, so the priority is to reduce the number of outflows since every outflow must be replaced by an inflow when the demand is constant. A TEMP want to work their desired hours, since their expected weekly wage is leading. In order to combine both perspectives, a MILP model could be used to calculate an optimal solution what to do in case that demand decreases in the upcoming period but increases in the period after that. Should you keep the current pool of TEMPs to save training costs or should you scale down the pool of TEMPs to make sure that every TEMP can work their desired amount of hours. The outlines of a MILP model are described in section 3.2.2, which indicates the variables, parameters and constraints in order to solve a hiring and firing problem. One variable that is not included in that model is the amount of TEMPs that are likely to leave the organisation, when a TEMP receives less work than desired.

The outcome of the latter one is very important, since it determines if a MILP model is needed to solve the capacity planning problem to an optimum. If it happens that there is a smaller percentage of

[1] The primary reason why TEMPs leave is that TEMPs don't successfully finish the trail period.

TEMPs that leave than the percentage of less work the TEMPs receive, a MILP model is needed. In this case, it is more cost efficient to keep a certain amount of TEMPs, since not all TEMPs will leave if demand decreases. Therefore the threshold criteria can be formulated as: use a MILP model if the outflow rate is lower than the percentage of less work a TEMP receives.

Consequently, a model is needed that determines the likeliness of outflow when a TEMP receives less work for a certain period of time. The model uses a data set consisting 12.500 TEMPs that worked between 2015 and 2019 for a certain period of time. The outflow rate is calculated by analyzing how much a TEMP usually works and how likely it is to leave every time that TEMP works less than usual. The most important outcome of the model is that the likeliness of outflow is higher than the percentage of less work a pool receives. It is estimated by the outflow rate model that the size of the pool of TEMPs can be at most 15% more than the actual needed amount of TEMPs, so the overcapacity rate is at most 15%, otherwise more TEMPs will leave than desired and unnecessary training costs are applicable.

5.3.3 Forecasting demand

The next step is to identify the behavior of the demand in order to adjust the size of the pool of TEMPs. A forecast model can be used to predict demand for a certain warehouse per client. If this forecast model is accurate enough, the predicted amount of needed TEMPs can be calculated together with the productivity rate of TEMPs.

First, section 3.1 explored the best forecasting methods by looking at forecasting competitions for time series data. This results in three methods where an additional method is proposed that may improve the performance of those three methods. In addition to that, it may be useful to combine the average results of different forecasts to create a better forecast. The forecast model evaluates the performance of 14 methods on 177 time series demand data. The methods that are likely to give different results when the forecast horizon increases and the methods that are likely to give different results when the forecast origin changes are excluded from the set of forecasting methods. In the end five forecast methods are likely to be robust enough, including two methods where the proposed improvement method is used.

The forecast model indicates the forecast accuracy per sector. The result is that the clients within the technology and retail sector have a three months ahead forecast error of respectively 8% and 9%. The clients within the healthcare and industrial sector have a forecast error of respectively 14% and 16%. The discussion is what forecast error is reasonable accurate enough such that the results of the outflow rate model can be used in order to improve the capacity planning strategy.

The outflow rate model advises that a overcapacity rate cannot exceed 15%, otherwise unnecessary outflow due to receiving less work occurs. This strategy towards the capacity planning is only applicable if a reasonable accurate forecast can be generated. A concrete maximum forecast error value can be approximated by verifying a worse case scenario. If a site wants to ensure that there is always a sufficient amount of TEMPs available, a site determines the capacity of TEMPs on the forecast value plus the maximum forecast error. It can happen that it turn out that the actual demand is lower than the forecast indicated, in this case overcapacity happens. If the restriction is that the overcapacity is at most 15%, the maximum forecast error can be approximated by equation 5.3. The result is that the maximum forecast error, to ensure that the overcapacity rate does not exceed 15%, is equal to around 9%. The assumptions are given below:

- The forecast predicts that 100 TEMPs are needed to fulfill demand. This is equal to the average poolsize of TEMPs at a site.
- A site wants to make sure that demand is met, so if the forecast error is equal to x than a site increases the capacity planning with half of forecast error. Any shortage of workforce can solved with overtime work, but for many cases there is enough workforce available. The capacity planning of TEMPs is equal to $forecast * \frac{1}{2} * x$.
- A worse case scenario is calculate, that means that the actual demand is equal to the forecast values minus the forecast error. The actual demand result in *forecast - forecast * x*.
- The overcapacity is determined by $\frac{capacity\ planning}{actual\ demand}$, this must be equal to 115%.

$$
\begin{aligned}
&\textbf{Worse case scenario:} \\
\frac{(capacity\ planning)}{(actual\ needed\ workforce)} &= 115\% \\
\frac{(100 + 100 * \frac{1}{2} * x)}{(100 - 100 * x)} &= 115\% \\
x &= 9 \\
maximum\ forecast\ error &= 9\%
\end{aligned}
\tag{5.3}
$$

A higher forecast accuracy could be achieved by extensive data cleaning. All special promotions and event must be removed from the data, but still the impact of future special promotions and events is unknown. Furthermore, this process will be labor intensive. Another approach is to include external variables in the forecasting model such as weather, social media and macro economic factors. This increases the likelihood of overfitting the data, when using a forecast model based on statistical method. To overcome this problem, a forecast can be created based on a method that uses machine learning. The hard criteria is that enough data must be available and it only works in case of many predictors. As noticed in section 3.1.4, a statistical model, which is based on time series data outperforms a forecast model that is based on a machine learning model.

5.3.4 Implementation of the proposed capacity planning strategy

A site can track the current and predicts overcapacity levels via a software tool. This enable every layer of the warehouse organisation to understand the size of the optimal capacity of TEMPs for a certain period. The constraint is that there is enough confidence that the forecast model produces reliable results and that the forecast model is accurate enough. However, the accuracy of the forecast model presented in this thesis is rather low, so there is definitely a discussion in what ways the forecast model should be improved. In case a forecast model can predict the demand accurate enough, a software tool can convert that forecast into the needed workforce along with additional variables and parameters. Examples of what elements the software tool can include are written below:

1. Include the lead time to find and hire a TEMP.
2. Define per site the percentage of TEMPs that do not succeed he trial period and include that parameter.
3. Include the increase in productivity during the first weeks since a TEMP started working.
4. Include the productivity rate as a variable, in stead of a constant, since there are external factors like the temperature inside the warehouse that influence the productivity rate.
5. Incorporate the influence of an increase in hourly wage rate of competitors of CEVA on the TEMPs.

A software tool should provide the employees on a site with an advice how many TEMPs the current pool needs to increase of decrease. Especially the warehouse supervisors will use this advice. The software tool creates one place where information about the capacity of the pool is visible. In addition to that, warehouse supervisors have insights to the workforce capacity of other department. Situations where there is a risk of under-staffing can be handled and situations where every department hires new TEMPs due to a slight shortage will be prevented. In addition to that, a site will be able to indicate over a period of a couple of months how many TEMPs they need towards the employment agencies. These employment agencies can help to anticipate to a certain increase or decrease of the pool of TEMPs. Besides the fact that a software tool reduces costs, it makes sure a bigger group of TEMPs is more satisfied since they receive the amount of work they expect to receive.

6 | Conclusions and recommendations

This chapter starts by mentioning the problem solving approach. This is followed by the conclusions about the outflow rate model and the time series forecast model. The final conclusion advises how the strategy towards the capacity planning of TEMPs can be improved. Since there is a set of advises, the recommendation section is added in order to provide the company with options to implement the insights into practice. Besides the recommendations about how to implement the insights, also the recommendations about further research topics are mentioned. It could be the case that it might be interesting to widen the scope at some points or verify some of the assumptions. First, the chapter starts with the conclusions.

6.1 Conclusions

The motivation to explore various improvements regarding the capacity planning of TEMPs started with observing a high inflow and outflow of TEMPs at all Dutch warehouses. Approximately around 50% of the warehouse blue collars are TEMPs, 50% of that work on a full-time base and 20% on a part-time base. The rest of the TEMPs work on average less than 20 shifts in total, so they are employed for only a short period of time. The problem that occurs can be described by the following reasoning. The inflow rate is a bit higher than the outflow rate of TEMPS, so ideally no outflow should be present. However, the outflow rate is rather high. Due to seasonality and a short-term employment preference of certain TEMPs, outflow cannot be avoided. In this case, there is a feeling that more outflow of TEMPs occurs than necessary. The question is what factors causes this high outflow rate and how can the high outflow rate be reduced.

The current outflow rate of TEMPs causes that 24% of the pool of TEMPs is renewed every month. Per year, this results in having 2.9 times a complete new pool. The costs that are involved with the inflow of a new TEMP is determined by the losses that occur during the onboarding and outboarding processes. Per TEMP the costs ranges between €800 and €1200, per year the total costs of outflow is estimated around €2.000.000 to €3.100.000. A TEMP flows out by the initiative of CEVA or on their own initiative. A survey among 1300 TEMPs indicated that one of the most occurring reason for a TEMP to leave the organisation is that they receive less hours than desired, which is outflow on their own initiative. It seems like a logical cause-effect relation, since TEMPs do not earn much. In addition to that, they are paid per week so they determine their budget on a weekly base. If a TEMP receives less hours for a set of consecutive weeks, a TEMP is more likely to leave the organisation than a employee that is paid per month. In order to verify this cause-effect relationship, the behavior of TEMPs when receiving less work than desired is analyzed. If needed, the capacity planning can change in general the amount of work a TEMP receives, therefore reducing the outflow rate.

The problem solving approach results in an advice how the capacity planning of TEMPs could be improved, based on a quantitative analysis. This is the main research question of this thesis. The scope of the research is limited to only use daily data generated by the TEMPs located in the Netherlands over a period between January 2015 till May 2019 and monthly aggregated data generated by the warehouses located in the Benelux over a period between May 2015 till May 2019.

The problem solving approach starts first by analyzing the relationship between receiving less work for a TEMP and the likeliness of leaving the organisation. In case there is a relationship present, an advice is formulated to what extent the pool of TEMPs should match the demand of needed workforce. This assumes that future demand is known, therefore the next step is to gain more insights to what extent three month ahead demand can be predicted. The purpose is to verify if a reasonably accurate forecast can be generated with the current available data. The forecast uses only aggregated monthly time series demand data about the warehouse activities such as the number of orderlines for different clients. To conclude, the strategy towards the capacity planning of TEMPs is formulated by the results of two models. These models are listed below.

1.	**Outflow rate model:**	*What is the likeliness that a TEMP leaves the organisation when the TEMP works less than desired.*
2.	**Time series forecast model:**	*What is the best method or set of methods to perform a long-term forecast of a client using only monthly time series data and how accurate can a long-term forecast be given a large set of time series data.*

6.1.1 Outflow rate model

This sections answers research question 2g: *How can the result of the outflow rate model be incorporated within the strategy towards capacity planning of TEMPs?*

The outflow rate model uses protime data as input data. The protime data consists of information about all the days a TEMP worked and the duration of each shift of a TEMP. This enables the model to calculate the average shifts worked per week during the employment period of a TEMP. The model splits the time of a TEMP at a site in two periods. Period 2, the review period, consists of the last 10 shifts before a TEMP left the organisation. Period 1, the base period, consists of all the shifts worked before the review period. The model identifies an outflow due to less work if a temp worked considerable less in the review period than in the base period. Furthermore, the model looks in the base period if the TEMP has more occasions where the TEMP worked considerably less. The likeliness of outflow is calculated by dividing the number of outflows by the number of occasions a TEMP worked considerably less. The output of the outflow rate model is a set of observations between a estimated outflow rate and a certain rate of less worked before outflow. These observations are used as input for a linear regression model to generalize the relation between the expected number of outflows for a give overcapacity rate. The overcapacity rate is the same as the rate a TEMP receives less work. The regression model is tested on robustness by experimenting with various number of shifts that determine the length of the review period. The exact formula of the regression line is: ($Estimated\,outflow\,rate = 1.09 * overcapacity$) where ($overcapacity > 15\%$). The minimum overcapacity rate is determined based on an estimation where receiving less work has an impact to likeliness of leaving the company. The conclusion is that the outflow rate is always higher for a certain ratio of receiving less work, given a minimum receiving less work ratio of 15%. The interpretation of that is when for example there is an overcapacity of 20% for a certain month, so on average the pool receives 20% less work, it is expected that ($1.09 * 0.2 = 22\%$) of the TEMPs within that pool leaves within that month. The advice is that the capacity of TEMPs must adapt to changes in the amount of needed workforce. The size of the pool may be up to 15% bigger than the actual amount of needed TEMPs [1].

For the year 2018, the cost savings are calculated if the pool of TEMPs did not cause outflows due to receiving less work than desired. The total cost due to receiving less work ranges from €300.000 to €450.000, but this is not equal to costs that can be saved since a site needs to deal with uncertainty. In case of an increase in demand, the assumption is that 50% of the costs due to receiving less work can be saved by adjusting the capacity planning in time. In case of a decrease in demand, the number of more outflow than desired is equal to the potential cost savings. Altogether, if the pool of TEMPs was adjusted on time to the demand, a potential cost saving of €110.000 - €160.000 could be realized.

6.1.2 Time series forecast model

This sections answers research question 3g: *Is the performance of the proposed forecasting model good enough or is there a need to search for alternative methods to determine a forecast?*

The previous model indicated how the capacity of TEMPs should change if demand changes. In order to

[1] The actual amount of needed TEMPs is defined as amount of aggregated hours of TEMPs that is spend on the warehouse operations multiplied by a factor 1.12 *(12%)* in order to deal with sickness and days off

know if the demand changes, a forecast model is made that predicts the demand for a set of warehouse activities, like the number of orderlines, over a period of 3 months ahead. The model must be able to generate a reasonable accurate long-term forecast using only time series data. The result of the model must deliver insights which methods deliver in general good results and how accurate a long-term time series forecast method(s) can predict demand for CEVA.

The literature about forecasting of time series data give many methods, most methods are build for a specific demand behaviour. Since the demand behaviour changes from time to time, this model needs a forecasting method that has in general a good performance. Unfortunately, many papers compare a new method with a set of predecessors, in stead of comparing a new method with a wide range of other methods. The result of international forecasting competitions provides an answer to search for the best forecasting method(s). The findings are written below:

1. Statistical learning models perform a better forecast than machine learning models when using only time series data.
2. A machine learning model needs at least a set of variables that has an explanatory value for changes in the demand data in order to outperform a statistical learning forecast model.
3. Three methods (ETS, ARIMA and Theta) had the best performance when forecasting on 100.000 different time series data sets.
4. Using the average value of multiple forecast methods, thus creating combinations of methods, could generate accurate forecasts.

About 177 monthly time series data are used as input for the model. Besides the three methods ETS, ARIMA and Theta, a fourth method is added that is expected to improve the performance of the other three methods. The ExtrP method tries to cope with a specific but frequently occurring situation for CEVA, where demand suddenly decreases after a high season. This sudden decreases happens somewhere after Christmas, Cyber Monday or any event where consumer good are bought in advance. It is sometimes not clear at what moment this decrease happens, so a seasonality factor of three mentioned forecast methods may not adjust the demand correctly. The ExtrP method is a multiplicative parameter that must be used together with a single forecast of the ETS, ARIMA or Theta methods or with a combination of those methods, the parameter intensifies a decrease in demand in order to improve the forecast.

A total of 14 methods and combinations of methods are evaluated by a test of overfitting (change in training data length) and a sensitivity test (change in test data length). The result is that five methods are likely to be robust enough. These five methods are implemented in the forecasting model, the results are written below.

1. The five robust methods or combination of methods are Theta, ARIMA, Theta-ExtrP, ETS-Theta and ETS-ARIMA-ExtrP
2. The most used forecasting methods are Theta *(35%)* and ARIMA *(25%)*
3. As mentioned in the literature, it is useful to combine different methods into a forecast since the Theta-ExtrP, ETS-Theta and ETS-ARIMA-ExtrP outformed the single method forecasts together in 38% of the times.
4. The addition of the ExtrP method is rewarding, since it improved the result of the Theta model 25% of the time. However, the ExtrP variable in combination with 5 of the 7 other methods results in a model that overfits the data and is too sensitive for multiple forecast horizons.
5. The activities with the lowest forecast error and that are representative as measure for the overall demand in a warehouse are:
    - Picking orderlines
    - Picking pallets
    - Shipping orderlines
    - Shipping orders
6. The forecast error (using the robust forecast methods, representative activities and a forecast horizon of three months) ranges between 8% and 16%.
7. The sectors technology and retail have the highest forecast accuracy (8% MAPE) of all sectors.
8. The forecast model does not improve the naive forecast for the clients within the healthcare sector, so it seems like the healthcare sector does not have a distinctive demand behavior.
9. The industrial sector has the highest forecast error (16%).
10. The desired value of a reasonable accurate forecast, given a maximum overcapacity level of 15%, is calculated in section 5.3.3 and equal to 9%.

6.1.3 Final conclusions

This sections answers the main research question: *How can the capacity planning of temporary workers at the CEVA Logistics Benelux warehouses be improved by an estimation of the outflow rate and a prediction of demand?*

Every month there are 24% of the current TEMPs that leave the company, so there is a outflow rate. This results in high costs of hiring new TEMPs and a lack of motivation among the pool of TEMPs. The yearly costs are estimated at a range from €2.000.000 to €3.100.000. The assumption is that on of the main reasons why TEMPs leave is because they don't get the opportunity to work the amount of hours that they desire, since the are very dependent of their weekly income.

The outflow rate can be reduced by determining the size of the pool of TEMPs, this is part of the capacity planning. The capacity planning determines in general the amount of work the pool of TEMPs receive. A model determined the relation between the reduction in work and the estimated outflow rate. The result is that unnecessary outflow due to less work can be prevented if a maximum overcapacity level of 15% on a monthly base is applied to the pool of TEMPs. The advice is that that the pool of TEMPs must not be bigger than 115% of the actual amount of needed TEMPs.

In order to adjust the pool of TEMPs in time, an accurate prediction of demand is necessary. A literature study determines the best methods to predict demand using only time series data. The result is that the clients within the technology and retail sector have an expected forecast error (MAPE) ranging from 8% to 9%. The clients within the healthcare and industrial sector have an expected forecast error of respectively 14% and 16%. These forecasts are made with a forecast horizon of three months ahead. A calculation in section 5.3.3 determined that a reasonably accurate forecast has a forecast error of 9%.

If the overcapacity of the pool of TEMPs was not bigger than the recommended 15% during the year 2018, a possible cost saving ranging from €110.000 - €160.000 could be accomplished. The condition is that the forecast error of a three months ahead forecast is not more than 9%, in order to the reduce the amount of uncertainty of the capacity planning. The forecast model indicated that in general the clients within the healthcare and industrial sector do not meet this condition. Therefore, the capacity planning strategy might not be applicable for those clients. In addition to these points, it is desirable from a ethical perspective to reduce the amount of uncertainty a TEMP encounters if a TEMP wants to know if he or she could work the amount shifts as desired. To conclude, the main research question can be answered by the following sentence:

"The capacity planning of TEMPs can be improved by applying a new norm that an average monthly maximum of 15% overcapacity is allowed for the pool of TEMPs, given that they work for a client within the technology or retail sector or have a three months ahead forecast error of at most 9%. The forecast model for the clients within the industrial and healthcare sectors need further research."

6.2 Recommendations

This chapter summarizes the findings of this thesis as an advice towards the company. The advice consists of suggestions how to implement the findings, provides the discussion points and lists further research opportunities. As previously stated, the final conclusion of this thesis is that the capacity planning of TEMPs can be improved by applying a new norm that the overcapacity level of TEMPs cannot exceed a rate of 15% on an monthly base, given that the TEMPs work for a client within the technology or retail sector or have a forecast error less than 9%. First, the steps that needs to be taken in order to improve the capacity planning by taking the overcapacity into account, are written below.

6.2.1 Implementation

This sections answers research question 1c: *How can the result of the capacity planning model and the forecasting model be implemented within the organisation?*

As mentioned in the final conclusion, the capacity planing can be improved by having a maximum of 15% overcapacity of the pool of TEMPs. The 15% overcapacity figures as a rule of thumb, since the outflow rate model estimates how many TEMPs are likely to leave when there is too much overcapacity.

The only way to use the rule of thumb properly, is that the overcapacity value must be made visible like a key performance indicator. There are three ways to implement this KPI. There is the basic option, by only displaying the KPI on current dashboards. The second option, the premium option, is to incorporate the KPI in a software tool that shows a prediction of the overcapacity value and advises how to react on that certain KPI value. The last option, the pro option, consist of a software tool that solves a MILP model, as suggested in section 3.2.2, to near optimal. It is recommended to first have a pilot project for just one site, this project represents a proof of concept. After a successful implementations, the scope of the project can be extended to more sites. These options are listed below.

Basic implementation
This KPI is relatively easy to explain, therefore there is a low threshold to implement the KPI at every site. Warehouse supervisors can report the past overcapacity values and make an estimation of the future overcapacity values by checking the current size of the pool of TEMPs and calculate the overcapacity using the monthly forecasts. A dashboard will indicate the desired maximum KPI value *(15%)* and the current KPI value. This enables the warehouse supervisors to proactively adapt the pool of TEMPs to changes in demand.

Premium implementation
A more advanced approach is to use software that reports to the warehouse supervisors the amount of TEMPs that needs to be hired or excluded from the pool of TEMPs at a certain moment in time. This saves potentially a lot of time, since previously a warehouse supervisor has to calculate the predicted overcapacity value. A software tool can include more variables in order to have a better estimate of the future overcapacity value of the pool of TEMPs. Variables that can be included are summarized below:

- Incorporate the lead time of searching and hiring new TEMPs.
- Take a lower productivity rate into account during the first 20 shifts of a new TEMP when determining the current capacity of TEMPs.
- Determine the capacity per warehouse competence, to create a risk pooling effect over all departments.
- In case there is a group of TEMPs that are highly motivated and skilled, it is desirable to give less work to other TEMPs when necessary. So the outflow rate model may not be applied to the whole pool of TEMPs, but only the TEMPs that are not assigned to the group of good performing TEMPs.

Pro implementation
The most advanced implementation of the rule of thumb is to incorporate even more variables. The difference with the overview of variables of the previous section, is that variables can be included which were fixed parameters before. The solution space increases when more variables are incorporated, the software tool must now might solve a MILP problem. The literature refers to this problem as an aggregate planning problem, this topic is also part of the further research section since it has a high value when implemented. The variables that might be responsible for such an increase of the solution space, so which are used in case of an aggregate planning (MILP) problem are enumerated below.

- The ratio between fixed blue collars and TEMPs
- The uncertainty of forecasts per demand of a client
- The local unemployment rate
- The influence of the hourly salary rate and the likeliness that a TEMP stays

Implementation considering the forecast accuracy
The rule of thumb of a maximum of 15% overcapacity can be used in practice as long as the forecast has a reasonable accuracy. Otherwise, an inaccurate forecast results in an inaccurate estimation of the overcapacity. The forecast model indicated that the clients within the retail and technological sectors have the lowest three months ahead forecast error of 8% to 9%. It is likely that the one and two months ahead forecast error will be less than that. The clients within the other sectors might have a higher forecast error, but ideally the forecast accuracy must be determined per client in order to adjust the pool of TEMPs in time to the predicted demand. Another rule of thumb is that as long as the forecast error does not exceed 9%, the maximum of 15% overcapacity of the pool of TEMPs rule can be used. Otherwise too much uncertainty is involved. In order to cope with that, some improvements of the forecast model are listed in section 6.2.3. The list below summarizes the recommendations.

- Implement as rule of thumb that the overcapacity of the pool of TEMPs cannot exceed the 15%.

- Create a new KPI that indicates the current overcapacity value and set the desired level to be within 15%.
- Give the task to the warehouse supervisors to predict the new overcapacity KPI value when they change the pool size of TEMPs.
- An alternative is to outsource that task to software, which has the ability to include more variables and is therefore better able to give a better estimation of the predicted overcapacity KPI value. The purpose is that the software advises the warehouse supervisors, they are still responsible for the size of the pool of TEMPs.
- The forecast error per client must not exceed the 9%, otherwise too much uncertainty is involved and the maximum of 15% overcapacity is not applicable.

6.2.2 Discussion

The purpose of this section is to mention different points of views towards the assumptions and interpretations of the two proposed models, since there might be some discussion if the two proposed models are 100% validated and verified. First, the section discusses the problem identification. Then the outflow rate model and time series forecasting model are discussed.

Problem identification
The core problems are formulated based on observations made by the management and a first look to the data. The following statements, that are used to formulate the core problem, can be discussed.

- A survey identified that receiving less work than desired is one of the main reasons why a high outflow rate occurs. It could be the case that there are other reasons applicable, but the survey does not provide many more details reasons as an option.
- If a TEMP must leave by the company, it could be the case that the TEMP is not motivated to answer the survey truthfully. The result of the survey might by not fully reliable.
- The initial estimate of the costs of the current outflow rate ranges from €2.000.000 to €3.100.000 per year. These costs are based on the current outflow rate multiplied by the estimated costs to replace a TEMP that leaves by a new TEMP. One part of the costs of hiring a new TEMPs is an estimation of the loss in productivity for the first couple of weeks in order to get familiar with the warehouse operations. This estimated is made by warehouse supervisors and is not based on measurements.

Outflow rate model
The discussion regarding the outflow rate model are based on how the model handles the data cleaning process and how the results are interpreted.

- The desired amount of work per week of a TEMP is based on what they worked on average before leaving the company. It could be the case that this does not correspond with the desired amount of work.
- Currently, the outflow rate is based on if a TEMP worked less during the review period (period 2). It could also be the case that a certain pattern of periods, where a TEMP worked less than desired, is one of the causes to leave the company. This is not included in the model.
- The assumption is that a TEMP is on a holiday if a TEMP didn't work within 10 days. The discussion is that there are definitely TEMPs on a holiday for only one week, but those cases are hard to filter since it is also possible that a TEMP is not asked to work for a week.
- It is not filtered out of the input data if a TEMP wanted to work less instead of needed to work less. The outflow rate could be lower than actual since this event may be marked as a TEMP received less work but didn't leave the company.
- Currently, the model assumes that the needed workforce per month is sufficient enough to deal with the fluctuation on a weekly or daily base. This is not verified, since no daily or weekly demand data is available for more than 1.5 years.
- The conclusion of the outflow rate model mentioned that an overcapacity rate of no more than 15% of the pool of TEMPs is desired in order to reduce the outflow rate. The threshold of 15% overcapacity is selected based on an objective interpretation of a figure, so there could be a discussion that this percentage can differ within a small range.

Time series forecast model
The discussion regarding the time series forecasting model is based on which data is selected and which generalizations about the clients are made.

- The model uses only the time series data as reported. In case of special event such as the opening of a new store of a client is not included as a variable in this time series data. The accuracy of the forecast model would increase if such variables are known.
- The process how clients are categorized between the retail and technology sector is not straightforward. Most clients that produce electronic goods sell them via stores or e-commerce, therefore some clients that are categorized as a technology client could also be categorized as a retail client. The differences with the industrial and healthcare sector are better distinguishable.
- The conclusion of the forecast model is that the clients within the industrial and healthcare sector have a low forecast accuracy. There are some clients within these sectors that have a very stable demand. Therefore the generalization about the forecast accuracy is not applicable to every client within that sector.

6.2.3 Further research

There are assumptions that need further research, since they were out of scope for this thesis or simplified due to time restrictions. An overview of the assumptions and how the further research may look like is described below. They are categorized per model, so one category is about the assumptions made for the outflow rate model and the other is about the assumptions made for the time series forecasting model.

Outflow rate model:

- The data cleaning process removed the dates of which a TEMP was potentially on a holiday. Right now it is assumed that if a TEMP did not work for 10 consecutive days, the TEMP is on holiday. It could be that a TEMP went on a holiday for a shorter period of time or that one of the 10 consecutive days involved a regular day off. In order to calculate the average amount of shifts worked per week, it is useful to perform more research when and how long TEMPs were actually on a holiday or wanted days off.
- Right now, the outflow date is determined as the last day worked. Maybe a TEMP was available for a longer period of time, but did not get the opportunity to work. So it could be useful to document the moment of outflow.
- The result of the model can be verified in a better way, if the opinion of the warehouse supervisor about a TEMP is added to the survey when a TEMP leaves.
- The result of the model can be verified in a better way if there is a new survey with questions specified if they leave due to receiving less hours than desired.
- Due to a lack of temporary employees at some parts of The Netherlands, it could be interesting to include a cost-benefit analysis to pay TEMPs more if they receive less work otherwise they are likely to leave the organisation .
- Due to a lack of temporary employees at some parts of The Netherlands, it could be interesting to include a cost-benefit analysis to determine if it is cost efficient to adjust the minimum required productivity after 20 shifts. It may be cost efficient to not exclude a TEMP from the workforce pool when the TEMP has a lower productivity because there is already invested in the TEMP.
- The speed of the model is slow right now, it takes about 36 hours to run the full model. Optimizing the run time will stimulate to perform more experiments, this increases the reliability of the model.
- The ratio between fixed blue collars and TEMPs is not a variable, since the company prefers to have a fixed ratio. It could be interesting to include the fixed blue collars in the outflow rate model and to make hire or fire decisions based on the whole workforce pool. This is called an aggregate workforce planning in the literature. A model that incorporates the expected outflow rate together with hire and fire decisions could result in potentially higher amount of savings.

Forecasting model

- As mentioned before, the overall forecasting performance is reasonable for clients within two sectors. The clients in the other sectors have a forecast error which is too high. If the forecasting performance must increase, the following methods could be applied:
  - Involve the client to make sure that they deliver an accurate demand forecast.
  - Use less aggregated data so use weeks in stead of months. This captures a weekly seasonality. The three months ahead forecast uses a monthly and weekly seasonality, which is likely to increase the forecast accuracy.
  - More effort can be put in data cleaning, that means filter special events out of the time series data. Special events are variables that for example determine if a new store of a client opened,

which product promotions a client applies for a certain period or if the site did effort to smooth out demand over a certain period in the past.
  - External variables that are likely to influence the demand can be integrated. Examples of external variables are: macro-economical, weather or social media influences.
  - If lots of detailed demand data is available with more than 10.000 observations and consists of a set of multiple variables, a machine learning model might be useful to increase forecast accuracy.
- When expanding the scope to CEVA global, the amount of available data increases. There are currently around 4.000 clients within 11 sectors. The performance of the methods of the forecasting model can be verified on more data, thus making the result of the forecasting model more reliable.
- Determine the potential cost savings of a forecast model with a certain accuracy, in order to create a business case. The purpose of the business case is to verify if purchasing forecasting software saves costs within a reasonable amount of time.

Glossary

AIC Akaike Information Criterion. 26

ARIMA Auto Regressive Integrated Moving Average. 25

BIB Benelux Innovation Board. 2

ETS A set of exponential smoothing models that includes an error, trend and seasonal component.. 24

ExtrP Extra Parameter, it is a multiplicative parameter that adjusts a forecast to some distinct demand behaviour.. 45

GDPR General Data Protection Regulation. 11, 39

KPI Key Performance Indicator. 83

LDA Linear Discriminant Analysis. 35

MAPE Mean Absolute Percentage Error. 28, 43

MASE Mean Absolute Scaled Error. 28, 43

MILP Mixed Integer Linear Programming. 20, 30

NA TEMP Not Available TEMPs, TEMPs who worked less than 20 shifts in total.. 13

R R is a software tool and programming language for statistical and data analysis purposes.. 7

Residual Sum of Squares Error measure of linear regression model fit. 34, 35

TEMP temporary employee. 3, 10, 19

WMS Warehouse Management System. 11, 42

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A Pseudo-code

Algorithm 6 Pseudocode - Forecasting model

```
Input: Time series data
Output: Per time series data, the best forecast method and MAPE value
Variable: Forecast horizon (default value = 3)

Load time series data
for all series ∈ time series data do
    if (Series has more than 24 observation) AND (no zero demand) then
        Continue with this series
    else
        Skip current iteration of loop and go to next series
    end if

    Create training set of the time series minus the last observations of the forecast horizon
    Create test set of the observations of the forecast horizon

    if (1^st quantile - 3*diff) ≥ observation ≥ (3^e quantile + 3*diff) then
        (the diff is defined as the difference between the 1^st and 3^e quantile)
        Create linear regression model for train set data
        Replace observation by value of linear regression model
        Delete the outlier in train set
    end if

    for all ExtrP_Parameter ∈ (1,0.96) do
        Compute ETS forecast
        Compute ARIMA forecast
        Compute Theta forecast
        Create all possible combinations (7 in total, a combination is the average forecast value of multiple forecasts)
        if forecast value goes down then
            Multiply forecast with ExtrP_Parameter
        end if
        Merge the forecasts in one table
    end for

    Calculate the MASE
    Calculate the MAPE
    if Forecast MASE ≥ 10% forecast lowest MASE then
        Delete forecast
    end if
    Arrange the forecasts on descending MAPE value
    Select the forecast with the lowest MAPE value.
end for

Return: The method of the best forecast, the MAPE value and the sector of the time series.
```

B | Additional tables

Table B.1: The MAPE values for a one month and three month ahead forecast per sector, using the robust forecast methods.

Sector	**Forecast error (MAPE) for different horizons**	
	1 month	*3 months*
Retail	6.3%	8.9%
Technology	7.0%	8.4%
Industrial	8.3%	16.2%
Healthcare	18.1%	14.1%

Table B.2: The inflow and outflow rates of TEMPs for nine sites during 05-2018 till 05-2019

Site	**Inflow (monthly in TEMPs)**	**Outflow (monthly in TEMPs)**	**Ratio of pool refreshed per month**	**Pool refreshed per year**
Born	12	9	23%	2.8
Born 2	4	5	21%	2.5
Den Haag	16	15	22%	2.6
Eindhoven	25	25	21%	2.5
Maarssen	8	8	16%	2.0
Roosendaal	65	55	26%	3.1
Venray 1	25	28	22%	2.7
Venray 2	44	50	26%	3.1
Venray 3	16	18	28%	3.4
Average of all sites	**23.9**	**23.7**	**24%**	**2.9**

C | Additional figures

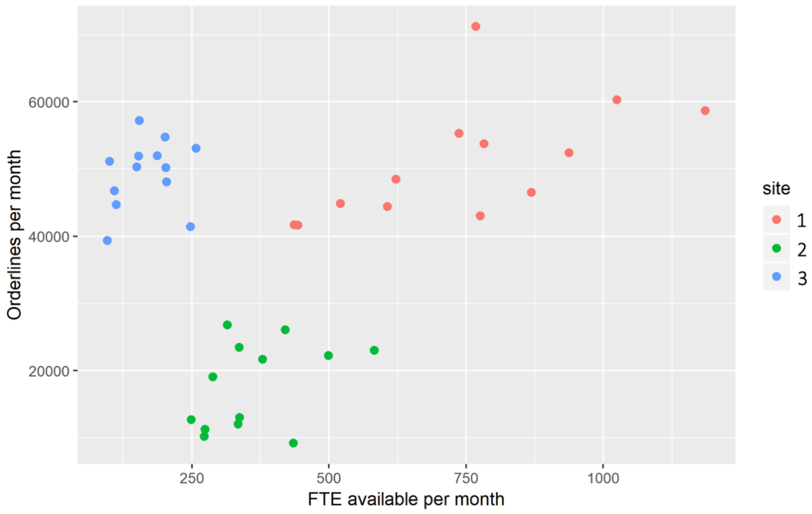
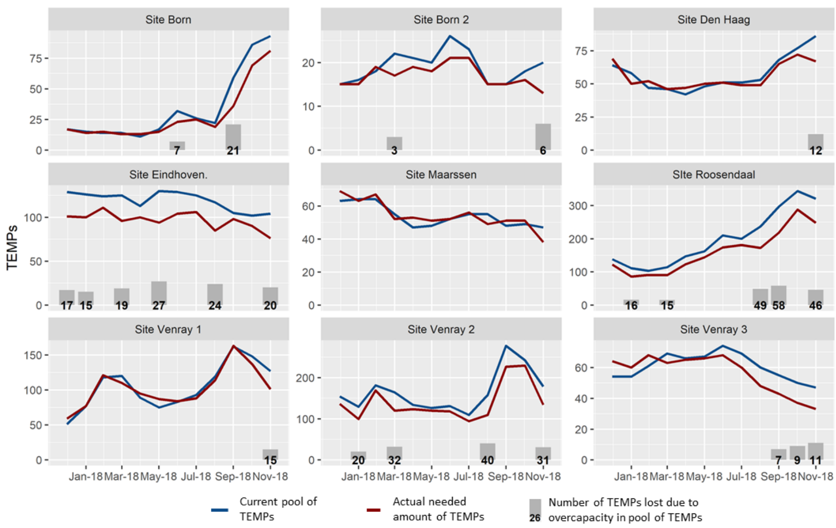


Figure C.1: An example of different productivity rates per sites.



Situation 2018	Number of TEMPs left	Potential TEMPs saving	Potential cost saving
1. *Demand increases*	258	129	€103.000 - €155.000
2. *Demand decreases*	262	37	€30.000 - €44.000
Total	**520**	**166**	**€133.000 - €199.000**

Figure C.2: The costs of the estimated number of outflows due to less work for maximum overcapacity level of 10% within the year 2018.

Source code of the outflow probability model

```r
# packages needed
library("dplyr")
library("lubridate")
library("data.table")
library("plyr")
library("ggplot2")
library("scales")
library("ggpmisc")

# variables
days = 10
ratio = seq(0.025,0.6, by = 0.025)
```

```r
# function that determines if an TEMP worked less during the last set of shifts and the
# value expressed in average shifts per week
lessshifts <- function(days){
  # keep track of the running time
  start_time <- Sys.time()

  # load data
  load("protime_clean.RData")

  # filter on employer
  protime_operations <- protime_operations[-c(grep("CEVA", protime_operations$Employer)),]

  protime_day <- protime_operations %>%
    rename(worked = RegularHours) %>%
    select(ID, Date, worked) %>%
    group_by(ID, Date) %>%
    summarize(worked = sum(worked, na.rm = TRUE))

  # clean data by filtering on >1 hour worked
  protime_day <- protime_day[(protime_day$worked >= 1),]
  protime_day <- protime_day %>%
    arrange(ID, Date)

  # identify the periods of holiday
  protime_day$gap <- c(0,diff(protime_day$Date, lag = 1))
  protime_day$idgap <- c(0,diff(protime_day$ID,lag = 1))
  protime_day$holiday <- 0
  protime_day$holiday[((protime_day$gap > 10) & (protime_day$gap < 40)) &
                        (protime_day$idgap == 0) ] <- 1
  rm(protime_operations)

  # remove the ID where there are observations for more than 40 days
  removeID <- protime_day[protime_day$gap > 40,] %>%
    distinct(ID)
  removeID$num <- NA
  removeID$num <- 0

  # if there was a holiday remove the holiday duration from the TEMP data, in a way we get
  # a data stream with only the dates worked, excl holiday
  continue = 0
  gap <- 0
  id <- protime_day$ID[1]
  iter <- nrow(protime_day)
  for (i in 1:iter){
    if(id == protime_day$ID[i]){        # if the ID is the same
      if(protime_day$holiday[i] == 1){
          gap <- protime_day$gap[i] - 2 + gap
          # minus two since assumption to replace holiday dates
        }
      protime_day$Date[i] <- protime_day$Date[i] - gap
    } else{                             # if there is a new ID
      id <- protime_day$ID[i]
      gap <- 0
      if(protime_day$holiday[i] == 1){
        gap <- protime_day$gap[i] -2
        protime_day$Date[i] <- protime_day$Date[i] - gap
      }
    }
  }
```

Figure C.3: An overview of the most important sections (1/3) of the outflow rate model, expressed in R script.

```r
  # look at the last couple of shifts worked, how many of them did an employee
  # worked less than a full shift
  lastrow = nrow(protime_day)
  protime_day$number <- NA
  a = 0
  # sort on ID and date
  protime_day <- protime_day %>%
    arrange(ID,Date)

  id = protime_day$ID[1]
  # number means the number of days a TEMP did work until then
  for(i in 1:lastrow){
    if(protime_day$ID[i] == id){
      a = a + 1
      protime_day$number[i] <- a
    } else{
      a = 1
      protime_day$number[i] <- a
      id = protime_day$ID[i]
    }
  }

  # select only the last "days" of working, use another table
  protime_day$help_column <- NA
  protime_day$help_column <- protime_day$number - (protime_day$numberOfDaysWorked - days)

  # determine the date where a TEMP started his 10th last working day
  date_Nlastworkingday <- protime_day[protime_day$help_column == 0,] %>%
    select(ID,Date) %>%
    rename(mid_date = Date)

  shift_dates <- protime_day %>%
    select(ID,start_date,end_date,numberOfDaysWorked) %>%
    distinct(ID,.keep_all = TRUE)

  # join the mid date
  shift_dates <- left_join(shift_dates,date_Nlastworkingday, by = "ID")
  shift_dates <- na.omit(shift_dates)

  # add number of shift p/w regular, an number of shift p/w of the last 10 shifts
  # weeks before and weeks after (round up)
  shift_dates$weekbefore <- ceiling((shift_dates$mid_date - shift_dates$start_date)/7)
  shift_dates$weekafter <- ceiling((shift_dates$end_date - shift_dates$mid_date)/7)
  shift_dates$before_shifts_pw <-  round((shift_dates$numberOfDaysWorked - days) /
  # save the table
  save(shift_dates, file = "shift_dates_10.RData")

  # determine running time
  end_time <- Sys.time()
  duration <- (end_time - start_time)
  return(shift_dates)
}
```

Figure C.4: An overview of the most important sections (2/3) of the outflow rate model, expressed in R script.

```r
# function that determines how much it occured that a TEMP worked less than desired

start_time <- Sys.time()
for (iter in 1:length(ratio)){

  # load data
  load("shift_dates_10.RData")

  # remove outliers: average hours worked per shift must be within 5 till 8 hours
  shift_dates$avgHoursPerShift[(shift_dates$avgHoursPerShift < 5)|
                               (shift_dates$avgHoursPerShift > 10)] <- NA
  shift_dates <- na.omit(shift_dates)

  diff = ratio[iter]
  # shift_dates <- lessShifts
  # determine if shift is
  shift_dates$impact[shift_dates$after_shifts_pw <= (shift_dates$before_shifts_pw * (1-diff))] <- 1
  shift_dates$impact[shift_dates$after_shifts_pw >= (shift_dates$before_shifts_pw * (1-diff))] <- 0
  shift_dates$impact[shift_dates$after_shifts_pw >= (shift_dates$before_shifts_pw * (1+diff))] <- -1

  # veranderen naar 0 of 1
  idList <- shift_dates[(shift_dates$impact == 0 | shift_dates$impact == 1),] %>%
    distinct(ID)
  idList$keep <- NA
  idList$keep <- 1

  # determine the number of shifts
  shiftData <- protime_day %>%
    group_by(ID) %>%
    summarise(Num = sum(num))

  # determine amount of period to consider
  library("plyr")
  shiftData$periods <- round(shiftData$Num / days, digits = 0) - 1
  detach(package:plyr)

  # determine start of first period
  shiftData$start <- shiftData$Num - (shiftData$periods * days)

  # for every TEMP determine the amount of occasions where the difference in avg shifts per period
  occurence = 0
  for(i in 1:nrow(shiftData)){ # for loop
    periodNum <- shiftData$periods[i]
    for (a in 1:periodNum){
      period1End <- protime_day$Date[(protime_day$number ==
                                      (shiftData$start[i] + days * (a-1))) &
                                     (protime_day$ID == shiftData$ID[i])]
      avgShift1 <- sum(protime_day$num[protime_day$ID ==
                                       shiftData$ID[i] & protime_day$Date <= period1End]) /
        as.numeric((period1End - protime_day$start_date[protime_day$ID == shiftData$ID[i]
                                                       & protime_day$Date == period1End]) / 7)
      period2End <- protime_day$Date[(protime_day$number ==
                                      (shiftData$start[i] + days * (a))) &
                                     (protime_day$ID == shiftData$ID[i])]
      avgShift2 <- days / as.numeric((period2End - period1End) / 7)
      difference <- round(1 - (avgShift2 / avgShift1), digits = 2)
      if(difference >= diff){
        occurence <- occurence + 1
      }
    }
  }
  # linear regression
  LR10 <- lm(outflowProb ~ diff, data = outflow_10)

  # polynomial regression
  PR10 <- lm(outflowProb ~ poly(diff,2), data = outflow_10)

  # create a figure with the regression model
  my.formula <- y ~ x
  png(file= paste("Probability of outflow due to less shifts.png"),
      width = 2000, height = 1400, res = 320)
  p <- ggplot(data = outflow, aes(x = diff, y = outflowProb)) +
    geom_point(size = 1) +
    geom_smooth(method = "lm",se = F, color = "red4",size = 1.2) +
    stat_poly_eq(formula = my.formula,
                 eq.with.lhs = "italic(hat(y))~`=`~",
                 aes(label = paste(..eq.label.., ..rr.label.., sep = "~~~")),
                 parse = TRUE) +
    xlab("Percentage of less shifts worked per week than usual") +
    ylab("Probability of outflow during the next 10 shifts") +
    scale_y_continuous(breaks = seq(0,0.8, by = 0.1),
                       labels = percent_format(accuracy = 1),
                       expand = expand_scale(mult = c(0.1,0.05))) +
    scale_x_continuous(breaks = seq(0,1, by = 0.05),
```

Figure C.5: An overview of the most important sections (3/3) of the outflow rate model, expressed in R script.