FACULTY OF BEHAVIOURAL, MANAGEMENT AND SOCIAL SCIENCES (BMS)

INDUSTRIAL ENGINEERING AND MANAGEMENT

ESTIMATING WORKLOAD THROUGH FORECASTING AND MONITORING PROCESSING TIMES

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Preface

Dear reader,

In front of you lies my thesis on ‘Estimating workload through demand forecasting and measuring activity performance. This research was performed at Actemium Zevenaar. In the past half year, I have gained valuable work experience and learned about the work-life outside the university.

I want to thank my supervisor from Actemium, Ordwin Notten for supervising me during the research. Actemium is a software company, which means that getting to know the ins and outs of the company is not as easy as when visual observations can be done. With this, Ordwin has helped me massively by constantly laying down his work to explain the company, the software system, and the problems that arose. I also want to thank Henk Tieltjes for allowing me to explore Actemium, and initially helping me get an assignment to graduate from my bachelor's program. Actemium has provided me with a nice atmosphere, helpful experts, and a good work environment.

Next to the employees of Actemium, I also want to thank my UT supervisors Derya Demirtas and Dennis Prak. Both have helped me a lot in making sure the report is academically sound and steering the experiment design in the right direction. I enjoyed the discussions and help I received from both of you.

Have fun reading my thesis,
Jeroen Assink

Management Summary

This research is focused on the possibility to use the current data of a warehouse management system on the operations of the clients of Actemium to support them in estimating future needs concerning the capacity planning of the employees. This should help the clients with their staff scheduling.

Introduction

Actemium is a supplier and consultancy firm in logistical automation located in Zevenaar Gelderland. The company provides its clients with a Warehouse Management System (WMS) that helps their logistical operations, such as the arrival, picking, and departure of orders in the warehouse. Actemium Zevenaar specializes in manual logistical operations. To stay relevant to customers, their system needs to evolve. Multiple clients have already expressed the wish to get a better indication regarding staff scheduling. This will cut the costs of delayed work (resulting in fines) or the overtime of employees.

Approach and results

To improve staff scheduling of Actemium, two main problems had to be solved. Firstly, the quantification of the workload in the warehouse is absent. Secondly, the lack of knowledge on forecasting future workload has to be solved. Resolving the two problems improves the dashboard fo Actemium's clients regarding capacity planning. Currently, support is only given in tasks left today. The goal is to translate the number of tasks to time and this is displayed for the upcoming weeks. This should be split for each operation.

Forecasting is a widely researched topic and therefore literature review was done to gain knowledge on what would be right for Actemium. Four models were identified: Moving average, Croston's method, Exponential smoothing, and ARIMA. Three requirements were defined when choosing the forecasting model. These are the ability to forecast trends and seasonalities, the ability to make a forecast based on a small dataset, and the simplicity of programming the model. Exponential smoothing scored best overall and was used when testing the forecasting method.

It became clear that there is too little data to forecast each product. Therefore, three ways of grouping products were investigated. Grouping all products together and directly forecasting the measured time was tried. Secondly, grouping the products by pick/bulk was tried, this was based on their amount of operations and the average time per operation. Lastly, grouping items based on their average pick time was tried. This was based on the number of operations and the average time per operation of each product group. The result of performing exponential smoothing, using these three methods can be seen in Figure 1.

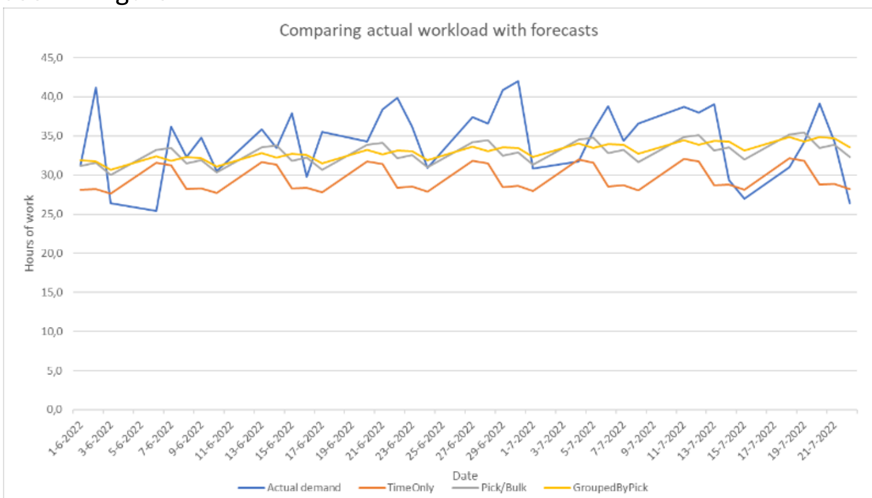

Figure 1: Comparison between forecasting methods during the time of the testing set

When comparing the results of the forecast with reality. It can be seen that all of the forecasting models are under-forecasting. This can be due to an increase in demand after the training set has ended. This is the main reason for the high accuracy measures. The Time only, and Pick/Bulk methods are following the seasonality better than the Grouped by pick times. However the Time only method is underforecasting more heavily. To compare the methods, the accuracy measures of all forecasting methods are calculated (Table 1). The values are based on the estimated and actual hours of work.

Forecasting method	MSE	MAD	MAPE	Bias
Time only	44.8 hours	5.6 hours	15.4%	-189 hours
Splitting Pick/Bulk	20.3 hours	3.6 hours	10.5%	-62 hours
Grouping by pick times	19.5 hours	3.7 hours	10.8%	-56 hours

Table 1: Accuracy measures for three different forecasting methods

The accuracy measures are used to support decision-making on a method to use. As can be seen in Table 1, the accuracy measures of the Time only method yields the worst results. Splitting Pick/Bulk and Grouping by pick times score very similarly, this can be supported by Figure 1 since the forecasting yields similar results for the latter two. Splitting by Pick/Bulk is chosen as the most accurate forecasting model since it follows the seasonality better than grouping by pick times.

As the second problem of Actemium, the current data is not representative for the workload. For this, identification of all operations is performed, mathematical equations to calculate the workload are set up, and advice is given to either measure or estimate the parameters in the equation.

Conclusion and recommendations

The result of this thesis is, just like the problem statements, twofold. First of all, forecasting workload through forecasting demand is explored. The most important recommendations on forecasting are stated. Next, some recommendations are done about the data that Actemium has.

It is found that the data on picking items in this dataset is too unstable when looking at each product separately. Meaning that no forecast can be made per individual product. Therefore, grouping items is necessary. It is advised to group these items based on their status as pick or bulk products. When forecasting, it is advised to use exponential smoothing (with trend and/or seasonality if necessary). When implementing the forecast model in the WMS, it is advised to add a level of adjustability for the clients so that factors like discounts and promotional actions can be taken into consideration.

Data should be gathered to monitor current workload, for this, the scanners can be used. This is an easy and accurate way of measuring workload since it does not require manual operations from the employees. An improvement to improve the data, is to measure handling times and traveling times in the warehouse separately. For each operation, the number of actions that consume time should be measured. Next to that, the different operations require different data. For each operation, the data should have (at least) these four attributes: Product that is being processed, date of the action, Time it took to process the product, and whether the product is in a pick or bulk operation. With this information, the correct data for the forecast is acquired.

There are options for further research. First of all, other ways of grouping products can be investigated. Grouping by pick times can also be investigated with another number of groups. This can affect the forecast. Another option is to forecast based upon zone in the warehouse. Another improvement for forecasting would be to base the forecasts of workload of operations on other factors than historical data. It is expected that the forecast of the arrival and put-away operation will become more accurate once based on the ordering policy. Lastly, forecasting should be done again once the stable data is gathered.

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1. Introduction

In this chapter, background information on the problem and the problem owner will be given. This explains the motivation behind the research. After this, the problem will be explored in more detail, and the results of the chapter will therefore be the research questions to be answered in this thesis.

1.1 About Actemium

Actemium is a supplier and consultancy in logistical automation located in Zevenaar Gelderland. The company started as Methec B.V. a standalone company that provides its clients with a Warehouse Management System (WMS) that helps their logistical operations, such as the arrival, picking, and departure of orders in the warehouse. In 2006, Methec B.V. sold its shares to Vinci, a French construction company. In 2009, the brand name changed from Methec B.V. to Actemium. Together with other Actemium business units (especially the business unit situated in Veghel), Actemium can provide full solution packages for all clients. Actemium Zevenaar is specialized in manual operations, whereas Veghel specializes in the automation of the warehouse. Location Zevenaar consists of around fifty employees and is focusing on wholesalers.

As stated, Actemium Zevenaar specializes in manual logistical operations. The focus is on companies that are growing too big to keep track of the warehouse on paper. These clients vary in their practices, therefore, the product of Actemium does not suffice for every client from scratch. To solve this, customization is performed for every client. The business consultants talk with the clients about the specific needs of the company and construct a plan to integrate the WMS into their company. The largest part of the organization consists of software engineers, who realize the plans of the business consultants and fulfilling the wishes of the client.

In practice, Actemium provides its clients with scanners and voice-picking machinery that clients use for processing incoming orders. The scanners display the current orders and tasks that the workers must process. Actemium also provides a dashboard with real-time information about the day and the orders that must be processed.

Figure 2: Handheld scanners being used

Figure 3: Voice pickers being used

1.2 Motivation for the research

The market in which Actemium operates is a competitive one. This means that clients will compare the product of Actemium with other products on the market. The current system already includes some decision-making assistance, but to stay relevant for customers, their system needs to be developed. At this moment, customers require too many changes to the system, and the system gets too expensive rapidly. Therefore, the standard product needs to be enhanced to fit the customers' needs better without a lot of expensive customization work.

1.3 Problem statement

This chapter describes the problem at its highest level. After that, the framework of Heerkens & van Winden (2016) is followed to get more information about the underlying problems, the so-called core problems.

The system does provide a real-time dashboard with information about the day and the remaining work but does not provide any predictive assistance for the planning of the upcoming weeks. This results in a very unpredictable workload. Moreover, the size of orders is not mentioned (since it depends on multiple factors like the variety and batch size of the products) in the dashboard. Therefore, the expected time for finishing the orders of the day is not given. Multiple clients have already expressed the wish to get a better indication regarding staff scheduling. This will cut the costs of unfinished work (resulting in fines) or the overcapacity of the personnel. Furthermore, for the employees in the warehouse that are executing the orders, an indication about the remaining time on the real-time dashboard can improve employee satisfaction, since expectations can be managed a lot better.

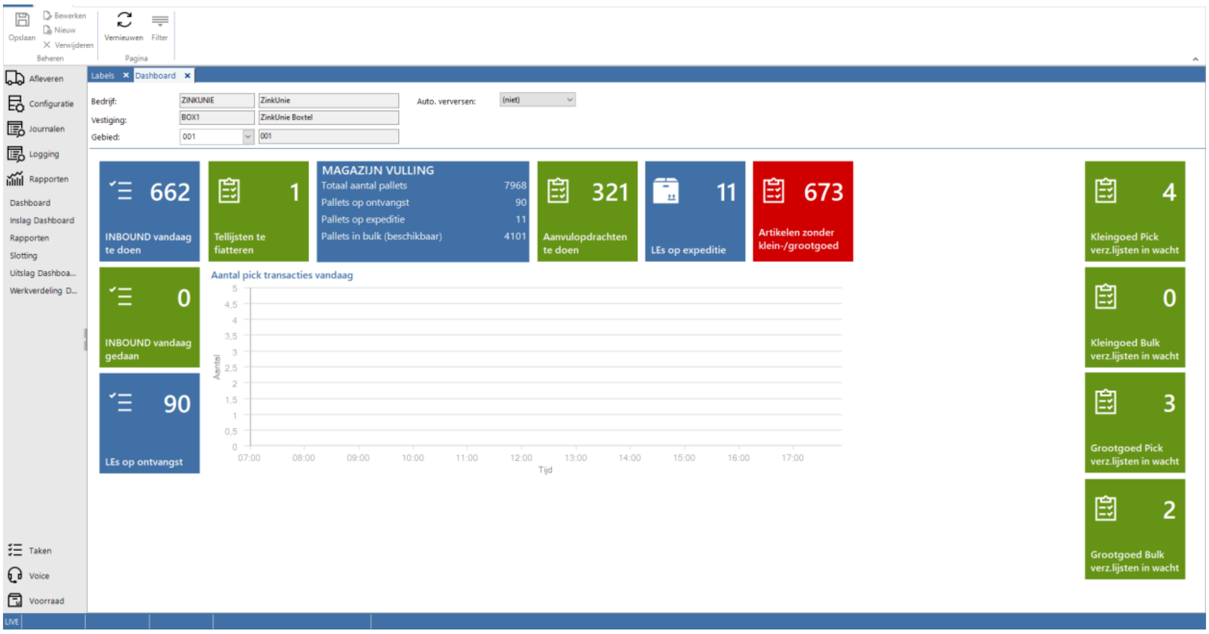

Figure 4: Dashboard WMS showing an overview of tasks (to be) completed that day

1.3.1 Problem cluster

To go from the action problem to the core problem. A problem cluster is made that displays the causal relations of different problems in the company. In the case of Actemium, the clients experience excessive costs for workers in the warehouse. The reason that clients schedule too many workers, or workers must work overtime, is that fines for delivering too late are extremely high. Therefore, the logistical manager of the clients prefers to have over-capacity.

Thus, the problem can be split out, on the one hand, there are costs due to overcapacity. On the other hand, fines occur when the delivery of goods is too late. These two problems both are due to the inaccurate scheduling of staff. This non-optimum again has two causes. The client is aware of the number of orders coming in today, however, no indication about the duration of the orders is known. The system does not support the employees in this regard.

Not only the current workload is unknown, but so are the future capacity needs. The Logistical Manager can provide an estimation of the orders coming in based on experience, but the system does not provide any assistance.

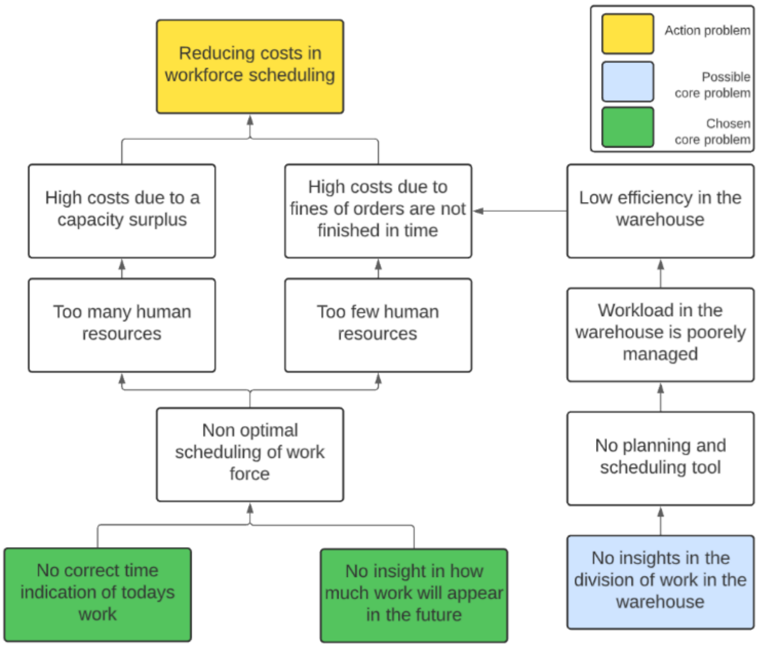

Figure 5: Problem cluster

1.3.2 Action problem

The action problem displays the discrepancy between norm and reality (Heerkens & van Winden, 2016). At this moment, too many costs due to inaccurate staff scheduling are the reality. For different clients, the main cause of the costs differs, at some clients, the employees are not flexible (due to a fixed contract), and these clients generate costs due to a capacity surplus. Other clients generate costs due to fines for unfinished/incomplete work. Next to that, some clients suffer from both and some already have a custom solution to the problem, but others don't. The problem, therefore, is that the logistical managers of the clients of Actemium do not know how many staff they should schedule. Actemium wants to support this in their WMS. Therefore the action problem is stated as follows:

"The logistical manager of the clients of Actemium should, by default, receive support from the WMS with regards to demand forecasting to assist decision making in staff scheduling."

1.3.3 Core problem

Working down the problem cluster, one arrives from the action problem to the core problem. Two core problems are intertwined and both need to be solved to solve the action problem. The company needs to be able to estimate the future workload to schedule people correctly. To achieve this, a time indication of how long actions in the warehouse take should be given. Therefore, the core problems are formulated as follows:

"The time an operation in the warehouse takes is unknown"
"There is no insight into the workload for the future"

1.4 Research design

After the specification of the problems, the main research question of this thesis is formulated as:

"How can Actemium Zevenaar use historical data to better forecast the workload requirements to optimize staff scheduling?"

To answer the research question, multiple sub-questions are set up to lead to an answer to the main research question. Throughout the thesis, answers to these questions are given. In this section, the questions will be introduced, and the motivation for and approach to the questions will be given.

1. What actions in the warehouse are time-consuming for its employees?

This research question is focused on gaining knowledge about general actions that are being performed in warehouses. To estimate future workload, identifying where the workload of employees lies is essential. This information will also be needed to define the correct scope for workload forecasting. Since the end solution should be client-general and not specific.

To accomplish this, a workflow of operations that the WMS administers for the client will be created. This gives an overview of what happens in the warehouse. After that, the workflow will be analyzed to identify the areas that lie in the scope of this thesis and to identify areas for future research. An answer to this question can be found in Chapter 2.1 and Chapter 2.2.

2. What are the wishes for better staff scheduling?

The requirements and wishes of the clients of Actemium are analyzed. This is important since it will steer the subsequent parts of the thesis in the desired direction. How do the logistical managers of the clients see the optimal solution? And how do the employees of Actemium see the optimal solution?

The answers to this question will be gathered via an investigation into the current WMS of Actemium and the identification of important insights the WMS might give. Next to that, an interview with the logistical manager of two clients of Actemium will be held. This will give deepening knowledge about the information that they seek in a workload forecast. An answer to the questions in this section can be found in Chapter 2.3.

3. What are relevant forecasting models for forecasting demand?

This research question focuses on acquiring knowledge about forecasting models that will predict future workload. The workload of every client is of course based upon the demand for their companies' products. Therefore identifying fitting models for demand forecasting is important.

Since there exist various methods already, literature research will be performed on the different methods available. Next to that, ways to assess the accuracy of these models will be identified. This can be found in Chapter 3.

4. How can demand forecast be translated to workforce resources demand?

After the demand has been forecasted, this should be translated into time to get valuable information for the clients concerning the workload. A lot of restrictions can play a role in the warehouse. Different routes of picking goods or different lists might deviate workload.

To answer this question, discussions with the business consultants of Actemium will be held. These employees know most of the general problems of clients, and the many different dimensions that each client encounters. An answer to this research question can be found in Chapter 4.

5. **What is the best way of forecasting future workload?**

The last research question focusses on forecasting the future. The end goal of Actemium is to estimate the time needed for its operations in the future. This might be forecasted in different ways. For example, the time can be measured and used as input for the forecasting model. Another possibility is to forecast the demand for a certain product and multiply this by the amount of time needed to process a certain product. These different approaches will be investigated to find out the forecasting method that best represents the real world for Actemium.

To answer this question, a case study is performed. Different methods are experimented with. Forecast errors will give the best indication of what the most accurate forecasting method will be. The answer to this research question can be found in Chapter 5.

1.5 Research design validation

The five constructed sub-questions are believed to be a good road to answer the main research question on how Actemium can forecast workload for its clients. First of all, the wishes of the client should be analyzed to know what to look for when looking into the other research questions. This heavily depends on the clients and Actemium. Their input is most important, this is why these two stakeholders are heavily involved in this part of the thesis.

After the wishes are gathered, an insight into the workload of a company starts with identifying the operations performed since these take up the time for the staff. The answer to this question (sub-question one) will give the desired data. For this, the Warehouse Management System Description document provided by Actemium will be used. This systematically explains every step in which the WMS supports the clients and is therefore believed to be a good information source for this research question.

After this, a literature review is performed to identify existing ways of forecasting the future is performed. Forecasting is a widely researched topic and enough information is available. Therefore literature review is viewed as the best way to answer this question. The identification of the workload and the explanation of the forecasting models together give the input needed in research question four, how can the demand forecast be translated to workload? This will possibly result in different ways workload forecasting can be done. Now, these ways should be compared to choose the best option possible.

The design of answering every question is explained separately, but the research design for the research as a whole is believed to be valid since every step is needed in the next step to get to the correct answer.

1.6 Research objective

The main research question should be answered at the end of the research. This will result in two objectives:

1. **Recommendations on how to translate from real-time workload from numbers to time**

At this moment, the dashboard of the WMS does give the upcoming work of the day in the number of actions that need to be processed. But the goal of this research is to find out how to translate this into the time that it takes to do this and therefore the expected time of finishing the tasks. The result will be a set of recommendations that will guide Actemium with this translation. Since these recommendations will include changes in the software of Actemium, it is not planned to already change this software and measure results in the timespan of this thesis.

2. Explanation of demand forecasting with a tool as a demonstration

At this moment, the WMS does not use the existing data to predict the future. But the goal of the research is to use this, especially concerning workload, to set the first steps in the direction of predicting future workload. The result explains the concept of forecasting, identifies fitting models, and measures the accuracy of the models. Next to that, a tool is built that demonstrates this process applied to one client of Actemium. Lastly, recommendations on how this can be implemented within the WMS of Actemium are given.

The thesis is structured as follows, in Chapter 2, the processes that are supported by the WMS are explored. Chapter 3 features a literature study on forecasting. Chapter 4 explains the concept of monitoring all workloads. Lastly, Chapter 5 gives a case study on estimating workload for one of the operations of Actemium.f

2. Analysis of the situation

This chapter will cover the practices of Actemium in further detail. It will explain the system that is provided for the clients and identify the workflows that are regulated/assisted by the WMS. This is done to identify time-consuming operations for employees. The information is based on the Warehouse Management System Description document (Actemium Zevenaar, 2021). After the system is explained, the wishes of Actemium and the client will formulate the desired situation. This will be done by creating a business process model on a high level. Next, all identified processes will be investigated concerning time consumption. Lastly, the chapter will explain the data that the WMS holds and the possible data gaps. At the end of the chapter, the first two sub-questions should be answered.

"1. What actions in the warehouse are time-consuming for its employees?"
"2. What are the wishes for better staff scheduling?"

2.1 Explanation of the Warehouse Management System

The goal of the WMS is to perform administrative and optimization tasks for clients that perform logistical operations. This is done by keeping track of all products in the warehouse; this means that these products, as well as the location for storage, are registered. Each storage location has been given a unique location code, just like all stock will be given a logistical entity (LE) code.

The WMS of Actemium consists of two components. First of all, there is the 'Manager application', which is the home of the software and is used at the offices or on a central computer in the warehouse. The other component is the equipment used by employees walking in the warehouse and performing operations such as putting items in the warehouse and picking them up. This will be done via handheld scanners or voice-picking with headsets. Depending on the product, either one of these will be used.

The scanners and voice pickers contain information on tasks to be done in the warehouse. The manager application is more advanced. It supports the client in four areas. First of all, it is used for the configuration of the system. This means that here data can be created, maintained, or deleted. This can for example mean an addition or change in warehouse locations that need to be processed. Next to the configuration, the manager application is the place where the tasks get controlled. Users can create different lists of tasks that will be sent to the scanners. The third function of the manager application is keeping track of the stock in the warehouse; this is displayed in real-time by the application and can provide the client with information. Next to stock, actions that are performed in the warehouse are being tracked by the WMS; this is all logged and is used by the client to trace back past operations. Lastly, the manager application provides some reports to the client in the form of a dashboard. Figures 6 and 7 show an example of the WMS, both of the configuration tab. These Figures display what the software looks like.

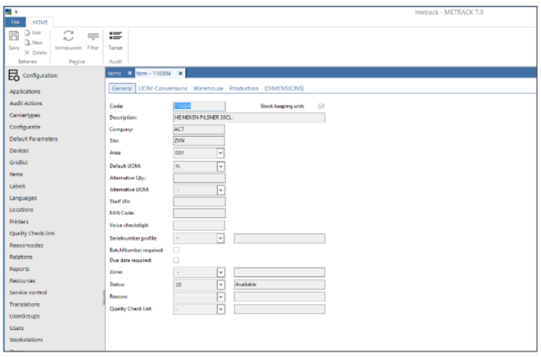

Figure 6: Configuration screen 1

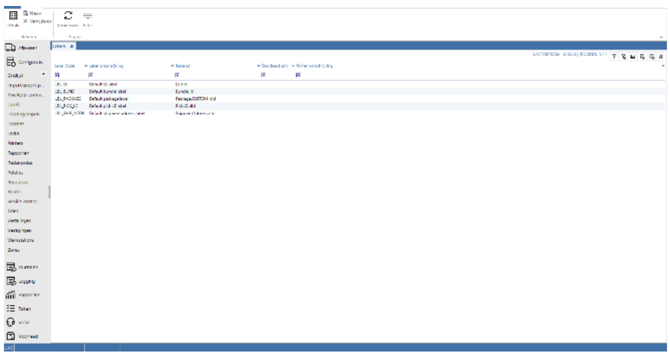

Figure 7: Configuration screen 2

Figures 8, 9, and 10 are examples of software that can be found on handheld scanners. The Voice headsets operate the same way by auditive assistance.

Figure 8: Log-In screen scanner

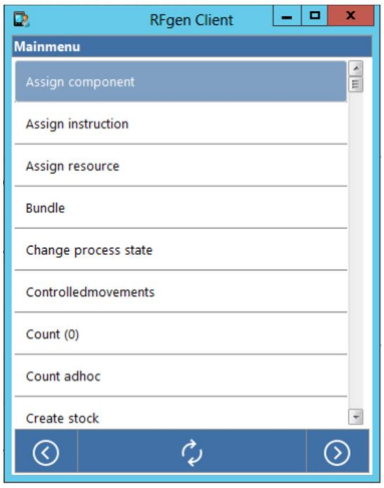

Figure 9: Main menu scanner

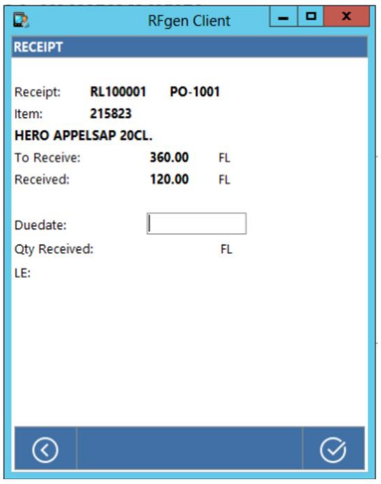

Figure 10: Scanner screen while used

2.2 Analysis of work

In this chapter, the general flow of products is created. This is based on conversations with employees of the company. A product flow model is created and can be found in Figure 11.

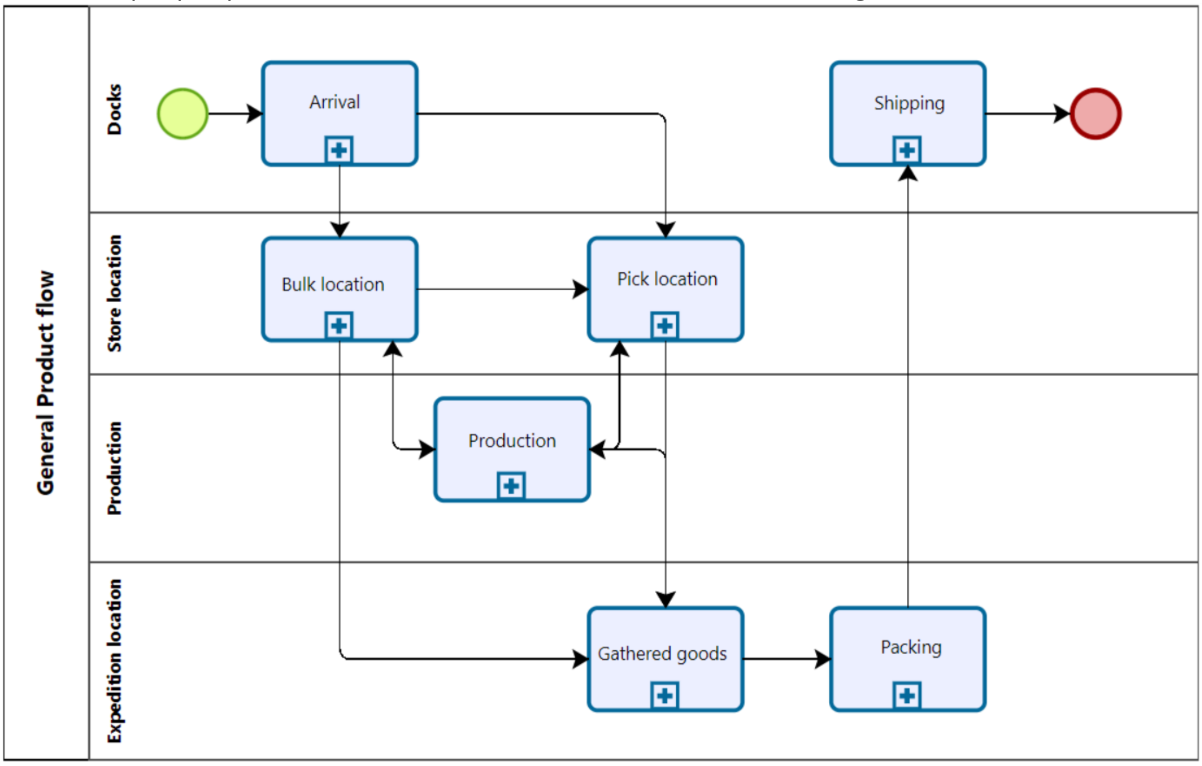

Figure 11: Product flow model

First of all, a product arrives at the client. This happens at the docks; the place where trucks (or other means of transportation) can drop off or pick up goods. Goods are unloaded from the trucks. After these docks, the products are stored in the warehouse; either at a pick location or a bulk location. The pick location is, most of the time, for smaller amounts of goods and is in an easier-to-reach location (based on distance). Bulk locations are larger locations, often harder-to-reach locations. After products are stored, products can be used for production, from where they can be put back into the warehouse (or moved to an expedition location directly). When the stock gets low in pick locations, the WMS automatically creates a task to replace goods from the bulk locations. This operation is called replenishment and occurs several times. When orders come in, the goods have to be picked up from the warehouse and gathered to the correct orders; this goes to the expedition location. The expedition location is a place close to the loading docks and is the place where an order is composed. Once the order is complete, it can be packed. This happens at the expedition location. Goods are moved to the docks and stored here until they are picked up by trucks and shipped.

This product flow is used to identify the operations that are time-consuming for employees and are therefore important to be taken into account. These operations are:

1. Arrival of goods
2. Put away goods in the warehouse
3. Replenishment of goods from bulk to pick and other transfers
4. Production of goods
5. Picking goods to the expedition location
6. Packing goods
7. Shipping goods

Appendix 9.2 shows the workflows which are created. The next sub-chapters will explain each operation in more detail.

2.2.1 Arrival of goods

There are three types of orders coming in, these enter the WMS via the ERP system of the company. This can be via purchased goods, returning orders from customers, or the transfer of goods between the client's warehouses themselves. When the incoming goods that will arrive come into the system, a so-called receipt list is created. This is the list that is used by the employees to collect and scan the goods on a pallet. There are two different types of pallets arriving. Homogenous pallets, these pallets contain a singular product, and heterogenous pallets, these pallets contain multiple products. The heterogenous pallets are unpacked and put away separately (in this case all products on the pallet need to be scanned).

In the manager of the WMS, a user can be assigned to a task. This way, work can be divided across the employees. Possibilities for other tasks are a quality check of arrived products (indicated by stock status: 'quarantine'), and a check whether all products that should be received are indeed actually received (a quantity check). All in all, the employees will work on unloading goods, scanning the arrived products, and optionally performing a quality check and quantity check.

2.2.2 Put away goods in the warehouse

Once the goods have arrived in the warehouse, they need to be stored in the warehouse. This is called the put-away process. First of all, the WMS has the feature to advise the location, therefore the employees do not have to decide upon this him/herself. Variation in the put-away process occurs when the location advice given by the WMS is a pick location. In this case, it is most likely that the whole batch of products will not fit there; so another pick or bulk location can be determined. This continues until the whole batch is stored.

There is a possibility of the put-away process being split up between two employees, this happens when pallets need to be stored at a high location. This cannot be done by every employee since one will need a high-level forklift. In this case, one employee will bring to pallet to a location, and the second employee will load the pallet into the warehouse. To conclude, time factors are bringing the pallet to the warehouse, and storing the pallet in the warehouse, which might be in multiple locations.

2.2.3 Replenishment of goods from bulk to pick and other transfers
These pick locations are easily accessible and used most frequently for picking items. However, these places are small and therefore stock runs out from time to time. Therefore a replenishment must take place. The WMS automatically detects when inventory is running low and replenishment is needed. The WMS creates a task for employees to perform such an operation within the warehouse. Another possibility is the manual creation of a transfer, this can be due to a lot of reasons and happens quite often. These tasks are straightforward but do take time.

2.2.4 Production of goods
The operations concerning production vary per client. One client can perform only one operation while another might have a complex production system. Next to that, the expertise of the employees might differ and therefore fall outside of this scope. Lastly, only a small percentage of clients even have operations of production to perform. Due to the limited amount of clients that are affected by production and the difficulty to generalize this operation, the production of clients is neglected in this research.

2.2.5 Picking goods to the expedition location
The picking process is part of the outbound process covering the orders coming in from customers. This is imported via the ERP system and can consist of either a bulk order or an order by pieces. Whether an order is declared a bulk order, depends on the quantity ordered. Whenever an order comes in, a picklist is created by the WMS, these picklists can consist of multiple orders, and orders can be split into multiple picklists. If a list has more orders, it is called multi-order picking. If the picklist is a list of pieces, the orders are sorted out onto carrier(s) per outbound order. After all, items are picked, the carrier is placed on the expedition location. If a picklist is a list for bulk, only complete carrier(s) will be picked and transported directly to the expedition location. Therefore the time consumed will either be from a bulk operation (often performed by a forklift and therefore slower) or a pieces operation, which often takes more than one run toward the warehouse.

2.2.6 Packing goods
Optionally, packing can be used on the picked carriers, multiple carriers can also be combined into one carrier. Packing can be started after picked items are delivered to an expedition location. This packing can be done with or without the registration of content details. This does change the time of the operation since all items need to be scanned. The packing of the carrier itself will take up most of the time.

2.2.7 Shipping goods
The shipping process is based upon the shipment list, containing information on the carriers that need to be loaded from the expedition location into each shipment. It is possible that packaging (such as pallets) goes out or comes in, this can be registered by the WMS and therefore needs to be scanned. The biggest time consumer within this operation lies in the unloading of packaging material and loading of the carriers onto the transportation.

2.3 Data storage, data display, and wishes
As stated in Chapter 2.1, the WMS registers operations in the warehouse. Next to that, stock levels are tracked and orders are managed. This is all stored in a database using SQL Server. This means that a lot of data is available and easy to access. If new data needs to be measured, the place to store the data is already present. This makes adaptions/additions easy to perform. For this assignment, two different parts of data are needed. First of all, data on the demand of a client should be measured over time to perform a forecast for the future. Next to that, the time needed needs to be measured for operations, there is already a lot of information on the operations that can be of use for this.

2.3.1 Demand information

To get the data from the database about the demand for the forecast that is suitable for forecasts, the data should be structured in the following way. First of all, different products follow different trends, therefore, the demand should be split out by products. This way, there is the possibility to combine the products into groups if wanted later. Next to a split per product, also the date when the demand for action was there should be noted. Lastly, the amount of the product that is picked at that time should be available.

All these factors are already present in the database, the demand is based on the table that holds the pick lists, called PickListJournalLines. This table is chosen since it only gets activated upon request of clients (therefore is demand), and includes all products. This table holds all the desired data, the quantity of picks per product per moment in time, from here, this data is extracted per product per day. Using the smallest time frame will allow the most room to combine or split again if desired. The time of picks is reconstructed and not collected with the idea that a forecast will be performed on the data. Therefore the data is most likely not accurate.

The main limitation of the usage of this table is that it only takes into account the picks that are performed by the employees. This means that if orders come in, but the product is not available, no demand will be recorded, or another product is included as a replacement. This can give a discrepancy between the real demand, and the picked products. The orders coming in are also documented, however, this data is only stored for thirty to sixty days. This means that not enough data is available. Therefore the picklists are the best reference for now.

2.3.2 Data on the operations

As stated before, a lot of data on the operations is already available. This data does not include a lot of time stamps, which means that no time indications are available at this moment. Only the process of picking items from the warehouse does hold a timestamp per operation that can be easily translated into duration. This however also has limitations, such as no possibility to identify the length of the first pick operation. Therefore at this moment, none of the tables give the correct data to translate into duration. However, these tables are identified as the correct place to store the new data, as they interact with the user during the operations. For every operation (except production) the corresponding table is stated:

1. Arrival of goods - ReceiptListJournalLines
2. Put away goods to the warehouse - MovementJournalLines
3. Replenishment of goods from bulk to pick and other transfers - MovementJournalLines
4. Picking goods to expedition location - PickListJournalLines
5. Packing goods - PackageJournalLines
6. Shipping goods – ShipmentJournalLines

2.3.3 Wishes of the client

To get a better view of the WMS, and to talk to a client to get their wishes. A visit to one of Actemium's clients was done. The client uses the WMS for quite some time and has experience with it. Next to that the company is a relatively large client of Actemium and does use the WMS extensively. Therefore, this is a good source to discuss their wishes for workload forecasting with them. The logistical manager of the company expressed the desire for an expansion of the dashboard (figure 4). This dashboard displays the current amount of tasks to perform. However, the logistical manager would like to see the time that these tasks will take. Next to that, he would like to know the future weeks as well. This is the main wish of the client. These wishes are confirmed by Actemium as a general wish from their company and more clients.

2.4 Conclusion

In this chapter, two sub-questions are answered, first of all, the research question: *"What actions in the warehouse are time-consuming for its employees?"* is answered. For this, the whole process in the warehouse is analyzed and the actions taken by employees are checked. For each operation, the time consumers are stated below

1. The arrival of goods: Unloading goods, scanning products, performing a quality and quantity check.
2. Put away goods in the warehouse: Store the pallet in the warehouse, either by foot or by forklift.
3. Replenishment of goods from bulk to pick and other transfers: Walking through the warehouse.
4. Picking goods to expedition location: Getting the goods, either walking or by forklift.
5. Packing goods: Packing items, and registering the goods on the carrier.
6. Shipping goods: Unloading package material, loading carriers, scanning items.

The size of the above-mentioned 6 operations depends on several factors. The demand of the clients is a major factor, but also the arrival of trucks, the way the goods are packed, and the different operations that different products need. Therefore it is important to get a good estimation of how many of these operations are needed. For a lot of operations, the clients can make proper forecasts. Forecasting demand, however, is more difficult. To solve this problem, a demand forecasting model should be created. Literature research on demand forecasting can be found in Chapter 3, and for all operations, clear guidelines on how to measure the time should be created. This is done in Chapter 4. Lastly, the application to Actemium of demand forecasting can be found in Chapter 5.

The other research question: *"What are the requirements and wishes for better staff scheduling?"* is also answered in this chapter. The biggest wish is an extension of the dashboard, at this moment, only the amount of orders to finish is given. The wish is that this is translated into time, and split out between the different operations within the warehouse. Next to that, at this moment, this information is only available about the present time, the clients are interested in this info for the future as well.

3. Theoretical framework

This chapter will explain the relevant literature concerning forecasting. First, several forecasting methods that are already explored will be explained, after that, the different methods to measure the will be explained. Lastly, an explanation of the way to choose a forecasting method will be given. The chapter will answer the following research question:

"3. What are relevant forecasting models for forecasting demand?"

3.1 Forecasting methods

A lot of forecasting methods are explored already, this can vary from simple static models to advanced machine learning methods. Chopra & Meindl (2015)and Safarishahrbijari (2018) both give an overview of the different methods that can be applied to solve a forecasting problem. The methods explained by both articles, and therefore deemed most prominent, are Qualitative, time-series, and Simulation.

Qualitative forecasts focus on human judgment, and the experience of the employees is used to make predictions for the next periods. This method is preferred when no data is available to use. The method is not preferred over methods that include historical data. Since there is historical data available, the qualitative forecast is not researched any further. Time-series forecasting does focus on historical demand, Both Chopra & Meindl (2015), and Safarishahrbijari state that time-series are useful if the assumption is made that history gives a good idea for the future. The third method, Simulation is a method that tests the behavior of a real-time situation over time. This method can answer what-if questions but can be very expensive and time-consuming. The focus is put on time-series forecasting since this method is believed to be most accurate with the availability of historical demand, but is faster and easier to develop than a simulation.

Some characteristics of forecasting are defined by Chopra & Meindl (2015), first of all, forecasts are always inaccurate, so keeping track of errors is important. This might indicate adapting the model to make it fitter. Another characteristic is that the long term is more inaccurate than the short term. This is self-explanatory but is important to keep in mind when deciding on the period(s) to make a forecast. The last characteristic is that aggregate forecasts are usually more accurate than disaggregate forecasts. These tend to have smaller standard deviations. This principle is important to keep in mind when focussing the forecasts on a single product.

Important to realize is that demand can be influenced by a lot of human factors, such as planned advertisements or marketing efforts, discounts, the state of the economy, or actions that competitors have taken. This however is not tackled within forecasts based on historical demand.

When choosing a forecasting method, it is important to know that both Chopra & Meindl (2015), and Axsäter (2006) state that the more advanced models are not always good by default. Since this means estimating more parameters, this will be more difficult. Axsäter (2006) states that looking into more general demand models is rarely done since it will require a detailed statistical analysis of the demand structure.

3.1.1 Basic principles of time-series forecasting

Chopra and Meindl (2015) describe two different types of forecasting methods, static and adaptive. Static is a model that does not change over time, based upon new demand data. Adaptive forecasts do change every new period. Their textbook explains that adaptive models usually give a better forecast for products, except when there is one period with a large deviation, the next forecast might be skewed. This however is not an event that occurs often. Therefore adaptive forecasts are the main models used. Next to static vs adaptive models, Axsäter (2006) gives an overview of the different types of forecasting. Constant models, trend models, seasonal models, or trend-seasonal models. As the names suggest, constant models will have a constant level that does not change heavily. Trend however does give an upwards or downwards effect on the forecasting model. While seasonal forecasts will yield demands that are swinging around a set level. Trend-seasonal forecasts combine the two latter and will swing around an increasing or decreasing level.

The following definitions of variables are given by Chopra & Meindl (2015), and these are used throughout all models:

- D_t = demand in period t
- F_t = forecasted demand for period t
- L = estimate of level at t = 0
- T = estimate of trend, an increase or decrease per period
- S_t = Seasonal index in t
- k_t = the number of periods in between zero demand

The error deviation is taken from Axsäter (2006), since Chopra & Meindl (2015) do not take this into account, the error does not affect the forecasts at all. But it is important to include them since they will be used for the accuracy testing of the model. Combining the theories from Axsäter (2006) and Chopra & Meindl (2015), the different methods can be described by the following formulas:

- A constant model can be described as: $F_t = L$
- A trend model can be described as: $F_t = L + Tt$
- A seasonal model can be described as: $F_t = LS_t$
- A trend-seasonal model can be described as: $F_t = (L + Tt)S_t$

To estimate variables, Chopra & Meindl (2015) have given a two-step approach. First of all, the demand should be deseasonalized, then linear regression can be run to estimate the level and trend of the demand. Once this is known, the seasonal factors can be calculated. This paragraph describes the basic principles of forecasting. In the next chapters, the different models that are built upon these principles are explained.

3.1.2 Moving average

The moving average model is based upon the constant model, only the level is estimated. Axsäter (2006) notes that it could be possible to take the average of all demand values. But sometimes a small movement occurs within the demand. Therefore the method takes the last periods and calculates the average over these periods. The formula is stated as follows:

$$F_t = \frac{D_{t-1} + D_{t-2} + \cdots + D_{t-N+_1}}{N}$$

The forecasted demand will be the same for all upcoming periods, the choice for the length of N depends on two factors, the speed of variation of the level, and the deviations. If the level varies quickly, and deviations are small, a small N can be chosen. However, if the level varies slowly, and deviations are larger, a larger N should be chosen to minimalize the influence of the deviations.

3.1.3 Regression models

The corporate finance institute (2022) defines regression analysis as a set of statistical methods used for the estimation of relationships between a dependent variable and independent variables.

3.1.4 Exponential smoothing

Exponential smoothing without trend and seasonality, also called simple exponential smoothing (SES) (Chopra & Meindl, 2015), is a technique similar to the moving average in many ways. The model takes the average of the previous values of the demand. The difference is the weight put on the past values (Axsäter, 2006). In exponential smoothing, the most recent values are receiving a bigger weight, exponentially decreasing the weight when going back in time and previous values. The formula is given by:

$$F_t = (1-\alpha)F_{t-1} + \alpha D_{t-1}$$

where α = is the smoothing constant and lies between 0 and 1, the forecast of period t is based upon the previous forecast, and on the actual demand of this period. If an α of 0 is chosen, the forecast is not updated and will take the value of the previous forecast, if an α of 1 is chosen, the new forecast will become equal to the last demand chosen. Axsäter (2006) recommends an α between 0.1 and 0.3 when months are chosen as periods. An α of 0.3 reacts much faster to changes than 0.1 but also lets the deviations affect the outcome more heavily. When a forecast is updated in smaller time frames. A smaller α should be used, according to Axsäter (2006), the following formula will give a correct new α:

$$\alpha = \frac{2}{(N+1)}$$

Whenever a forecast is started, an initial forecast is needed. A simple estimate can be used as starting value if no such estimate exists. The F_{t-1} can be set equal to 0, but a large α is needed to make the forecast adapt quickly to the new more accurate forecasts based on demand. If a small α is chosen, it will take a long time for the model to become reliable.

When a sudden shift in demand takes place, a reset of the forecast model will result in a far more accurate forecast. Chopra & Meindl (2015) recommend a technique by McClain (1981). The declining α method. This takes an α of 1, letting the model take on the last demand data available entirely. Then the α will decrease alongside the periods and will approach the desired α value of ρ, this is done via the following formula:

$$\alpha = \frac{1-\rho}{1-\rho^t}$$

3.1.5 Exponential smoothing with trend

Axsäter (2006) explains exponential smoothing with a trend, this is possible with the model suggested by Holt (2004). The model is based upon the same principle as exponential smoothing without trend, since the values of the level and trend will update based on the previous forecast and the past demand. The formula for the demand is given:

$$F_t = L_{t-1} + T_{t-1} \text{ and } F_{t+n} = L_{t-1} + nT_{t-1}$$

Where n is the number of periods into the future. After the forecast is calculated, the level and trend are updated based on the following formulas:

$$L_t = (1-\alpha)F_{t-1} + \alpha D_t$$

$$T_t = (1-\beta)T_{t-1} + \beta(L_t - L_{t-1})$$

Where β is a value between 0 and 1. The new level will be calculated based on the expected level from the previous forecast, plus the actual demand for that period. Then the trend will be updated according to the previous trend and the actual trend that took place. Both Chopra & Meindl (2015) and Axsäter (2006) suggest using a small β since errors in the trend will give large errors for long forecast horizons.

3.1.6 Exponential smoothing with seasonality

Exponential smoothing is also possible with seasonal influences (Winters, 1960). This model is only used for products with very clear seasonal variations such as Christmas decorations or ice creams. The seasonality is a parameter that cannot be updated the same way as trend and level but is a parameter manually added to each calculation. The formula for the demand is stated as:

$$F_{t+1} = L_t S_{t+1}$$

The forecast for the next period is based upon the level of the current period, multiplied by the seasonality factor S. The level is updated differently than normal, since the

$$L_t = (1-\alpha)L_{t-1} + \alpha \frac{D_{t-1}}{S_{t-1}}$$

The new level will be determined by the previous level and the actual level is deseasonalized by dividing it by the seasonal factor.

3.1.7 Exponential smoothing with trend and seasonality

When combining the methods from Holt and Winters, a method that is seen as a generalization of exponential smoothing with a trend is created. The so cold Holt- Winters' trend-seasonal method. The model alters the way that de demand is forecasted according to the following formula:

$$F_{t+n} = (L_{t-1} + nT_{t-1})S_{t+n}$$

This is the same formula as for exponential smoothing with a trend, except the outcome will be multiplied by the seasonal factor. The updating procedure for the level will change, however, the updating procedure of the trend stays the same as with exponential smoothing with a trend:

$$L_t = (1-\alpha)(L_{t-1} + T_{t-1}) + \alpha(\frac{D_t}{S_t})$$

$$T_t = (1-\beta)T_{t-1} + \beta(L_t - L_{t-1})$$

The new level is based upon the old level and trend (so without seasonal influences), and on the actual demand that is also deseasonalized.

3.1.8 Croston's method

It is possible that demand only occurs very seldom, but quantities are impactful on the forecast. This might be the case with one customer that orders large amounts at one time. Croston (Croston, 1972) has developed a method to tackle these situations. This is a forecast that changes only when demand is non-zero, next to that, the amount of periods in between these 'peaks' is administrated. The forecast is updated the same as simple exponential smoothing and the intermittent period of no demand is also updated the same way. If the demand equals zero, the forecasting and updating formulas are:

$$F_t = F_{t-1}$$

$$k_t = k_{t-1}$$

If demand is not equal to zero, the forecasting and updating formulas are:

$$F_t = (1-\alpha)F_{t-1} + \alpha D_{t-1}$$

$$k_t = (1-\alpha)k_{t-1} + \alpha k_{t-1}$$

If the average demand is requested, this can be given by the following formula:

$$A_t = \frac{F_t}{k_t}$$

3.1.9 ARIMA

ARIMA is a technique suggested by Box and Jenkins (Box & Jenkins, 1970), this is a technique that takes into account the deviations between the forecasts. It assumes that there is some correlation instead of independency. This can be positive-negative (i.e. someone has bought the products, but he/she does not need them anymore for the upcoming period). Or positive-positive (i.e. the product is bought and gets more exposure, and it gets sold more often).

The technique can handle correlated stochastic demand variations and other more general demand processes. A non-seasonal demand model is known as an autoregressive integrated moving average (ARIMA) model. There are multiple models, the most common is to use the notation ARIMA(p, d, q). Where:

- p = order of the autoregressive part (AR)
- d = degree of first differencing involved (I)
- q = order of the moving average part (MA)

The technique is known for its more extensive computations and its need for a large record of historical data. Axsäter (2006) states that using ARIMA can only be justified and motivated for very few important products. Makridakis (1998) explains how seasonality can also be used within ARIMA. By first deseasonalizing, subsequently forecasting using ARIMA, and personalizing again. The advantage of ARIMA is that, according to (Hyndman & Athanasopoulos, 2018), it usually is more accurate than

Exponential Smoothing in most cases. Requirements for ARIMA are higher, such as that it receives a stable and reasonably long dataset. Next to that, developing a forecasting model in ARIMA requires higher programming skills and therefore takes longer to develop.

3.2 Accuracy of methods

Calculating the accuracy of the methods used is important to assess the validity and reliability of the model. The information that it gives can be used to determine whether the forecasting method is correct, or whether systematic errors occur (Chopra & Meindl, 2015). In this chapter, the different measures and their purposes will be covered.

3.2.1 Mean squared error

Chopra & Meindl (2015) state that the mean squared error (MSE) is another good measure of variance. The MSE penalizes large errors much more significantly than small errors. This will result in a higher mean squared error if a few values are extremely off than when all values are a bit off. Therefore this measure is recommended if the second situation is preferred over the first one. The MSE is calculated as follows:

$$MSE_n = \frac{1}{n}\sum_{t=1}^{n} E_t^2$$

3.2.2 Mean absolute deviation

The mean absolute deviation (MAD) gives an impression of the variance (Axsäter, 2006). The MAD gives a better measure than MSE if the forecast error does not have a symmetric distribution. The MAD is calculated as follows:

$$MAD_n = \frac{1}{n}\sum_{t=1}^{n} |E_t|$$

3.2.3 Mean or average absolute percentage of errors

The mean or average absolute percentage of errors (MAPE) is a good measure when the underlying forecast has significant seasonality, it calculates the percentage that the forecast deviates from reality. If this is high, it means that the forecasts vary a lot from the forecast, this happens often with seasonality. The MAPE is calculated as follows:

$$MAPE_n = \frac{100}{n}\sum_{t=1}^{n} |\frac{E_t}{D_t}|$$

When picking a smoothing constant, Chopra & Meindl (2015) suggest that the minimization of the error that the manager is most comfortable with must lead, however in the absence of a preference, the MSE should be used.

3.2.4 Bias

The bias is a good measure to see whether the demand is not structurally off. The bias is the sum of errors and should fluctuate around zero in a correct model. If this is not the case anymore, a trend might be occurring that is not taken into account. The bias is calculated as follows:

$$bias_n = \sum_{t=1}^{n} E_t$$

3.2.5 K-fold cross-validation

Where all previous measures are indicators of errors, there exists a technique that will test the used forecasting technique. K-fold cross-validation is a well-known technique to compare different methods based on their accuracy. The demand data is split into two sets, a training set, and a testing set. The training set is used to declare the parameters for the forecasting method and to train the method. Cerqueira et al. (2020) state that a typical approach when using K-fold cross-validation is to randomly shuffle data, to split up the data in k blocks of equally large data points. After this is done, each block is taken as a test set, while all other blocks (so k-1) are used to train the set.

In time-series forecasting, the train and test set cannot be chosen as random samples since the future values cannot predict past values. There is a temporal dependency and that relation must be preserved when testing (Shrivastava, 2020). Shrivastava suggests cross-validation on a rolling basis. This means that first a small subset at the start of the data is taken as a training set, and a small subset is chosen as a test set. After this, the test set is added to the training set, and a new subset (chronologically later) becomes the new test set. This is continued until the whole set is covered.

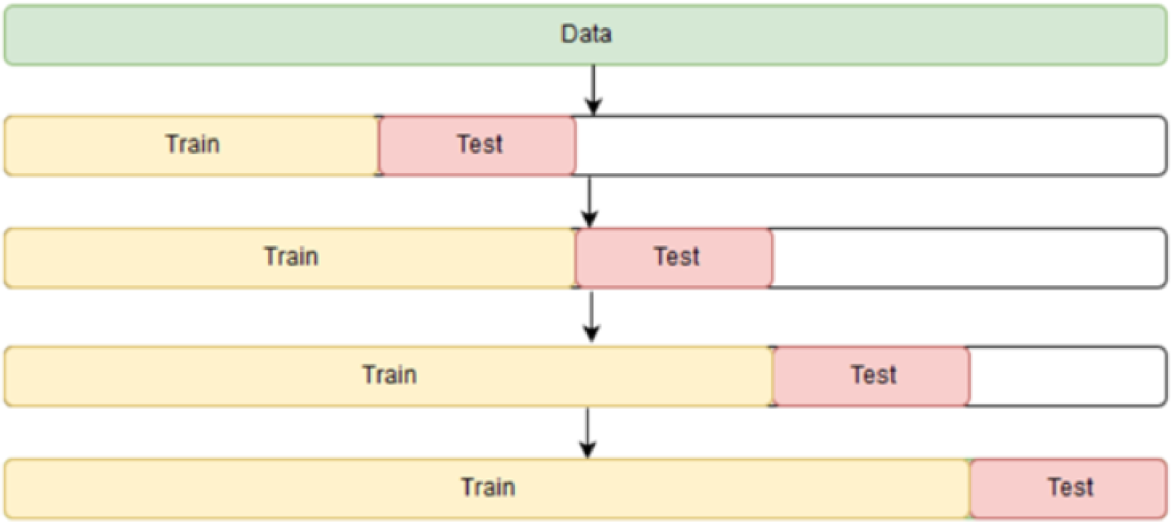

Figure 12: Visualization of K-fold cross-validation. Taken from Shrivastava (2020)

3.2.6 Monitoring forecasts.

Forecasts are made on the level of products or product groups, this means that a lot of different forecasts are made and it will be impossible to check them all manually. Therefore Axsäter (2006) recommends running automatic tests on the models to check for two things. A check on the reasonability of the demand can be done. This will check whether de demand and the forecast do not deviate so much that it is impossible. Whenever this event occurs, the product and its model can be checked manually. Another control possibility is to check whether the forecast represents the mean. This can be done by checking if positive and negative errors are of the same size. Over a longer period, the summation of these errors should be close to zero. If this is not the case, a product and its model can be checked manually to resolve the problem.

3.3 Conclusion

In this chapter, the research question: "What are relevant forecasting models for forecasting demand?" is answered. For this, several models have been looked into. Moreover, the way to assess the models has been identified, this was important to decide later on what good models are for this problem.

Demand forecasting features 3 aspects, the level of demand, the trend of demand, and the seasonality of demand. This means that there are several possibilities for forecasting patterns. First of all, stationary forecasting means that the product's demand does not increase or decrease significantly. If it does, an upwards or downwards trend can be included, this means that demand is linear, but not stationary. Seasonality shows the cycles in which a product will be higher and lower in demand. Important to note that both Chopra & Meindl (2015), and Axsäter (2006) state that the more advanced models are not always the best ones, since including more parameters means more estimations, which is prone to forecast errors.

The methods explained are moving average, regression analysis, exponential smoothing, Croston's method, and ARIMA. First of all, the moving average is widely acknowledged as a good forecasting method, it takes the average over the past n periods and predicts this value as the forecasted demand. The downside is that it cannot take into account trends and seasonality. Regression analysis relies on features that will predict the future. This, however, is not the case in this research and does not apply to this data set, since we will base our future predictions on past demand. Exponential smoothing is a method that takes a percentage of the last actual demand, and a percentage of the previously forecasted demand to predict the next demand. This method can take into account trends and seasonality. Therefore exponential smoothing is a good method. Croston's method takes the parameter of time in between orders into account. This is meant to estimate products that are only demanded occasionally. ARIMA is based upon the deviations in the forecast and can handle correlated stochastic demand variations. It is known for its extensive computations and needs a lot of data points. Axsäter (2006) states that using ARIMA is only justified for a few very important products.

K-fold cross-validation on a rolling basis can measure the accuracy of the model based on historical demand, it takes a part of the dataset as training data and another part for the testing set. Based on the equality of the forecasted demand and the testing set, the model can be described as accurate or not. This can help in deciding which model is best.

Other accuracy measures are based on the errors in the forecast, these include mean squared error, mean or average absolute percentage of errors, and bias. These measures can help in deciding upon the parameters used in the forecasting method. In most general cases, minimizing the MSE will result in the best forecasting method. A high MAPE can indicate seasonality and result in a change in the method used. Difficult is the definition of high, so one can argue when an indication is valid or not.

The most important factor to choose a fitting forecasting method is the data. In Chapter 5.2. the data is analyzed. After that, in Chapter 5.3, a choice is made and the reasoning for this is given. Chapter 5.4 displays the results of the forecasting, of each way of forecasting, the MSE, MAD, MAPE, and Bias are calculated. The MSE will be the main accuracy measure to assist in choosing the best forecasting method. The MAD will be the main accuracy measure if the error does not display a symmetric distribution. MAPE will be used to spot whether seasonality is applied properly. Lastly, Bias will be important to spot whether the forecasting method is structurally off. The k-fold cross-validation method is not used, since multiple forecasts will be performed. Calculating the accuracy measure is a time-consuming operation for the number of forecasts made, applying k-fold cross-validation does not fit within the scope of this thesis.

4. Measuring current workload

Time-consuming operations are identified in Chapter 2. In this chapter, the research question: "How can demand forecast be translated to workforce resources demand?" is answered. First of all, the main idea behind estimating workload is given, after which a detailed explanation is given about what this means for each operation. Note that the result of this chapter are pieces of advice on how to measure the time used for each operation. The implementation of this advice will be a software change to the system of Actemium, this will not fit in the period of this thesis. And therefore results cannot be generated and reviewed.

"4. How can demand forecast be translated to workforce resources demand?"

4.1 Estimation of workload

Actemium's software system is an advanced system that administrates (almost) all actions taken in the warehouse of the clients. There is a large presence of data, and next to that, there are opportunities to receive/generate the desired data. By scanning items multiple times before and after different actions. This allows Actemium to change the software, such that time is measured with minimal changes for the client in their actions. In Chapter 4.2, a split in all operations is made, per operations, clear guidelines on the measurement will be given. Next to that, the unit of work on which to base the workload is specified. In the end, the total workload is given by:

$$\begin{aligned} Total\ workload_t &\\ = Arrival\ workload_t &+ Put\ away\ workload_t + Replenishment\ workload_t \\ &+ Picking\ workload_t + Packing\ workload_t + Shipping\ workload_t \end{aligned}$$

4.1.1 Information collection

To answer the question of how much time each operation takes. A discussion with employees of Actemium is held. The business consultants of Actemium are involved in the discussion. These employees have the most experience in the general practices of the clients since they are involved with every client of Actemium.

4.2 Each operation split out

Each operation is different, and therefore requires a different method of time estimation. For example, the arrival of goods comes per truck, and cannot be based on individual products, while the put-away process and the picking of goods are product based. At this moment, there are no methods in the WMS that estimate any future units of work, this means that there is no information about the arrival of trucks to bring or receive goods. Next, there is no information on the demand for products. For the latter, the forecasting models are implemented. There are also opportunities for Actemium to include information about the other estimators for units of work. Clients often do have this information for themselves, but this is not integrated with the WMS.

4.2.1 The arrival of goods

The arrival of goods comes in two variations, either the driver of the truck unloads the goods himself, and in this case, no time is needed from the employees in the warehouse. Sometimes the employees do unload the truck themselves, nothing is registered in the WMS (i.e. no products are scanned). This means that the best estimator for the time needed is a standard average time per truck that can be configured in the WMS by the client and is a time based on the number of trucks arriving.

Products arrive on pallets, and these pallets can either be homogenous (one product on it) or heterogenous (multiple products). Homogenous pallets are ready to be put away in the warehouse without any required actions, therefore it takes no time. A heterogenous pallet, however, has to be unloaded to scan all the products, this takes time. The time needed for this is a standard time to be configured in the WMS by the client and is based upon the number of heterogenous pallets to be unloaded.

Some of the products on a heterogenous pallet do not have a label yet, in that case, the employees have to print a label for these products. This takes a standard time and is based upon the number of products that need this operation. It is known which products need this labeling action, therefore the time needed for this can be based on the forecast of this product.

Products require quality and quantity checks, the time for this can be neglected since this is a quick scan of the pallet arriving. A different case however is when a product arrives Retour from customers (instead of delivered from suppliers). In this case, the products have to be checked thoroughly. A separate standard time should be included for each 'Retour arrival'. When calculating the workload, the following formula is applied:

$$Arrival\ workload_t = F_t^{Pl} \times Avg_{Pl} + F_t^{La} \times Con_{La} + F_t^{Un} \times Con_{Un} + F_t^{Ret} \times Con_{QC}$$

Where:

- $F_t^{Pl} \times Avg_{Pl}$ are the forecasted number of heterogenous pallets and the measured time per pallet
- $F_t^{La} \times Con_{La}$ are the forecasted number of labels to be printed and the configured time per printing of label
- $F_t^{Un} \times Con_{Un}$ are the forecasted number of trucks to be unloaded and the configured time per unloading
- $F_t^{Ret} \times Con_{QC}$ are the forecasted number of Retour shipments and the configured time per quality check

4.2.2 Put away goods in the warehouse

Putting away the goods in the warehouse can be separated into two scenarios. The first one is a bulk operation and the operation is known in the system, an operator scans the products and gets the location, once, at the location, he scans the product again. The time needed for this operation is therefore measured and very accurate. The number of pallets to be put away is based on the demand forecast of the product.

Sometimes, the put-away process of bulk is performed by two employees, the first employee brings the pallet to a location, and a second employee puts the pallet away (this often happens if one employee operates the high-level forklift). When such a second person is active, the second action should be added as a separate action to the total workload. This person operates in the same way, by scanning the product at the start, and the location at the end. The time is based on the number of tasks for the second employee. This can

The second scenario is putting away per piece, this can be seen as the reverse picking process, and therefore the time measurement and forecasting will also be in the same way as the picking process. Chapter 4.2.4 explains this process. When calculating the workload, the following formula is applied:

$$Put\ away\ workload_t = F_t^{PA} \times Avg_{PA}$$

Where:

- $F_t^{Pl} \times Avg_{PA}$ are the forecasted number of products to be put away and the measured time per put-away action[1]

4.2.3 Replenishment of goods from bulk to pick and other transfers

Replenishment comes in two scenarios, a single operation (often placing pallets from the top to the bottom shelf), or a combined operation. The single operation can be measured since the employee

[1] Not all products have the same put away time, in Chapter 5, a more extensive explanation is given about how to deal wil this

scans the product at the start and the location at the end. So the total time is measured and is based on the number of single replenishment tasks for the employees.

The combined operation can be seen as partly a picking and put-away process. Products are gathered and put on a cart or pallet. This can be measured the same way as the picking process. Then the products are moved to another location. Afterward, the products are put away per piece, which can be measured and forecasted in the same way as stated in Chapter 4.2.4. When calculating the workload, the following formula is applied:

$$Replenishment\ workload_t = F_t^{Rep} \times Avg_{Rep}$$

Where:

- $F_t^{Rep} \times Avg_{Rep}$ are the forecasted number of products to be replenished and the measured time per replenishment action[2]

4.2.4 Picking goods to expedition location

Again, there is a split between picking bulk items, or picking per piece. Bulk items are simple since these are scanned at the start, and the end of the operation. Just as with putting away the bulk items. The measured time should be multiplied by two since the way back is not included and is based upon the number of pallets to be picked, the number of pallets to be picked can in its turn be based upon the forecast of the product.

Picking per piece can in its turn be split up into two different scenarios, single- and multi-order picking. An important thing to note is that it is extremely hard to get the right pick time per product since it differs every time. Picking times are dependent on the other products on the list since this is not done piece by piece. This results in a different time indication for one product each time. So only an average time needed can be taken. The time needed per product can be measured by taking the scan of the product as the start, and the scan of the next product as the end. The average of the measured times s taken as workload time and is based upon the number of products to be picked, this in its turn is based upon the forecast of the total amount of products.

An opportunity to improve the estimation of the picking process can be by splitting up the walking time and actual picking time of the employees. Since products differ, their picking times also differ. The walking time can only still be an average of all products and is based upon the total amount of products (this cannot be specified since the routes of employees are different most of the time) , but the actual picking time can be measured by adding an extra scan for the employees, note that this does change the process of the client. The picking process is then also a measured time and can be based on the individual products.

Clients use two ways of picking, single-order or multi-order picking, multi-order picking is a method that helps the routing of the employees while picking products. Therefore a different average should be taken for single and multi-order picking. The basis of the workload of the pick operation lies in the demand for the products since this triggers a pick operation. When calculating the workload, the following formula is applied:

$$Picking\ workload_t = F_t^{Pi} \times Avg_{Pi}$$

Where:

- $F_t^{Pi} \times Avg_{Pi}$ is the forecasted number of products to be picked and the measured time per pick action[2]

[2] Not all products have the same put away time, in chapter 5, a more extensive explanation is given about how to deal wil this

4.2.5 Packing goods

Bulk pallets often do not need packing at all, however, smaller products do get packed. The products will get scanned before going into the packaging material. Afterward, a label is put on the packaging and scanned. This means that the end and start times of the material are noted. Therefore the time is measured and is based on the number of piece orders.

Some customers require registration of the content of the package. This requires more time from the employees, therefore, separation should be made in packing with- and without registration of content. The time needed for this operation is again measured and is based on the number of piece orders. When calculating the workload, the following formula is applied:

$$Packing\ workload_t = F_t^R \times Avg_R + F_t^{WR} \times Avg_{WR}$$

Where:

- $F_t^R \times Avg_R$ is the forecasted number of packings with registration and the measured time per packing with registration
- $F_t^{WR} \times Avg_{WR}$ is the forecasted number of packings without registration and the measured time per packing without registration

4.2.6 Shipping goods

Just as unloading goods from a truck, loading the goods can be performed by the truck driver him/herself. In this case, no time is needed. When the client does perform the shipping process, all pallets or boxes need to be scanned. Scanning the pallets does take more time than boxes. However, separating these two will be difficult since there are no indicators of whether a product is a pallet or box. The time needed for this operation is not a time that can be easily measured by the WMS, therefore a standard time should be configured by the client and is based on the number of pallets/boxes that will be shipped. When calculating the workload, the following formula is applied:

$$Shipping\ workload_t = F_t^B \times Con_B + F_t^P \times Con_P$$

Where:

- $F_t^B \times Con_B$ are the forecasted number of box shippings and the configured time per box shipping
- $F_t^P \times Con_P$ are the forecasted number of pallet shippings and the configured time per pallet shipping

Examples of the correct data to be gathered can be found in Appendix 2.

4.3 Conclusion

In this chapter, the research question: “How can demand forecast be translated to workforce resources demand?” is answered. For every operation, a way to measure the time needed for the operation is generated. In some cases, this is based on the products and their forecasts. For other operations, the time was not based on the products and therefore not based on demand. For this, other units of work are identified. This however means that these also require a forecast to predict future workload. This falls outside the scope of this thesis but is a good opportunity for future research.

Measuring the time is not always possible, since this would change the workflow of the clients, which is not desirable. Only in the picking process, a change in workflow is suggested. This is expected to make the forecasted time significantly more accurate. In other cases where measuring time is not possible, a standard time is suggested. This can be taken as a norm for the clients and should be configured in the WMS so that clients can adapt the norm to make it more accurate.

5. Forecasting the future workload

In Chapter 4, the way to monitor the workload is investigated. This information can be used to forecast the future workload of clients. In this chapter, forecasting will be the main subject. There are different ways to forecast the future. These include grouping different products while forecasting. This chapter will answer the following research question:

"5. What is the best way of forecasting future workload?"

This chapter will function as a case study that can be used by Actemium to forecast all products of all clients. A dataset of one client is used. This can function as an example of how Actemium can use forecasting for all clients. All considerations about why a certain method is chosen must be well explained. This will make sure that Actemium can use this case study to make their considerations. Referring back to the total workload function, this chapter will only cover the Picking workload:

$$\begin{aligned} Total\ workload_t &= \cancel{Arrival\ workload_t + Put\ away\ workload_t + Replenishment\ workload_t} \\ &\cancel{+}\ Picking\ workload_t \cancel{+ Packing\ workload_t + Shipping\ workload_t} \end{aligned}$$

5.1 Different ways of forecasting

A forecasting model is based on historical data and is one-dimensional, meaning that you only need one type of data concerning time. The data, however, can be presented in multiple ways. To forecast the workload, it makes sense to forecast the measured time based on past time. Another possibility is to base the forecast on the demand per product and multiply this demand by the time it takes per product. The third possible option is to group products by pick and bulk status, this will make a split in products that need different operations. Lastly, grouping products based on historical pick time will group products that look like each other. These are the four identified ways of forecasting that are explored.

5.1.1 Forecasting time only

The first possibility for input data of the forecasting model is to use the time of each operation as a total of the day, and based upon this data make an estimation for the future. It might be a good way of forecasting since the time will be measured directly and the errors are also time-based. This will mean that no intermediate calculations, which are also prone to errors, have to be performed. A downside of this method is that at this moment, only pick times are measured, which can help us in the case study but is therefore not representable for all operations at this moment in time. The forecast unit (F_t) in this case, is given in seconds. The workload is given by:

$$Picking\ workload_t = F_t$$

5.1.2 Forecasting single products

Another input for the forecasting model is the demand of every single product split out. This will mean that the time will be measured for operations on each unique product separately. The demand forecast for each product (F_t^{Pr}) has to be multiplied by the average time it takes to perform operations on that product (Avg_{Pr}). This will be summed up to one total by adding all unique products. An advantage of this method might be that a good split in each product is made, so the employees of the client can see exactly where the larger time consumers are. A downside of this method is that data is very prone to errors since only small samples are taken for the forecasting model. The forecast unit (F_t) in this case, is given in the number of pick operations. The workload is given by:

$$Picking\ workload_t = \sum_{Pr=1}^{4335} F_t^{Pr} \times Avg_{Pr}$$

5.1.3 Grouping products by pick and bulk

The third input data is by splitting out the demand of bulk and pick operations. This is chosen since the two require very different handling and are therefore different in terms of workload. The main advantage of this method is that a lot of data can be combined and therefore the forecasting models are less prone to errors. The downside is that only little insight can be given into where the workloads are expected to be high and where they are low. The workload is calculated by multiplying the Forecast (F_t^B or F_t^P) with the average time for picking a bulk or pick product (Avg_B or Avg_P). This means that all pick operations of bulk products are aggregated, and all pick operations of pick products are aggregated. The forecast unit (F_t), in this case, is given in the number of pick operations. The workload is given by:

$$Picking\ workload_t = F_t^B \times Avg_B + F_t^P \times Avg_P$$

5.1.4 Grouping products based on pick time

The last possible input data can be seen as a middle way between forecasting single products and grouping by pick/bulk. Products can be grouped by looking at the pick time. This way, the larger and smaller-time consumers can be combined. The workload is calculated by multiplying the Forecast (F_t^g) with the average time for picking a product from that group (Avg_g) The forecast unit (F_t), in this case, is given in the number of pick operations. The workload is given by:

$$Picking\ workload_t = \sum_{g=1}^{28} F_t^g \times Avg_g$$

These four methods of forecasting will be evaluated in Chapters 5.2 and 5.3. Based on the results, a recommendation to choose demand or time as input for the forecast will be given. Next to that, the split in products will receive an evaluation to determine the best option for Actemium.

5.2 Data analysis

In this chapter, the data that is used for forecasting is analyzed. First, an explanation is given about the gathering of the data and the information it holds. Afterward, the data is modified so that it can be used when forecasting. Lastly, the feasibility of the four different ways of forecasting is analyzed.

5.2.1 Data collection

The dataset used for the case study is received from Actemium and is an example of one of their clients. This is directly imported from the database that Actemium holds for this client. It is the information on the pick operations. The chapter, therefore, focuses on the operation called 'Picking goods to expedition location'. This operation is chosen since it depends mostly on the demand of the clients and the dataset of this operation is the most fitting.

5.2.2 The dataset explained

This data includes the pick actions performed on each product per certain date type (day, week, and month). Next to that, the number of products picked and the duration of that pick action are given. Lastly, the amount of times an employee picked up a product is given (this is unequal to the total quantity since an employee can take two or more units of one product at a time). Table 2 gives an overview of the 7 months that one product was picked. In the other months, demand was equal to zero.

Data	ID	Product	Pick actions	TotalQuantity	PickDuration	AvgSecondsPerPick
3-2021	1	Product X	4	7	56	14
6-2021	1	Product X	4	5	12	3
7-2021	1	Product X	9	12	37	4

8-2021	1	Product X	8	13	1110	138
9-2021	1	Product X	7	13	33	4
10-2021	1	Product X	4	9	29	7
11-2021	1	Product X	6	11	17	2

Table 2: Overview of data received

Before a type of forecasting method can be chosen, the input data has to be analyzed. Therefore, the different ways of forecasting explained in Chapter 5.1 will be analyzed.

5.2.3 Cleaning up the data

The dataset received is not usable in its initial state. The data has to be 'cleaned' before it can be used. Six changes have to be made. First of all, as can be seen in Figure 13, the number of picks starts to rise from week 25-2021. This is the case since the official release date of the Actemium software was in week 26-2021. Before that, the system was used side by side with another system, or not used at all. Therefore, all data before week 26 is deleted to gain representable data.

Figure 13: Overview of the total number of picks over time

The second changes are the exclusion of the holiday weeks 52-2021 and 01-2022. Thirdly, some limitations of the calculation of the processing time result in a time measured overnight. Resulting in a processing time too high. This is recalculated from the start of the day. In some cases the process misses a start time, resulting in a processing time of zero. This zero value is replaced by the average of that product. Lastly, weekend days are taken out of the dataset since, on these days, zero items have been picked. This remains 268 days.

The fifth problem is that no outliers can be taken out of the dataset since this dataset is reconstructed and no attention has been paid to processing times in the past. There is no way to validate the results or to justify taking out outliers.

5.2.4 Period of data taken & Forecasting single products

The dataset given by Actemium, according to the company supervisor, is representable for other databases of the clients of Actemium. The first question that has to be answered is, what kind of period do we use as input for the forecasting method? This can be per day, per week, per month, or anything else. However, these three are the most standardized time frames and are used as planning time frames by clients. The planning of most clients is made per day, next to that, if weekly seasonality is occurring, it can only be spotted by forecasting days as periods. Next to that, the downside of taking a larger period for the forecast is that there is no precise information for the clients. Therefore this is not preferred and days are chosen as the forecasting period. When looking into the data, it becomes clear that most of the products are not picked systematically, and therefore are very variable. This makes forecasts less accurate. Taking larger periods will decrease the variability of the data. However still a large amount of products show a large variability when taking weeks or months as the period./

The conclusion is that grouping of products is necessary and single product forecasting is not an option, Items can be grouped in various ways so that enough data points are achieved per group. Therefore there is a freedom of choice in the period of the data. Days are chosen as periods since this will allow foreseeing daily seasonality.

5.2.5 Grouping products by pick and bulk

Grouping the items by pick and bulk is a way to generalize products that look a lot like each other. The advantage of grouping pick and bulk is that for pick operations almost 100% of the data points are covered. In Figure 14 and Figure 15, the number of picks is displayed.

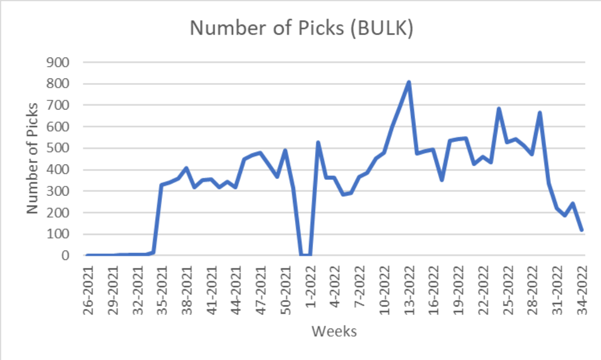

Figure 14: Overview of the total number of Bulk Picks

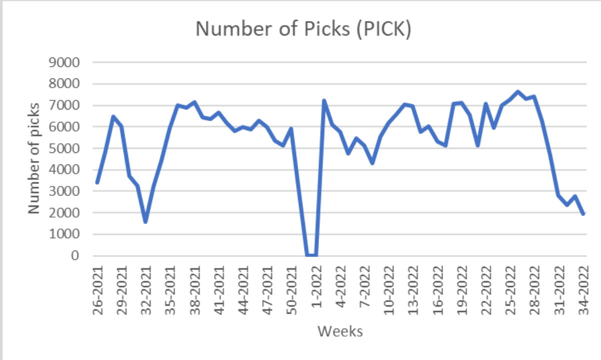

Figure 15: Overview of the total number of Pick Picks

The reason to make the split between pick and bulk is the expected difference in pick duration of both operations. In Figure 16 and Figure 17, the pick times are compared to validate the suspicion of a large time difference.

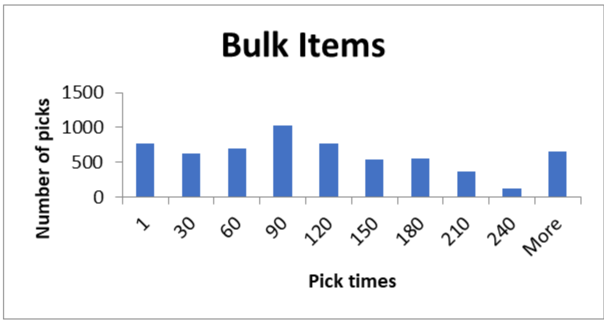

Figure 16: Histogram about the pick times of Bulk items

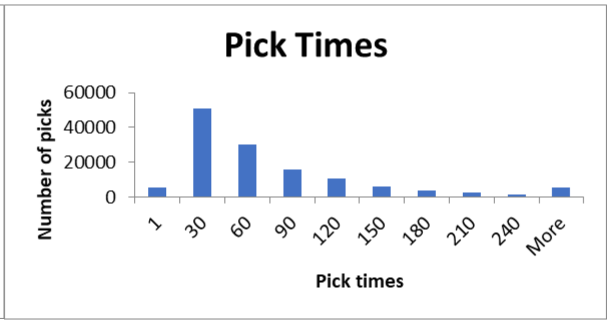

Figure 17: Histogram about the pick times of Pick items

As can be seen, the time it takes to pick bulk items varies more than pick actions, the average time is 158.34 seconds while picking pick items takes on average 72.35 seconds. This is a significant difference, indicating that splitting the forecast based on bulk and pick is a good way of forecasting the time needed.

5.2.6 Grouping on pick times

Another way of sorting data is by grouping all items based on their pick times. This allows splitting products that differ a lot from each other in workload. Therefore, the average amount of seconds needed to pick each product is calculated. This is done by adding all pick times for each product separately and dividing it by the number of times it is picked. To get an overview of how long each product on average takes to get picked. The histogram in Figure 18 is created.

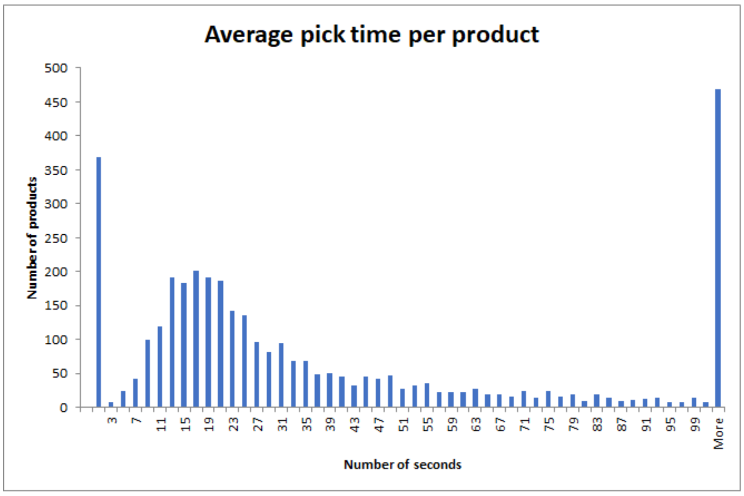

Figure 18: Histogram of the average pick times per product

As can be seen in Figure 18, the difference in average pick time per product ranges from 3 seconds until around 100 seconds. Indicating that grouping by pick times might be a good solution. It can also be seen that pick times of 1 second and pick times larger than 100 are regularly appearing. The hypothesis is that these numbers are outliers, but as stated in Chapter 5.2.3, there are no valid grounds to exclude them.

When the groups of products are made as small as possible, the time prediction is expected to be more accurate, but enough products have to be grouped to construct a usable and reliable dataset. Chopra & Meindl (2015) and Axsäter (2006) even state that generalizing the forecasting model often gives more accurate answers. Therefore, this is a weigh-off between accuracy and reliability. The average time per group is chosen as the deciding factor in the number of groups. Taking too many groups makes the average between the groups under 0.1 seconds, since this is negligible, it is chosen to select a different average per group of one second. This results in 28 groups of products. All these groups have enough data points for an accurate forecast. The division of average time per pick (per group) is displayed in Figure 19:

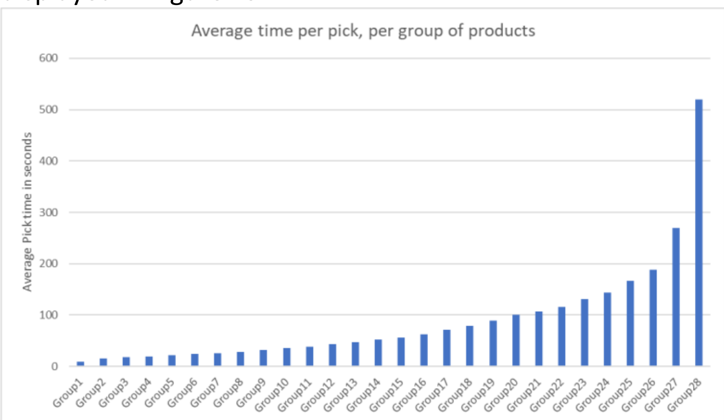

Figure 19: Overview of average pick time per group of products

As can be seen in Figure 18, in the last groups of products, the average pick time rises significantly. The origin of this happening is not known. So it cannot be validated whether this input is correct or not. The suspicion is that these pick times are incorrect and another event occurred in the warehouse.

Concluding, splitting the products into groups based on their pick time itself is very suited for the forecast models. It should be tried out to see if this method is more accurate than splitting by pick and bulk.

5.2.7 Forecasting time only

The last identified method to forecast the workload is by taking the average workload per week. And use this as input for the forecasting. This method can be viewed as the simplest. And might be accurate on the workload since it does not need any other calculations which are prone to error. In Figure 20, the total pick duration is displayed per week.

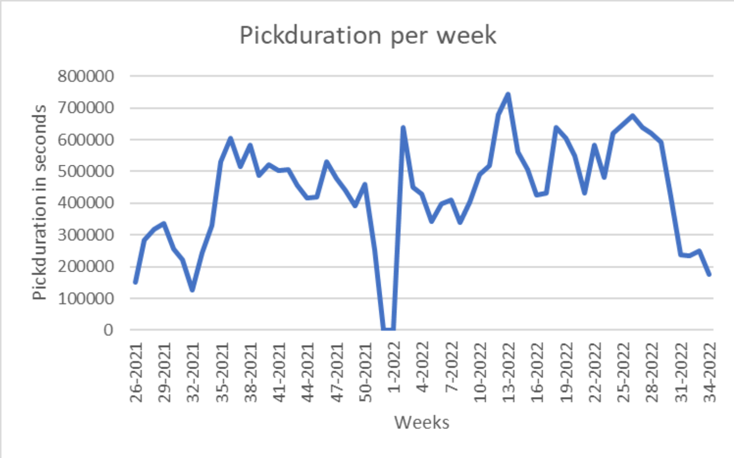

Figure 10: Overview of Total pick duration per week

Since all products are combined in this method, all weeks have data, which is also already very generalized. These are advantages of forecasting the pick duration. The main downside of this forecasting method is the lack of understanding of why certain weeks are high and certain weeks are low. This is because the forecast is not split out per product, product group, or by pick and bulk.

5.3 Forecasting models

In Chapter 5.2, the different possible ways to input the data into the forecasting model have been analyzed. These are 1. Inputting the number of picks for Pick products, and inputting the number of picks for Bulk products. This yields two vectors. 2. Inputting the number of picks of different products combined, based upon the average time it takes to pick these products. This yields 28 vectors 3. Inputting the amount of Pick duration per day. This yields one vector. Now that the input vectors are calculated, it is important to acquire them with the correct forecasting method. This is done by the analysis of each vector. Afterward, the forecast will be run on a training set and compared to the testing set. From this, the mean squared error will be calculated to check whether the forecast is accurate. The forecasting model is based on the cleaned-up data, as explained in Chapter 5.2.3.

5.3.1 Choosing a forecasting model

In the theoretical framework, four forecasting models are investigated and explained. When comparing the four models, three aspects are taken into consideration. First of all, the forecasting model should be able to follow the pattern of demand. Secondly, enough data should be available for an accurate forecast with that model. Lastly, the development of the model and its difficulty can be limiting factors.

The moving average model immediately shows its limitation since it is unable to cope with fast varying demand. It cannot capture the trend. As can be read in Chapters 5.3.2, 5.3.3, and 5.3.4, the patterns do display a trend. Therefore this model cannot be used.

The exponential smoothing method does fit the requirements. Exponential smoothing can cope with trends and seasonality. For Exponential smoothing, enough data is gathered to make the model accurate. Lastly, exponential smoothing is a model that can be programmed rapidly.

Croston's method is an odd model, this model forecasts the time in between two demand periods and the size of that demand. This model can be a good fit for a few of the products that the clients sell since these products have a sporadic demand. However, the length between these periods and the size of the demand are inconsistent. This makes Croston's method not fit the requirements.

Lastly, ARIMA is an advanced model, and it is said to outperform the other forecasting models (Hyndman & Athanasopoulos, 2018). The model, however, performs best on a stable dataset without any trends or seasonality. Next to that, it requires a reasonably large dataset, which is not the case for the dataset received. Lastly, ARIMA is more complicated to develop without programming experience. All in all, this made ARIMA not optimal to use.

Concluding, the exponential smoothing model is the only model that fulfills all requirements. Therefore this is chosen and performed on the received dataset.

5.3.2 Grouping products by pick and bulk

When looking at the bulk vector (figure 21), a strong increasing trend can be seen. This however does occur mainly in the first few weeks, the demand is extremely low. When these weeks are excluded (figure 22), the trend is less steep, but still there.

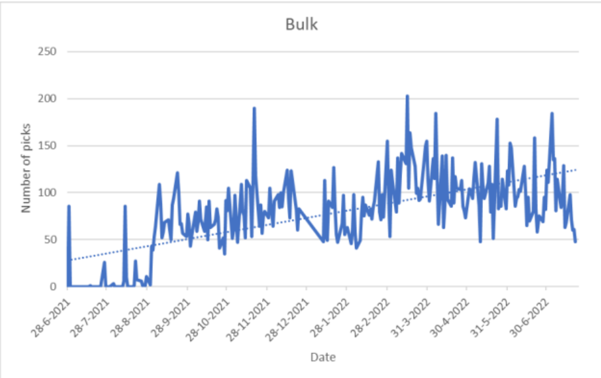

Figure 21: Bulk items picked each day

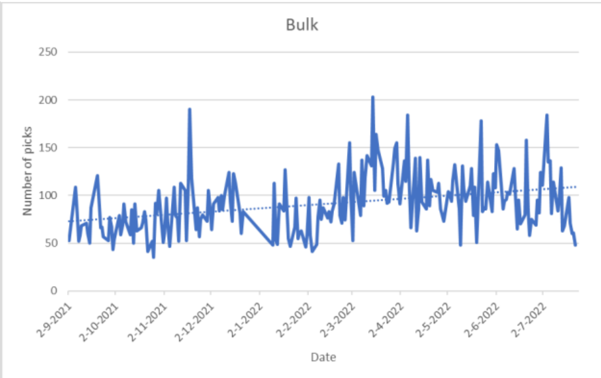

Figure 22: Bulk items picked each day, excluding the first weeks

To spot daily seasonality, the daily totals are added together and displayed per day (figure 23). As can be seen, Monday until Wednesday has a slight decrease, but Thursday and Friday are the busiest days when looking at bulk. Therefore, there is daily seasonality. Holt-Winters forecasting method will be used when forecasting bulk. The dataset that will be used is based on Figure 22, this is chosen based on the assumption that the first week's demand is not a good representation of reality.

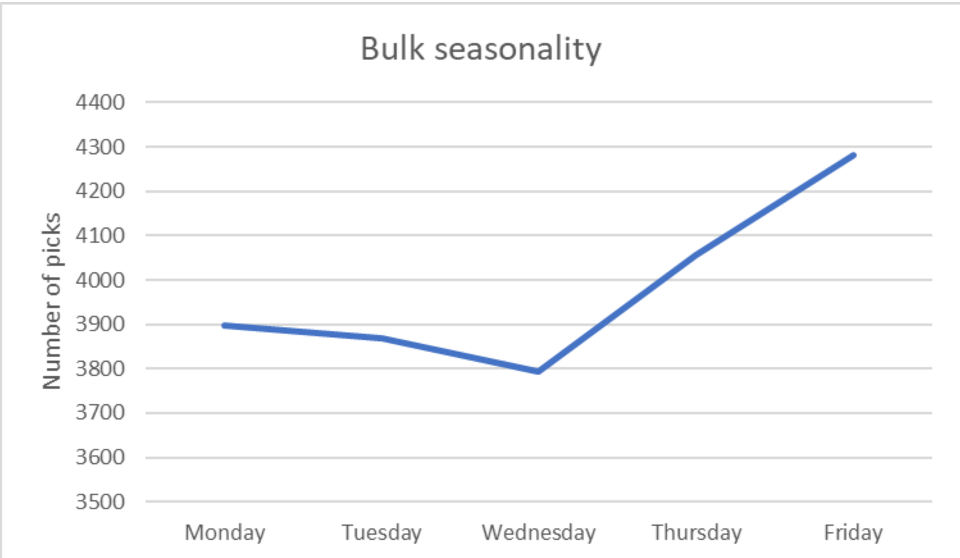

Figure 23: Bulk seasonality

When looking at the vector for pick operations, it can be seen that there is a small trend occurring Figure 24). Over the whole year, this is significant enough to take into consideration when choosing a forecasting model. When looking at seasonality (figure 25), a clear seasonality can be found. This is opposite to the bulk seasonality since the high workload will be at the start of the week, while during the week, fewer picks will be performed. Since both trend and seasonality are included, Holt-Winters will be used.

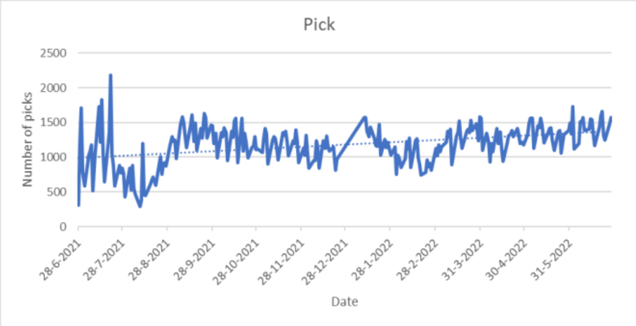

Figure 24: Pick items picked each day

Figure 25: Pick seasonality

5.3.3 Grouping items by pick times

When products are grouped by average pick time, 28 vectors have to be analyzed, this results in different forecasting models. Most of the vectors except two do display a trend. Next to that, 17 of 28 vectors do display seasonality. In Table 4, an overview of all groups, their characteristics, and the chosen forecasting method. The abbreviation are Simple exponential smoothing (SES), Exponential smoothing with a trend (EST), Winters forecasting method (W), and Holt-Winters forecasting method (HW).

Group	Seasonality	Trend	Forecasting method
1	no	yes	EST
2	yes	yes	HW
3	yes	yes	HW
4	no	yes	EST
5	no	yes	EST
6	yes	yes	HW
7	no	yes	EST
8	Yes	yes	HW
9	yes	yes	HW
10	no	no	SES
11	yes	yes	HW
12	yes	yes	HW
13	yes	yes	HW
14	yes	no	W
15	yes	yes	HW
16	yes	yes	HW
17	yes	yes	HW
18	yes	yes	HW
19	yes	yes	HW
20	yes	yes	HW
21	no	yes	EST
22	no	yes	EST
23	no	yes	EST
24	yes	yes	HW
25	no	yes	EST
26	yes	yes	HW
27	no	yes	EST
28	no	yes	EST

Table 4: Overview of chosen forecasting method per group

5.3.4 Forecasting time only

When forecasting time only, there is one vector included. This makes the analysis simple and short. First of all, a clear increasing trend can be found (Figure 26). Secondly, the seasonality is very clear (Figure 27). Thursdays have the peak of the week, while at the start and end of the week, there is a lot less work. This result is also expected when comparing the bulk and pick seasonality, since pick decreases over the week, and bulk increases significantly at the end of the week, there is no surprise that Thursday holds the highest amount of time needed. Again, the Holt-Winters forecasting method would be a good fit for this vector.

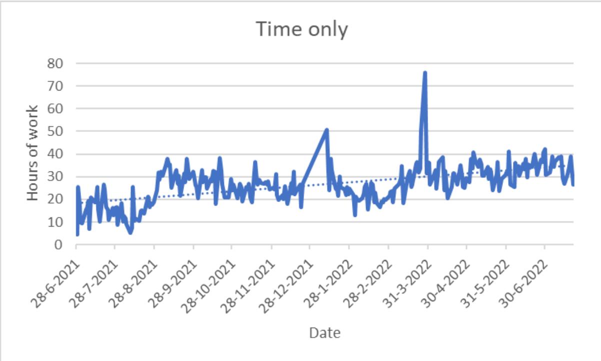

Figure 26: Total pick time per day

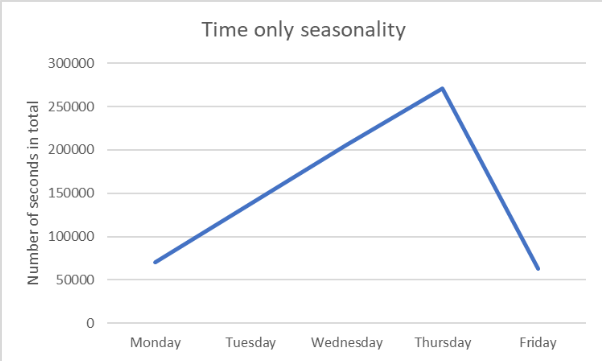

Figure 27: Time-only seasonality

5.4 Results of forecasting

In this chapter, the results of the forecasting methods are presented. For this, the mean standard error is the main indicator. As stated by Chopra & Meindl (2015) in Chapter 3, When picking a smoothing constant, the minimization of the error preferred by the manager must lead. In this case, however, Actemium does not have a preference, The literature suggests that the MSE should be used. Secondly, the MAD and MAPE are used as secondary accuracy measures to support decision-making.

Forecasting is performed using the Holt-Winters package in python, the package automatically fits the dataset and performs the forecast for the requested period (the 30 days of the test set). In Figure 28, the comparison of the different forecasting models with reality is displayed.

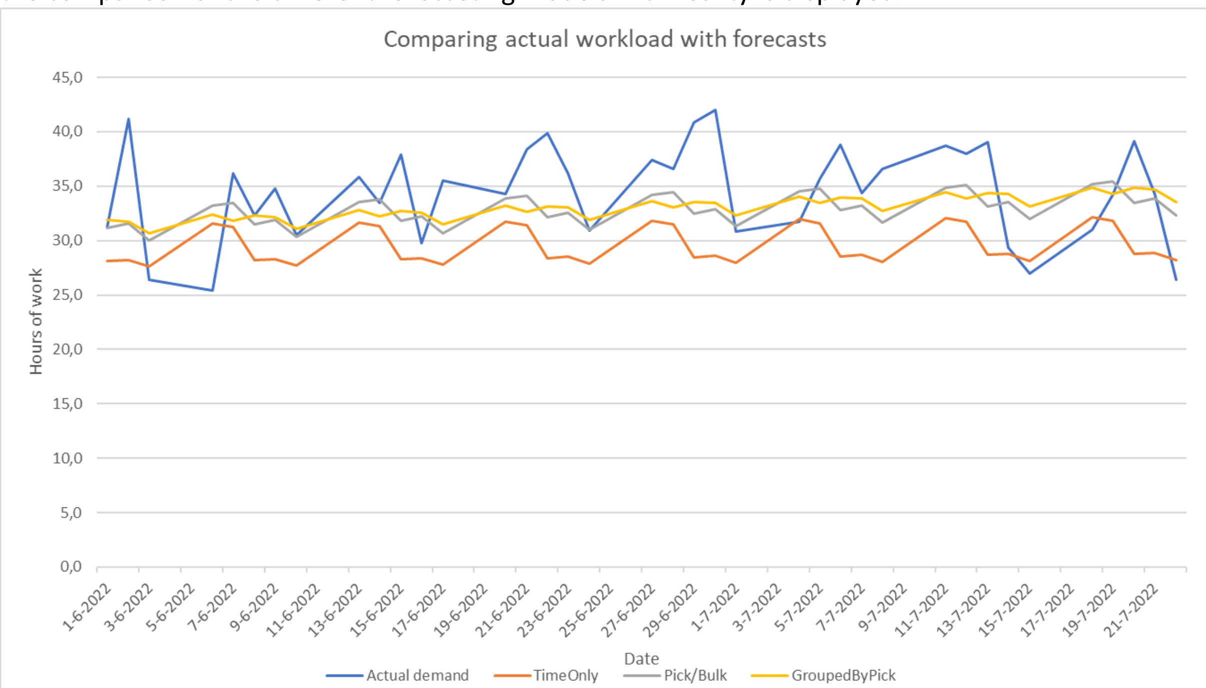

Figure 28: Comparison between forecasting methods during the time of the testing set

5.4.1 Error analysis

When comparing the results of the forecast with the reality, an important finding is that all of the forecasting models are under forecasting slightly, this can be seen by the bias. A possible explanation can be the slight increase right after the training set has ended. The Time only, and Pick/Bulk methods are following the seasonality better than the Grouped by pick times. However the Time only method is under forecasting more heavily than splitting Pick and bulk and then grouping by Pick times. To compare the methods, the accuracy measures of all forecasting methods are calculated (Table 5). The values are based on the hours of work estimated and the actual hours of work.

Forecasting method	MSE	MAD	MAPE	Bias
Time only	44.8 hours	5.6 hours	15.4%	-189 hours
Splitting Pick/Bulk	20.3 hours	3.6 hours	10.5%	-62 hours
Grouping by pick times	19.5 hours	3.7 hours	10.8%	-56 hours

Table 5: Overview of the performance of forecasting methods

Figures 29, 30, and 31, display the distribution of the errors of each forecasting method. As stated by Axsäter (2006), the MAD is a better accuracy method if the errors do not display a normal distribution.

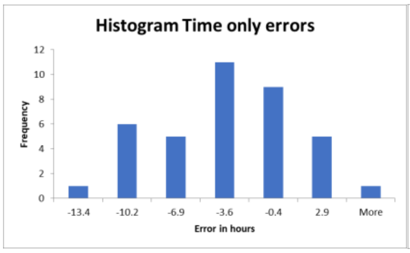

Figure 29: Distribution time only errors

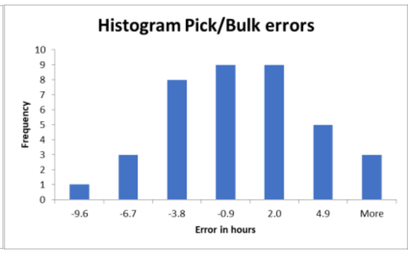

Figure 30: Distribution Pick/Bulk errors

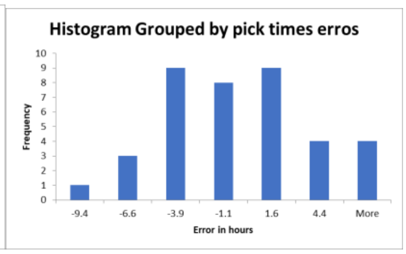

Figure 31: Distribution pick time errors

As can be seen in the figures, all errors follow a normal distribution. Therefore, the mean squared error is the main accuracy measure. Forecasting time only has the highest deviations. This forecasting method is therefore viewed as the worst method, however, when visually looking at Figure 27, it does follow the seasonality of the actual data quite well, a bit more than the other two forecasting models. A possible explanation can be the first weeks of the dataset, where a lower amount of time was used. The other two forecasting methods have accuracy measures that lie very close to each other. No clear better forecasting method can be pointed out. When looking at Figure 27, splitting pick and bulk follows the seasonality of the actual demand data better than grouping by pick items. This method does have a higher mean squared error, but the values are very close.

From Table 5, it becomes clear that the accuracy measures display that the forecasts are off. Especially the bias shows that the level of the forecasts is too low, the trend and seasonality seem to be followed correctly. To validate this, Figure 10 (which displayes the total workload over the whole dataset) will assist in explaining a possible reason. In this figure, it can be seen that at the start of the dataset, the variance was extremely high, and the total picktime was on average lower than later in the dataset. From week 35-2021 onward, the level of the data became higher, variance became lower, and the data started showing a slight decreasing trend. This however switched to an increasing trend again from week 3-2022. This may have disturbed the level of the forecasts. To validate the expected reason of the large errors in the forecasts, new forecasts are to be made which did not fit the time span. K-fold cross validation is used as a method to increase the fitting of the forecasting model to the training set, this is however not used in this thesis. It is expected that applying K-fold cross validation increases the accuracy of the forecasts.

5.5 Model justification

The model is believed to be valid since the forecasts given are very comparable to the testing set, the biggest difference is the under-forecasting of all three methods (especially time only). As stated in

Chapter 5.4, there is a suspicion why this is the case. Therefore the result is in line with the expectations. Next to that, the accuracy measures give a reasonable error.

The model does not directly relate to reality at this moment in time, and therefore cannot directly be used by Actemium. This is because the time estimation is not performed based on the recommendations given in Chapter 4. Therefore this data does not contain all the operations performed in the picking process. Next to that, the way the data is gathered is too sensitive for mistakes. First, the data should be gathered according to Chapter 4. After this, it can be used as input for a forecasting model that does relate to reality.

5.6 Conclusion

In this chapter, the research question: "What is the best way of forecasting future workload?" is answered. First, the data has been analyzed to spot how the input should be given to the forecasting model. This resulted in excluding the forecasting of single products, based on the small amount of data available for that. The exponential smoothing method is chosen as the forecasting model. This model can forecast the trends and seasonality, can make an accurate forecast based on the length of the dataset, and can be developed in a reasonable period.

Three ways of grouping data are tried. First, splitting the items by pick and bulk and using the average time needed for these operations was tried, this results in enough data points and the average time for pick and bulk operations were so significantly different that it seems like a valid split. Secondly, to make the method more accurate, grouping products by their average pick time was an option explored. Since as many products as desired can be grouped, the situation can be managed so that enough data points are available. Next to that, average pick times were significantly different. This, therefore, seems a valid way to group products. Lastly, forecasting the total time in the warehouse per day, seemed feasible and was tried, this has enough data points and is easiest in computing since there is only one parameter included.

For assessing which of the three ways of forecasting, the dataset is split up into a training and testing set. The training set is used to fit the forecasting model to the data. The test dataset will compare the forecasting model with the actual data. This gives us our answer to the research question. Forecasting time only resulted in higher error measures than the other two methods and is therefore not the recommended method to use. Forecasting by splitting pick and bulk, as well as grouping by pick times, are good ways of forecasting demand. Splitting pick/bulk follows the seasonality better. Next to that, this method is easier to compute, since it only uses two input vectors compared to the 28 (this amount can differ of course). The recommended method of forecasting is therefore to split the items based on pick and bulk. For further research, it can be checked whether grouping by pick times or using much fewer groups (4 for example) will follow the seasonality better than 28 groups. This is expected to give an even better outcome.

6. Conclusion

In this chapter, the research performed is discussed. First, the conclusion of the findings is given, together with a set of recommendations directed at Actemium. Afterward, a discussion on the research is done and limitations are stated. Lastly, the scientific relevance and an advice for future research are discussed.

6.1 Conclusion

To improve staff scheduling of Actemium, two main problems had to be solved. The quantification of the workload in the warehouse is absent. Secondly, the lack of knowledge on forecasting future workload had to be solved. Resolving the two problems improves the dashboard for Actemium's clients regarding capacity planning. Currently, support is only given in tasks left today. The goal was to translate the number of tasks to time and this is displayed for the upcoming weeks. This should be split for each operation.

The problems are solved by providing Actemium with recommendations on how to calculate the workload for each operation are given, these will give the client insights into their capacity planning. These calculations did require forecasting, which is this field is successfully explored and recommendations are made. The forecasting workload is found not to be uniform for all operations. Since time restrictions do not allow all to be performed in this thesis, the operation 'Picking goods to the expedition location' are reviewed.

6.1.1 Calculating workload

Six of the seven operations are identified as important to include in the research. These are 1. arrival of goods, 2. Put away goods in the warehouse, 3. Replenishment of goods from bulk to pick and other transfers, 4. Picking goods to expedition location, 5. Packing goods, 6. Shipping goods. The production operations are left out, this is because not many clients have production in their company at all. Next to that, this operation is so unique for each company, that unity in the end solution is not possible. For all six operations, a way to calculate the workload is given. For each operation, different time consumers are identified, the number of times this occurs is multiplied by a measured (Avg) or estimated/configured (Con) time.

1. Arrival: Unloading truck (Con), Printing labels (Con), Unpacking heterogenous pallets (Avg), and performing quality checks (Con)
2. Put-Away: Full put-away action (Avg)
3. Replenishment: Full Replenishment action (Avg)
4. Picking: Full Picking action (Avg)
5. Packing: Packing with registration (Avg) and packing without registration (Avg)
6. Shipping: Loading truck with boxes (Con) and Loading truck with pallets (Con)

With the forecasts of actions and the advice to measure (Avg) or configure (Con) the time needed for each operation. The total workload can be calculated.

6.1.2 Forecasting demand

When choosing a forecasting method, it became clear that forecasting features 3 aspects, the level of demand, the trend of demand, and the seasonality of demand. The behavior of the input data determines whether trends and seasonality are to be included. The Exponential smoothing method (and its variations) was able to fulfill all requirements, such as forecasting with trends and seasonality and forecast based on the relatively small dataset. Therefore, exponential smoothing is used in the case study. To assess the accuracy of the forecasts, the data that is used has to be split into a training (80% of the data) and a testing set (20% of the data). The training set helps the model fit the pattern the data displays. The test set has been used to check whether the forecasted part is accurate for reality. This is measured by the mean squared error, mean absolute deviation, mean absolute percentage error, and bias.

Four ways to present the data to the forecast model were investigated. 1. Forecasting the time as a whole, 2. Forecasting the bulk demand and pick demand, and multiplying it with the average bulk and pick times. 3. Forecasting demand of groups of products based on their pick times and multiplying it by the average of that group. 4. Forecasting single products and multiplying them by the average of that product. The latter immediately was disregarded as a good model, since demand data on a single product was not enough to forecast accurately. The other methods are tried and ranked based on the accuracy measures. Forecasting time only became third, this method is under forecasting heavily. The other two are good ways of forecasting demand. Splitting pick/bulk follows the seasonality better. Next to that, this method is easier to compute, since the input for the model is only two sets of data. This is in comparison with the 28 sets of data when using grouping by pick times. The recommended method of forecasting is therefore to split the items based on pick and bulk.

Grouping the forecasting method of splitting pick and bulk, together with the set of recommendations on how to measure the workload accurately, should lead to a valid representation of reality. Once the data is collected correctly, exponential smoothing with trend and seasonality can be used on the bulk dataset and the pick dataset. This will yield the workload of the picking operation that can be presented on the dashboard. Together with the other operations, this will lead to a better understanding of the capacity needs.

6.2 Discussion and Limitations

As in every research, some things are not optimal and that can be improved. Therefore a good reflection on the performed research is done. First, the methods and design of the research are discussed. After that, there are some limitations stated regarding the resources received.

6.2.1 Discussion on the research design

The first research question was focused on the wishes for the solution. One client was visited and their wishes are taken into account. This is a small sample on which to base requirements, and might not work for other clients. Therefore, external validity is not guaranteed.

A second limitation is the lack of present time in the warehouse, seeing the warehouse management system performance in real life would improve the experiences with the system. This would mean that information is gained firsthand. Currently, receiving information relied on the experience of the employees. Ideally, more time was spent in the warehouses of different clients.

Thirdly, the focus of the thesis is two-fold, demand forecasting and time measurement. Due to this split in focus, the theory of forecasting is only researched until a certain point. The concept of forecasting is more advance and can go further than was possible to do so in this research. Therefore, the more advanced forecasting methods are not explored/tried out. For example, ARIMA could have been applied and reviewed if more data was available.

Forecasting is performed for one of the six operations in the warehouse. For this operation, the workload is based on the demand forecast. However, the other operations are not explored. This makes the total workload incomplete and open for future research.

K-fold cross-validation is a good accuracy measure and helps make the forecasting method more accurate. This, however, is very time-consuming, therefore it was decided not to include it when fitting this dataset. This could have improved the accuracy of the forecast.

Since no information is available on possible discounts or advertisements, these can have a major impact on the demand for certain products, and therefore on the workload. This is not taken into consideration in the forecasting. Ideally, these factors would have been included in the forecasting model. But because the time for the research is limited, it was decided not to include it.

6.2.2 Limitations of data

In chapter four, the ways to measure the workload accurately were explained, but since these were not used to gain the later used dataset. This data is not accurate at the moment of use, which makes the end answer not usable. This however could not have been prevented, when these recommendations are incorporated into the software of Actemium, the data will become a good representation over time.

Next to that, the data that was used still had a lot of possible outliers. A lot of the products featured an extremely low pick time, and some featured an extremely high pick time. These points are most likely to be outliers, but no valid arguments to exclude them are found.

The third limitation of the data was the fact that it is based on the actions performed in the warehouse. The demand of clients is imported to the ERP system, which means that there is no information on that in the WMS. This makes forecasts based on actual performance in the warehouse instead of based on the demands of the clients.

The last limitation is the number of dates in the dataset. Preferably, an investigation into seasonality was done per year as well. To see whether for example at Christmas the demand would rise. For this, data from multiple years is necessary. This was unavailable because Actemium has not been active for that long at the used client, and the fact that Actemium does not save the data for longer than is currently necessary.

6.3 Recommendations

There are a few recommendations for Actemium on how to use this research to get better insights into the future workload. First, some advice on what should be done with the data they have is given. Secondly, the changes that should be made to the way their system records the data are discussed. Next, the recommendations for the implementation of a forecasting model are given. Lastly, some fields that can be explored even further are mentioned.

6.3.1 What data should be saved?

First of all, if the forecasting model was based on the demand of the customers, the desired workload is forecasted and not the expected workload. The way this demand data is gathered is up for discussion, possibly by extracting the data from the ERP system of the client.

The next recommendation is to create a table with the desired data for each operation. This data should hold the following information: The product that is being processed, the date of the action, the time it took to process the product, and whether the product is in a pick or bulk operation. This data should be saved permanently to allow yearly seasonality in the forecast.

6.3.2 How should the workload be measured?

The advice is to measure the operations in the following way. 1. Measure the average time of unloading a heterogenous pallet by recording the start scan and final scan. Configure times for labeling, unloading trucks, and performing quality checks. 2. Record the start and end of putting away each product. 3. Recording the start and end of transferring every single product. 4. Recording picking each product 5. Recording the start and end of packing a full order with and without registration separately. 6. Configure the time spent on loading boxes and pallets separately.

Time spent on each product can be split out into two categories, traveling to the location, and performing the handling. A possibility for improvement is to record and average traveling time (since this deviates in each sequence of the picking operations) and to record the handling to assign to that certain products. Making the possibilities to analyze time-consuming products better.

6.3.3 The forecasting model

The advice is to use Exponential Smoothing to forecast the workload, this method is widely acknowledged, easy to use, fits the received dataset, and its variations (Holt, Winters, and Holt-Winters) can forecast trends and seasonality. This should be used on a dataset of pick operations and a dataset of bulk operations.

The forecasting model does not take into consideration any advertisement or discount actions. Since this can influence the workload, the advice is to allow clients to adapt the expected workload manually in the WMS. The way this should be done is up for discussion, a possible way can be to increase all workload with an expected percentage.

Including K-fold cross-validation can make the forecast more accurate. When applying the forecast to the real dataset, it is recommended to include k-fold cross-validation when fitting the forecasting model.

Lastly, the forecast is now translated into the workload, but not multiplying the expected demand by the time also gives a lot of valuable insights for clients, such as products that will be high in demand in the upcoming time. Therefore this information can be used for other purposes as well.

6.3.4 Recommendations for future research at Actemium

The grouping of products is now done in 28 groups. This did not yield the best forecasting model, however, this might be different with another number of groups. Forecasting fewer groups will move the forecast closer to the split by pick and bulk. Forecasting more groups means that more valuable information is available for the clients. This can still be explored.

In this thesis, only the pick operation is forecasted, this can be done in the same way for putting away goods and replenishment of goods. The other three operations however are not directly related to the products themselves and have a different structure than based on products. There can still be looked into how this can be forecasted as well. For example based on the ordering policy of the client, or the shipment characteristics.

Lastly, at this moment, the datasets are analyzed manually to determine the correct forecasting model to use (with or without trend and seasonality). Research to automatically let a script analyze the data and test the set on trend and seasonality could be considered. For example by decomposing the data, this is a method used to split up the original data in a trend set and a dataset. From this, the period of seasonality can be discovered, such as the total trend of the data. Decomposing the data makes sure that not much manual work has to be done with setting up the forecasting models.

6.4 Scientific relevance and Future research

In this research, two things stood central, workload measurement, and demand forecasting. These two topics are already widely researched. Monitoring of the operations in itself is not an academic challenge and is unique for each operation. In that regard, this thesis did not contribute to any breakthroughs. Next to that, the concept of demand forecasting is used, there are no extensions or adaptions made to the models which would make them unique. This thesis is a case study of existing knowledge when talking about demand forecasting.

However in this thesis, instead of only applying existing knowledge, some solutions were new and self-explored. In the literature, there is not much found on the grouping of products or other ways of forecasting than forecasting a single product. Since this was not possible in this case, new ways had to be explored. It was found that grouping items, which will together form a new pattern, can be forecasted quite well and can be accurate. Grouping of items therefore can be a good way to forecast. The downside of this method is that the items that are grouped cannot be viewed individually anymore.

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8. Appendices

8.1 Workflow of operations

This chapter features an extensive overview of all actions that have to be performed in the warehouse and the steps taken by the employees. The workflows are organized per operation.

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8.2 Data gathering per operation

In this appendix, the data that should be gathered are displayed. This is split out per operation. Note that the data in the tables are randomly generated and do not represent the reality.

8.2.1 The arrival of goods

Date	# Pallets	Time measured (s)	# Labels	# trucks unloaded	# Quality checks
01-01-2023	4	1500	19	2	0
02-01-2023	7	2400	2	3	1

8.2.2 Put away goods in the warehouse

Date	Product	# actions	Time measured (s)
01-01-2023	Product A	3	190
01-01-2023	Product B	1	65
01-01-2023	Product C	5	240
01-02-2023	Product B	3	200

8.2.3 Replenishment of goods from bulk to pick and other transfers

Date	Product	# actions	Time measured (s)
01-01-2023	Product A	3	190
01-01-2023	Product B	1	65
01-01-2023	Product C	5	240
01-02-2023	Product B	3	200

8.2.4 Picking goods to expedition location

Date	Product	# actions	Time measured (s)
01-01-2023	Product A	3	190
01-01-2023	Product B	1	65
01-01-2023	Product C	5	240
01-02-2023	Product B	3	200

8.2.5 Packing goods

Date	Product	# actions	Time measured (s)	Registration
01-01-2023	Product A	3	190	Y
01-01-2023	Product B	1	65	Y
01-01-2023	Product C	5	240	N
01-02-2023	Product B	3	200	Y

8.2.6 Shipping goods

Date	# Actions	# time measured (s)	Pallet/box
01-01-2023	6	80	B
01-01-2023	6	240	P
02-01-2023	2	20	B
02-01-2023	4	180	P

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