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Optimizing the inventory replenishment planning policy at Mantel Arnhem BV

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Optimizing the inventory replenishment planning policy at Mantel Arnhem BV

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Preface

Dear reader,

The bachelor thesis that you are about to read is about optimizing the inventory replenishment processes at Mantel in Arnhem. It is titled “optimizing the inventory replenishment planning policy at Mantel Arnhem BV.” The research conducted is about long-term forecasting of demand and optimizing the inventory planning strategy. This research was done as a graduation assignment for the bachelor study of Industrial Engineering and Management at the University of Twente in Enschede.

I would like to thank my supervisor at the company, Roel Jacobs, for giving me the opportunity for conducting this research at Mantel, for supervising and helping me throughout this process. Besides, I would like to thank Rik Kroep, who introduced me at Mantel and so helped me in achieving an assignment for graduating my bachelor.

I would like to thank my UT supervisor Amin Asadi, for guiding me through the process at writing this thesis at the University of Twente, for giving me feedback on my writing and for helping me increasing the quality of this report. Also, I would like to thank Dennis Prak, for being my second supervisor.

Finally, I would like to thank my family and friends for support during my studies and conducting this research.

Koen Kroep

Enschede, September 2022

Management summary

In this bachelor thesis, research is conducted regarding the delivery of orders in the warehouse of Mantel. Mantel is a company with headquarters located in Arnhem, the Netherlands. Mantel has a webshop that sells throughout many European countries and has several stores in the Netherlands. It sells bicycles, parts and accessories for these bicycles. Since the cycling is a seasonal sport, the demand of these products also follow a seasonal demand where the spring is the beginning of the season, while around October the season ends.

In this management summary a brief description of this thesis can be found. The main bottleneck that occurred from both the data analysis for the current situation and these models is that the planning process is struggling to keeping the warehouse from overflowing. There are a lot of different type of products that Mantel sells and many products ordered and delivered at once at several weeks, while the week before or after that has low deliveries. This makes that the warehouse is often struggling to keep up with processing these products.

When a lot of products are entered in the warehouse at once, the logistics department is struggling with processing these orders. If these products are aligned better throughout the year, the processing of these products will take place better, resulting in a better workflow in the warehouse.

The main bottleneck in the current process for planned orders is the forecasting system. The current forecasting system is based on human experience and estimations and does not incorporate relevant historical data. By implementing the historical data patterns of seasonality, trend and the level, the forecast can be made more accurately than when only based on human experience. This human experience can still be implemented by adjusting the factors that are used as input to the different forecast method. In this case, this chosen forecast method, like linear regression or ARIMA, will result in better solutions than other researched forecast methods and will lead to better forecasts.

As second bottleneck, the orders are not aligned with the capacity at the logistics department. The orders should be aligned more to prevent the logistics department from overflowing. This means that the optimal order quantity should be optimized. This can be done by taking the average of the forecasted demand and selecting as constraint that the optimal order quantity cannot be more than three standard deviations away. In this way, there is less fluctuation between subsequent orders throughout the year, which means that the deliveries are more aligned, preventing high peaks in delivery. By taking the total holding costs of having an item in inventory, having shortage costs of one item and costs for ordering one item, an analysis of different order quantities and safety levels can be made. This results in the optimal situation. This is done by minimizing the total costs by means of changing the order quantity per period and optimal safety inventory level.

After calculating the optimal order quantity per week, for a total of all products in a product category, a re-order point is calculated. This assures that when the inventory is at or above this level, lost sales are minimized. This means that the orders arrive with as low costs as possible, when combining costs for ordering, holding and shortage of products. When having the total order quantity per product category, a planning can be made per product, by scaling down the total needed number of products,

The level of inventory that results from the order policy should be sufficient to meet demand and minimize the total costs. The inventory level follows a specific pattern throughout the year, where at the beginning of the year low inventory is held. Up to the rest of the year, more inventories should be held, as the sales during summer and spring are higher than in winter. At the end of the year, the inventory level will decline again.

The orders delivered throughout the year all have an approximately same quantity, making sure that there are no peaks to disrupt the process in the warehouse at the logistics department. The safety inventory should decrease the number of lost sales, as there is a risk of failed delivery or larger error in forecasted demand compared to the real situation. The safety stock can be changed, since deliveries are lower, which means that the products are delivered more frequently. Three up to seven months in advance, depending on the supplier, the sales and forecast can be reviewed and adjusted to review the forecast and adjust this to prevent lost sales or too much inventory.

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Reader's guide

1. Introduction

In Section 1, a brief overview of the company, together with the assignment description and brief overview of the thesis is given. The main problem is described in broad terms and the assignment is given.

2. Methodology

In Section 2, the methodology used during this research is described. A quick analysis of the main problem and causes is derived, and a problem cluster is set up. Then, the core problem, action problems and knowledge problems are determined. A plan of approach for researching this core problem and action problem is described and research questions per chapter with several sub questions for the research are determined.

3. Current situation of procurement process

In the third section of this bachelor thesis the current situation of the procurement process is analysed and described, and bottlenecks of this process are found. Per department and stakeholder the role of these stakeholders in the process is explained. A visual representation of this model is made and elaborately described. Also, the current data and data patterns are analysed, to make the core problem more visual and to determine the causes of these problems.

4. Literature review

In Section 4 of this thesis, an extensive literature review is conducted to find an overview of both the different forecasting models for the long term, as well as the optimal order quantities for inventory planning. In the first part, several different forecasting techniques are investigated and reviewed, while in the second part the different methods for optimal ordering quantities are reviewed from the literature.

5. Data analysis

In Section 5, the models described in the literature review in Section 4 are analysed on the data of 2021, and the performance of each of those models are compared. In Section 5.1 the forecasting models are analysed and in Section 5.2 the model for the optimal order quantity is described with the 2021 sales data and forecasting data.

6. Conclusions, recommendations and discussion

In Section 6 a general conclusion will be given to the proposed models and methods in Section 4 and 5, and the downfalls, advantages and disadvantages of those models will be discussed, together with a general plan of practical implementation to the company. A discussion of the results is given, with future research and limitations of the models, applied to the situation of Mantel.

Appendix

At the end, the appendix gives the main results numerically and visually. All calculations, results and pieces of code can be found in this appendix. Appendix A consists of the results and code text of forecasting models. All results regarding the different models, are listed in this appendix. Appendix B describes the results of the best forecasting method and Appendix C consists of the results of the model calculating the optimal order quantity.

1. Introduction

Mantel is a company that sells bikes and accessories for bikes across Europe. In the Netherlands, it has 4 superstores and several service centres throughout the country, but mainly sells through the web shop. Besides the sales of all kinds of bike-related products, Mantel offers high service operations to their customers, with their own delivery service and customer help service.

Mantel purchases products, without looking at the capacity constraints of the warehouse, which leads to the fact that a lot of products enter the warehouse at the same time, which all have to be processed at the same time. The logistic department, that is responsible for this, is not capable of processing that. These high peaks are caused by both regular orders, and planned orders. Regular orders are ordered a short time in advance, while planned orders are ordered far in advance and are more important products for the profit margin of Mantel. Planned orders are scheduled a year in advance, while regular orders are ordered by looking at the current level of inventory. Also, backorders can be the case which make sure that there will be a larger delivery. There is now no insight in what is expected to enter the warehouse at what day, causing problems in the processing of the incoming goods. Therefore, the suppliers and their requirements, capacity of the warehouse and both planned and regular goods should be researched while optimizing this process.

Planned orders are orders that are made far in advance based on a budget analysis. Suppliers request this information in advance. Because these products are the most important, “category A” goods, the planning is made in advance. This to make sure the supplier can deliver these orders. Other orders, which are not covered by “category A” orders, are placed in order shorter before delivery, through regular orders. These regular orders make sure that changes in demand, due to a price change, weather change or something else, can be taken into account. Also, less important products, profit wise, are ordered more by regular orders.

The assignment consists of optimizing the delivery of incoming goods. Now, the peaks of the deliveries are too high for the warehouse to handle. Therefore, these need to be aligned. An optimal purchasing strategy needs to be implemented while keeping track of the capacity of the warehouse and the safety inventory. To investigate this, the products in “category A” and “category B” of the product category “drivetrain”, with the brands Shimano and SRAM are analysed. Bike chains, derailleurs and gear shifters among others are placed under this category. The drivetrain category has a large impact on the total revenue of Mantel, with 8.79% of all products sold being one of the largest categories. Shimano and SRAM are for 7.67% responsible of all the sales of Mantel. This means that a significant share of the revenue is coming from the drivetrain products with brand Shimano and SRAM, making it a large share of the problems occurring in the warehouse.

In this thesis, first the methodology of performing this research is described in section 1.2., with an extensive description of causes of the main problem, as is described in the assignment description above. Then, the current procurement processes at Mantel are researched and visually represented in models in section 2. Afterwards, a literature review has been performed researching optimality ordering models and forecasting methods. This can be found in section 3. These methods and models are thereafter investigated and applied to the real data from Mantel, resulting in a best method. These methods and results are described in section 4. A description for implementation and restrictions of the chosen models is added afterwards, in sections 4 and 5.

1.1. Problem Identification

Due to failure in the process at the procurement department, the peaks of delivery of incoming goods in the warehouse exceeds the capacity of this warehouse. This can be seen as action problem, highlighted in green in the cluster below. In this problem cluster the problems encountered are visualized, where the cause of the problems is below the problem itself (Heerkens & Van Winden, 2017). This leads to a core problem of a non-optimal planning strategy. This core problem is the main cause of the action problem. This action problem is the overflow of capacity in the central warehouse.

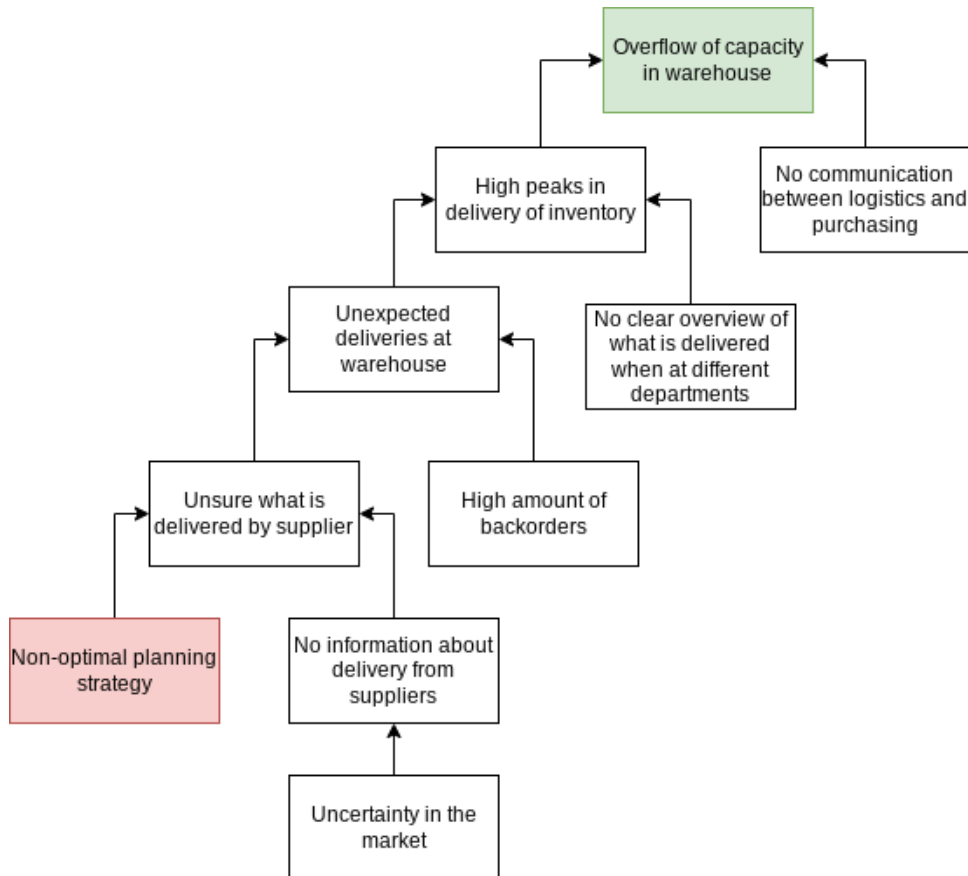


Figure 1: Problem cluster

Overflow of capacity in warehouse

The overflow of capacity in the warehouse is the action problem that needs to be solved. This means that the capacity is overflowed at times that too many products have entered the warehouse. The norm is that these overflows do not occur anymore.

The overflow of the capacity is caused by two factors. First, there is no communication, or at least a lack of communication between the logistics and purchasing departments about the number of pallets and packages to deliver. Now, a new warehouse has opened in another location, meaning that the distance between purchasing and logistics has grown. This makes the communication even more difficult. This leads to the problem that there is at the warehouse no information available about how many boxes need to be processed, and how many products will enter the warehouse at what point in time, leading to a wrong work schedule. Another issue is that there are high peaks in the delivery of inventory, which will be discussed below.

High peaks in delivery of inventory

Because a lot of products follow a seasonal demand, the delivery of goods occurs at several big deliveries. This causes the warehouse to overflow. Every delivery moment, lots and lots of goods are entering the warehouse at the same time, causing disruption at the processing of incoming goods in the logistics department. Planned orders, which are already planned according to a budget planning, together with regular orders, which are ordered just before delivery, are combined in delivery. The planned orders are scheduled in advance, while the regular orders are delivered a few days after, at the moment that the company desires. Moreover, backorders are also delivered, at unexpected times. Because of uncertainty in the market, there are more backorders occurring, leading to more uncertainty in what will be delivered. Both these reasons are causing the high peaks in delivery of inventory. Suppliers do not always notify what is delivered, how many pallets are delivered at what moment in time. It is unknown up to the last moment what suppliers are delivering. There is no clear overview of what is delivered when.

Unexpected deliveries at warehouse

Because of the different types of orders, a lot of orders are entering the warehouse, without knowing what orders these are and why they are delivered at the warehouse. Multiple orders are stacked at the same pallet, leading to unclarity in the deliveries. This is caused by a high number of backorders, the uncertainty and the fact that it is unknown what is delivered by the supplier at what moment. The number of backorders at Mantel is taken care of now. This is due to COVID-19 production problems at suppliers and a higher demand at these suppliers. Now, this is controlled and is therefore not the most important cause of the main problem and will therefore be out of scope for this research.

Unsure what is delivered by supplier

Suppliers are not communicating well in advance what they are delivering. They do not possess this information, or do not let Mantel know about what they are planning on delivering. Therefore, it is unsure by Mantel, both at the purchasing department and logistics department what will arrive at the warehouse at what point in time, for most of the times. Some suppliers send this information. However, this information is not always complete or most accurate. This is both caused by unknown information by the supplier, but also because of the process in which planned and regular orders are ordered and delivered. It is unknown what is exactly delivered, and this makes the planning insecure.

No optimal planning strategy

The cause of the uncertainty of what is delivered by the supplier is twofold. One part caused by the fact that the supplier does not provide information about what they will deliver at what period. Another reason is the uncertainty in the market of bikes and bike particles that currently exists. There is higher demand than what can be produced by suppliers, which causes a shortage in delivery. However, part of this is caused by the planning strategy.

Therefore, the core problem is that the planning strategy of the products in the A and B category is not optimal for the deliveries that are occurred in the warehouse.

1.2. Problem solving approach

As can be seen in the problem cluster and the description in the previous section, the core problem is that there is no optimal planning for the purchasing strategy. This will be elaborated on in the next chapter, where the current situation of planning the incoming orders and the flow of products from ordering through delivery and processing in the warehouse is described. This is therefore the core problem that is causing the action problem. In this section, the research questions will be described that will be investigated to answer and then help solve the core problem, leading to an improvement of the action problem.

1.2.1. Action problem and research question

The action problem is defined as above can be seen in the problem cluster. This action problem is:

The capacity of the central warehouse is exceeded with the delivery of incoming planned orders.

From this action problem, an overall research question is set up to get to a solution for the action problem:

In what way can Mantel create a delivery schedule to optimally select time of ordering to prevent the capacity of the warehouse from overflowing?

Capacity can be measured in multiple ways, which makes it difficult to have one correct way of accurately measuring the capacity of the warehouse. This is operationalized to make this measurable. Information about how capacity is defined, and how to measure capacity is needed to operationalize this variable. The warehouse can be identified as several different parts of the process: receiving, storage, order picking, sorting and shipping (Ramirez-Malule et al., 2021). All these factors have their own capacity, which leads to their own indicators. However, this assignment focuses on the inbound processes of the delivery, and not on the processing of the goods in the warehouse, and therefore these processes are not investigated. The first two processes in the warehouse of Mantel are deliveries and processing. These can be measured by the total number of boxes that are processed at one day, and the total space that is available for the unpacking and delivery of goods. Also, the total number of boxes that can be processed in one hour by one employee is a capacity indicator for the processing of the goods.

1.2.2. Measuring core problem and norm and reality

The core problem should be made measurable. This means, that the total number and deviation of deliveries should be measured in order to set a norm and reality. This can be done by calculating the deviation from the mean number of delivered products per week. This deviation should be as small as possible, but there is a threshold of no more than three standard deviations compared to the mean of the number of deliveries per week. This situation should not occur during any week. The reality of this norm is calculated in section 2 about the current situation.

1.2.3. Research questions

This section describes the research question and sub division of this research question. Also, it describes the structure of the remainder of the thesis.

The knowledge problem is constructed as follows:

The capacity and purchasing process of Mantel are not synchronized, resulting in overflow of warehouse capacity.

To perform this research, data and information needs to be gathered. Especially, the information about the seasonal demand uncertainty, the purchasing processes that Mantel is currently working with and the criteria that exist for implementing the purchasing process. Besides, capacity should be measured to be able to measure how to prevent the warehouse from overflowing. For this, the following 5 research questions are set up, followed by knowledge questions concerning what information is needed for answering the research questions.

- 1. What is the current method of planning of the purchasing process?**
 - i. What process is used with ordering and planning products?
 - ii. What main bottlenecks are occurring in the current planning system?

iii. What is the current capacity of the warehouse?

2. What forecasting method is best for the data patterns occurred at Mantel?

- i. What forecasting method works best for seasonal demand patterns in the data?
- ii. How can the forecasting method be evaluated?

3. What purchase planning processes are available for seasonal demand patterns?

- i. What different purchasing strategies exist for seasonal patterned demand?
- ii. How can the planning of the order process be evaluated?

4. What order policy method is best for Mantel?

- i. What are existing bottlenecks in the current solution?
- ii. Are the restrictions regarding capacity and safety inventory met?

5. How does the chosen process perform?

- i. How can the inventory model be used?
- ii. What improvements can be made at the model?

All these questions addressed above are answered throughout the remainder of this thesis. Subquestion 1 is answered in Section 2, subquestions 2 and 3 are answered in Sections 3.1 and 3.2 respectively. Subquestions 4 and 5 are answered in Section 4.

1.3. [Research design](#)

In this section, an overview is given of what is described, what methods are used and what impact this has on the solution of the problem.

Section 2 describes the current situation. The process of ordering a product, by regular orders or by planning is analysed. Also, the data from the past years is visualized, to quantify the core problem as described in Section 1.1. This current situation leads to the determination of the main bottleneck of the purchasing process, and leads to the direction of the literature review. It shows how the problems impacts the process of purchasing products. Also, this section visualizes the problem.

In Section 3 is different sources of existing literature described to find the most useful type of both forecasting method and optimal order quantity model. Also, a way to evaluate these models is found. These methods are used to find the optimal model to improve the situation of planning the purchases at Mantel. The best method is chosen based on the error measured on the real data. The results of this method will be used to improve the order quantity model.

In Section 4, different models from Section 3 are investigated on the real data of 2021. The best model of forecasting is chosen, and an optimal order quantity model with reorder point and safety stock is created, based on different type of costs of holding inventory or having lost sales. In Section 5, a conclusion is given with recommendation for Mantel, a discussion of the results and possibly further research. This model gives an inventory position and optimal order quantity which can be used to improve the work schedule of the logistics department and the purchasing department. The inventory position of the warehouse will be visualized in graphs.

2. Current situation of procurement process

In this section, the current situation of the purchasing process will be elaborated and analysed. In this process analysis, three different entities are considered, across two different departments. These are the tactical and operational purchasing sub-departments at the purchasing department, and the logistics department.

The process considered is the process from where a product is ordered, by the tactical purchasers and the operational purchasers, up to the point in time that the logistics department has processed the products in the central warehouse, and the product has ended in the warehouse at a pick-up location, ready to be sent to a customer or to the shops. These three departments are considered because these are the most important in the process of ordering and can influence the number of products to be delivered. Therefore, the problem as described in chapter 1 can be influenced by these departments, or the result of improvement will be seen by these departments, as a more fluent flow of products in the warehouse should be seen in the end.

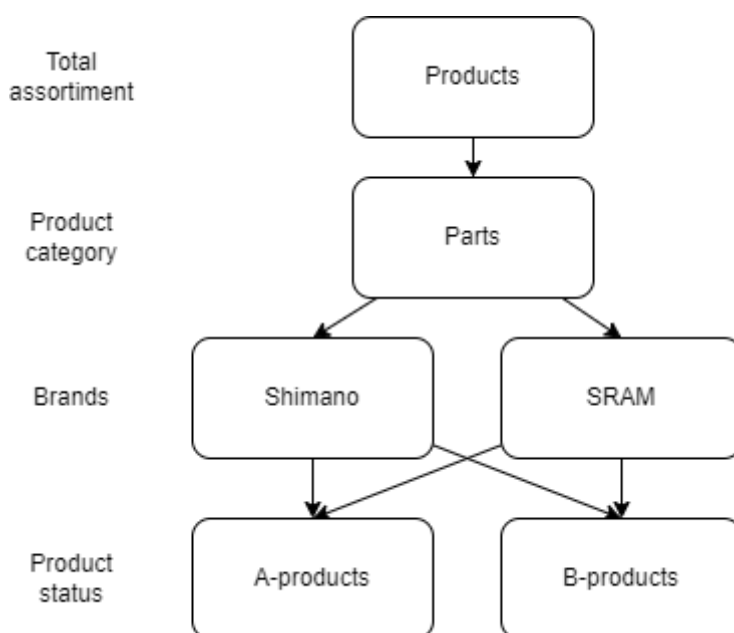


Figure 2: Division of products

For this research, only the brands 'Shimano' and 'SRAM' for the product subcategory 'drivetrain', which is located under the product category 'parts', is considered. Also, this research focusses on A and B products. A-products are 100% ordered through planning, while B-products are ordered for 60 to 70% through planning. This means that of the expected demand, this percentage is ordered via planning in advance. The rest is regularly ordered. This is shown in the flowchart in Figure 2. These products make up about 7.7% of the revenue of Mantel, and is therefore an important category to consider, as Shimano is one of the largest suppliers in the bike industry. In the planned orders, the part of Shimano is the biggest category of products that are delivered at Mantel. The following table shows the share of Shimano and SRAM in the total revenue and amount of products sold at Mantel.

Total Revenue	100%	Total Parts	100%
Parts Revenue	30.04%	Drivetrain Shimano on total parts	10.89%
SRAM + SHIMANO Revenue on total	7.67%	Drivetrain SRAM on total parts	3.72%
Accessories revenue	7.15%	Accessories Tacx/Elite on total parts	0.33%

Table 1: Revenue and sold products Shimano and SRAM

In this table can be seen that the share of parts is one third of total revenue, and SRAM and SHIMANO have around 8% of the total share. This means that a significant large amount of share is caused by the revenue of SRAM and Shimano Drivetrain parts. Also, in the total of parts, drivetrain with brand Shimano is around 11% responsible for the total products sold, while SRAM is around 4% responsible. For example, the accessories, another product category has 7.15% of the total revenue, where two brands Tacx and Elite have a share of 0.33% of the total revenue. There can be concluded that drivetrain products with brands Shimano and SRAM are a significant part of the revenue of Mantel, making it an important product category and therefore important to optimize the number of products delivered and kept in inventory in the warehouse.

To be able to identify how the purchasing process can be improved, an analysis of the current process of purchasing, carrying, and delivering the orders up to the warehouse is included in Figure 3. BPM Notation is used for scheduling and modelling this process. By this model, it can be seen how the purchasing department has impact on the logistics department, and what factors depend on ordering and delivering a product. By analysing this process, there can be concluded how the bottleneck of a lack of planning strategy will impact further processes, and eventually the process at the logistics department in the warehouse. Also, an analysis of the data of 2020 is considered to see how many products are delivered per month and per week. This gives an overview of the problem in planning strategy. A data analysis is made to visualize the current situation of inventory levels, with deliveries and sales.

First, an analysis is given of the current situation of deliveries per month, per week and the inventory levels and sales levels. Afterwards, in the next subsections, the different processes at different departments or sub-departments are analysed and are discussed, and an explanation is added to provide clarity in the causes and different flows of the process. Some actors, like the delivery companies are left out of the process, as this is beyond control and communication of the company and the supplier.

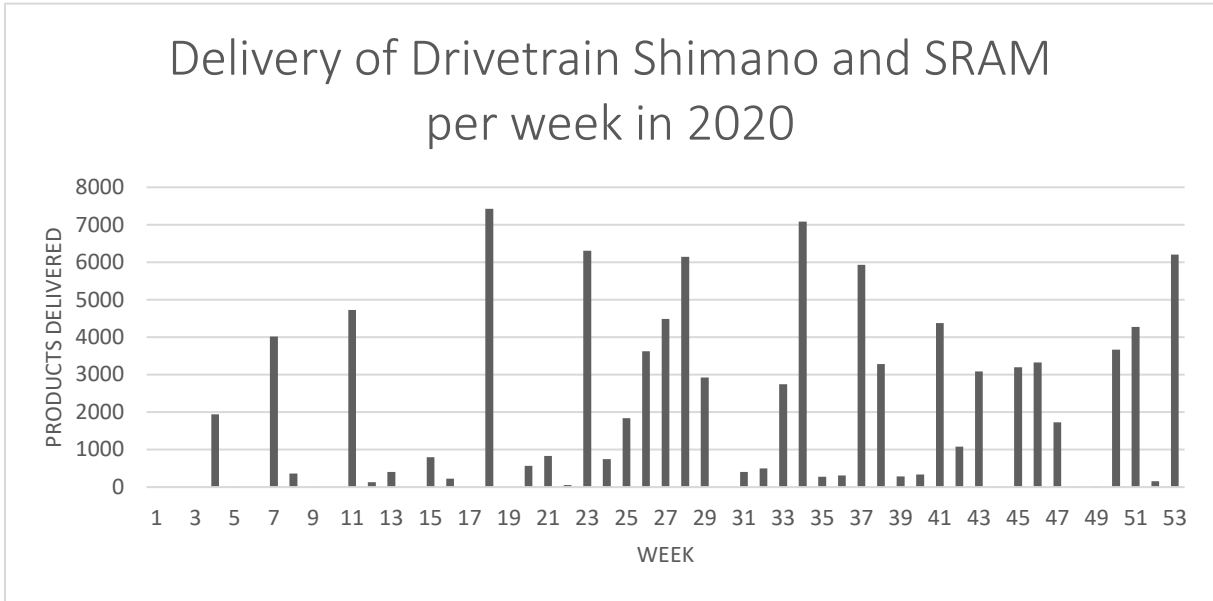


Figure 3: Delivery of drivetrain products per week (2020)

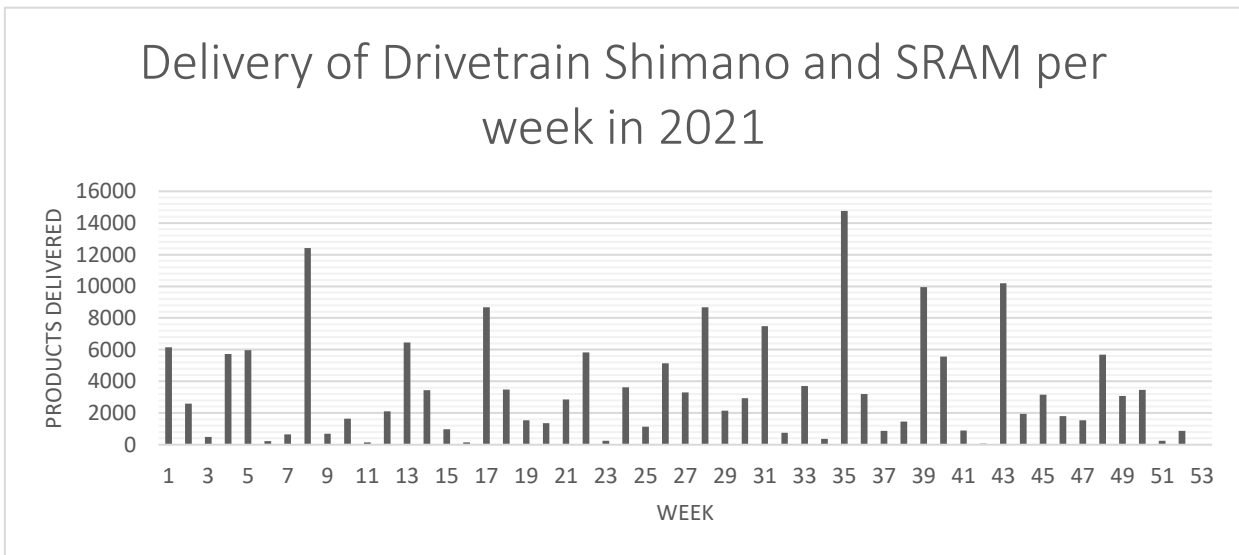


Figure 4: Delivery of drivetrain products per week (2021)

In the graph in figures 3 and 4, the total deliveries over 2020 and 2021 spread per week are visualized. In these graphs, products in categories A, B and C are considered, to give a complete overview of the situation. “Category C” products are products that are ordered through regular orders, a short period in advance of delivery. These products are not ordered through a yearly planning. In both graphs can be seen that in certain weeks, like for example week 8 and week 35 in 2021, the deliveries are very high, with up to 15000 products that are delivered, while in other weeks as for example week 16, there are just around 1000 products delivered. This shows visualized in data the current problem at Mantel, where there are a lot of orders delivered at the same time, while at other periods in time, less products are delivered. A high number of delivered products causes disruption in the process in the warehouse, while there is capacity in other weeks to have more products delivered. This results in problems for

the logistics department. This graph only shows the total number of deliveries of the drivetrain category with Shimano and SRAM products.

In 2021, the mean of delivery is 3429.7. The standard deviation of the deliveries is 3368.14. The max is at 14758, which is 3.36 times the standard deviation away from the mean. The minimum amount of deliveries in one week is 0, which means that this is 1.01 standard deviations away from the mean.

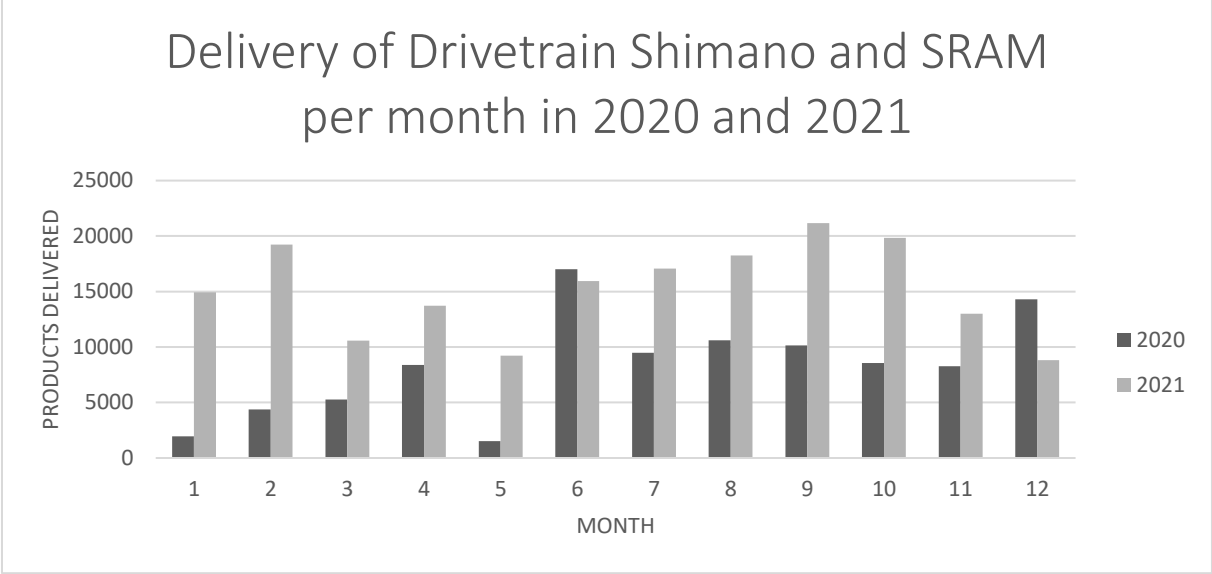


Figure 5: Delivery of Drivetrain products per month (2020/2021)

The demand follows a seasonal pattern, as the biking season only starts around March or April and ends in August or September, often depending on the weather. Therefore, these months have higher orders and deliveries expected. This can also be concluded in the data of 2021 in the graph in figure 3. There is depicted that in the months April and June up to September, the deliveries are increasing, and at the end of the season in November and December, the deliveries are decreasing. This shows that seasonality occurs in the demand and is also depicted in the purchases and deliveries.

In 2020, throughout the year the demand is increasing towards the summer months, except in May. However, the trend in 2020 looks the same as in 2021, where in the summer months, the deliveries are higher than in other months, which corresponds with the season of the bike industry.

The seasonality that occurs throughout the year can be seen in Figure 5. Both in 2020 and in 2021, the deliveries are higher in some months and lower in other months. This means, that the inventory levels are higher in certain months. For example, in June up to September in 2021, the deliveries are relatively high, while in May and December of that year, the deliveries are relatively lower. This shows that the amount of deliveries throughout the year is fluctuating, which is a cause of the disruptions in the warehouse as is described in Section 1, and also shown in Figures 3 and 4.

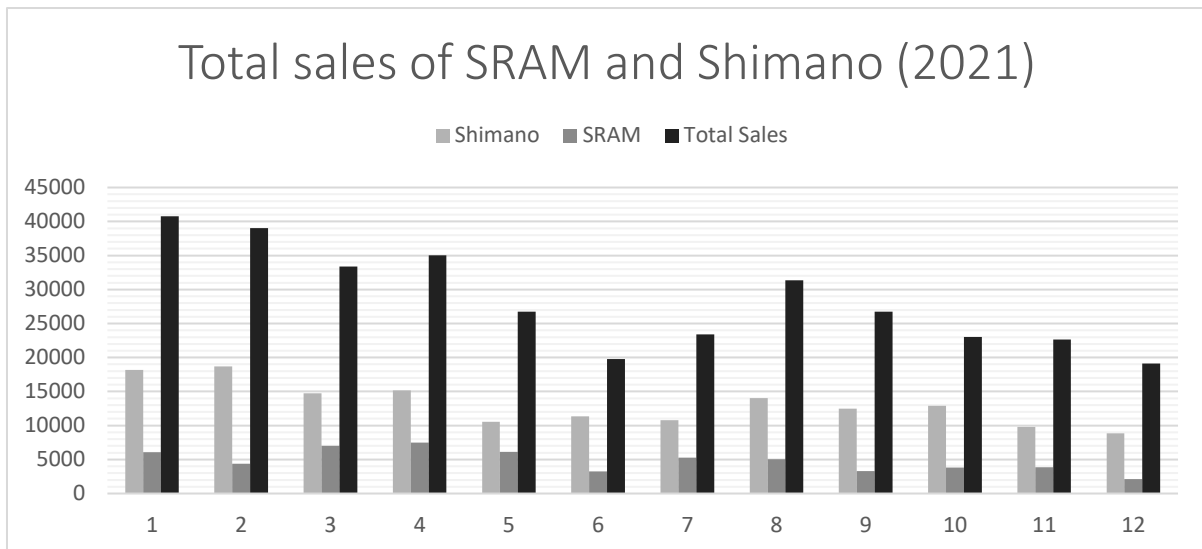


Figure 6: Total Sales of SRAM and Shimano

Now that the current situation of ordering and the delivery of products is clearly described and visually represented in graphs, where the problem is made clear, a concise description of how the purchasing process at Mantel works is described below and visualised in a BPMN model. The complete model can be found at the end of this section. Per department, a section is described with all the processes going on regarding the ordering and the delivery of the products, both planned before and regularly ordered.

2.1. Purchasing department

The purchasing department is divided into two subdepartments: the tactical purchasing and the operational purchasing departments. These two are responsible for the procurement of Mantel. The tactical department is responsible for long-term orders, while the operational department is responsible for the short-term orders, coping with changes in demand or other factors. Also, the operational department is responsible for the contact with the supplier on operational level, to make sure the order will be delivered at the right day and time with the correct number of products. In the next subsections, these two departments will be described in detail. At the end, the total BPMN model of the purchasing and logistics departments can be found in Figure 7. First, the processes from different departments are described.

2.1.1. Tactical purchasing

The tactical purchasing department creates planning, based on a budget and experience from previous years. This is distributed among the months as is done in history, with taking care of the seasonal patterns. However, it is not described yet how this is done, and mainly is based on experience of the tactical purchasers and the historical data.

The process starts with deciding to what class the products belong. The classes A, B and C are divided between the influence of the profit margin of one product to the total profit. The most important products, class A, have the highest profit margin while the products in class C have the lowest profit margin. This holds for most products, however, there are exceptions. For example, products which are important to always have in stock are classified as A products as well.

Class A products are planned 100-110% of the time, and not purchased in another way. This means that all products in this class, and even more than the expected demand is purchased on a planning basis. B products are planned around 70%. The remaining 30% is purchased through regular orders. C

products are not planned, and only purchased on regular basis. The tactical purchasing department therefore only takes care of products in class A and B.

After classifying the A, B and C products, the planning of purchasing the products is made. This planning is made using a budget and expected and desired sales and revenue. The number of products that is desired to sell is calculated, based on data from previous years and an expected grow per year. For this, there is calculated how much products need to be sold to achieve these sales.

After this planning, a division is made to determine how many products should be ordered each month. This is mainly done based on historical data, without looking at seasonal patterns, but only looking at the growth rate per month.

When the planning is finished, it is sent to the supplier, to get confirmed that the supplier can deliver what is expected. When this confirmation is received, the planning is sent to the operational purchasers to process the order in the inventory management system, the so called Backoffice.

One of the other tasks besides making a planning is to check large orders of operational purchasers. When orders are large and have a main impact on the delivery, the tactical purchasers should give permission to continue with the order. If this permission is given, the operational purchaser can continue with processing the order. The tactical purchasing process is visualized in Figure 7 at the first pool from above.

2.1.2. Operational purchasing

As operational purchaser, there are different tasks to fulfil. First, the operational purchasers are responsible for ordering the necessary B products and all C products. B products are planned partly, and C products are not planned. Therefore, these should be purchased regularly throughout the year. To start with this, the order advice is retrieved from the system. In this order advice, the current inventory status is analysed together with the safety inventory and the lead time. The system gives an advice on how many products to order. This is checked and verified and changed whenever that is needed. If this is a big change, the tactical purchasers should also check it and give permission. If this is not the case, and if there is permission by a tactical purchaser, the order can be processed in the system, to keep the inventory level up to date and the order can be sent to the supplier.

Also, the planned orders are sent by the tactical purchasers to the operational purchasers. The task of the operational purchasers is to process these orders in the system. When the order is received, the operational purchaser puts the planning order in the system, with the several product IDs linked to the order. In this step, also the amount ordered and the delivery date and sales price is added. Then the order is sent to the supplier.

If the confirmation from the supplier is different from what is ordered, the operational purchaser should decide what to do with the remaining products that cannot be delivered. The operational purchaser should decide what remain in backorder and what will be cancelled. This is the task of the company and not of the supplier. The decision to make is to keep parts of the order in backorder or to cancel the delayed part of the order. This should be processed in the Backoffice. The supplier normally sends the information with the number of pallets and the delivery date to the company. These details are adjusted in the Backoffice.

When the order is delivered, the delivery is opened in the Backoffice, to make sure it can be processed by the logistics department. When all the goods are processed, there will be checked if everything is complete. If this is not the case, the purchaser will contact the supplier to verify this. Another option is that the failure is caused by an employee at Mantel, which results in a change in the backoffice. The

operational purchasing department is visualized in the image in Figure 7 at the bottom of the first pool from above.

2.2. Supplier

The supplier is an important factor in the process, as the supplier is responsible for delivering the orders and communicating the delivery details to the company, to make sure the logistics department and the purchasing department can handle the orders. The supplier should confirm the amount that can be delivered at a certain time and date.

Suppliers have different demands and requirements on the times of ordering and have certain lead times, which should be satisfied. The supplier process is visualized in Figure 7 in the second pool from above.

2.3. Logistics department

The logistics department takes care of the handling and processing of the incoming goods. After the orders have arrived, the delivery is created in the system by the operational purchasing department. All the products are scanned and counted. This is saved in the backoffice. The backoffice shows whether the products need to go to a pick-location, ready to be sent to the customer, or should wait in the warehouse, before going to a pick location.

If the process is not complete, a message is send to the purchaser, which will try to solve the problem. If the delivery is complete, the process of ordering up to the delivery and processing in the warehouse is complete. The process of the logistics department is visualized in the bottom pool of the image in Figure 7.

In the next image, the complete process is shown in a Business Process Management model, where each decision and message to another department or entity is shown and depicted with arrows, and every single activity of an entity is shown in the square boxes. All the relations and messages between the different entities are described and shown.

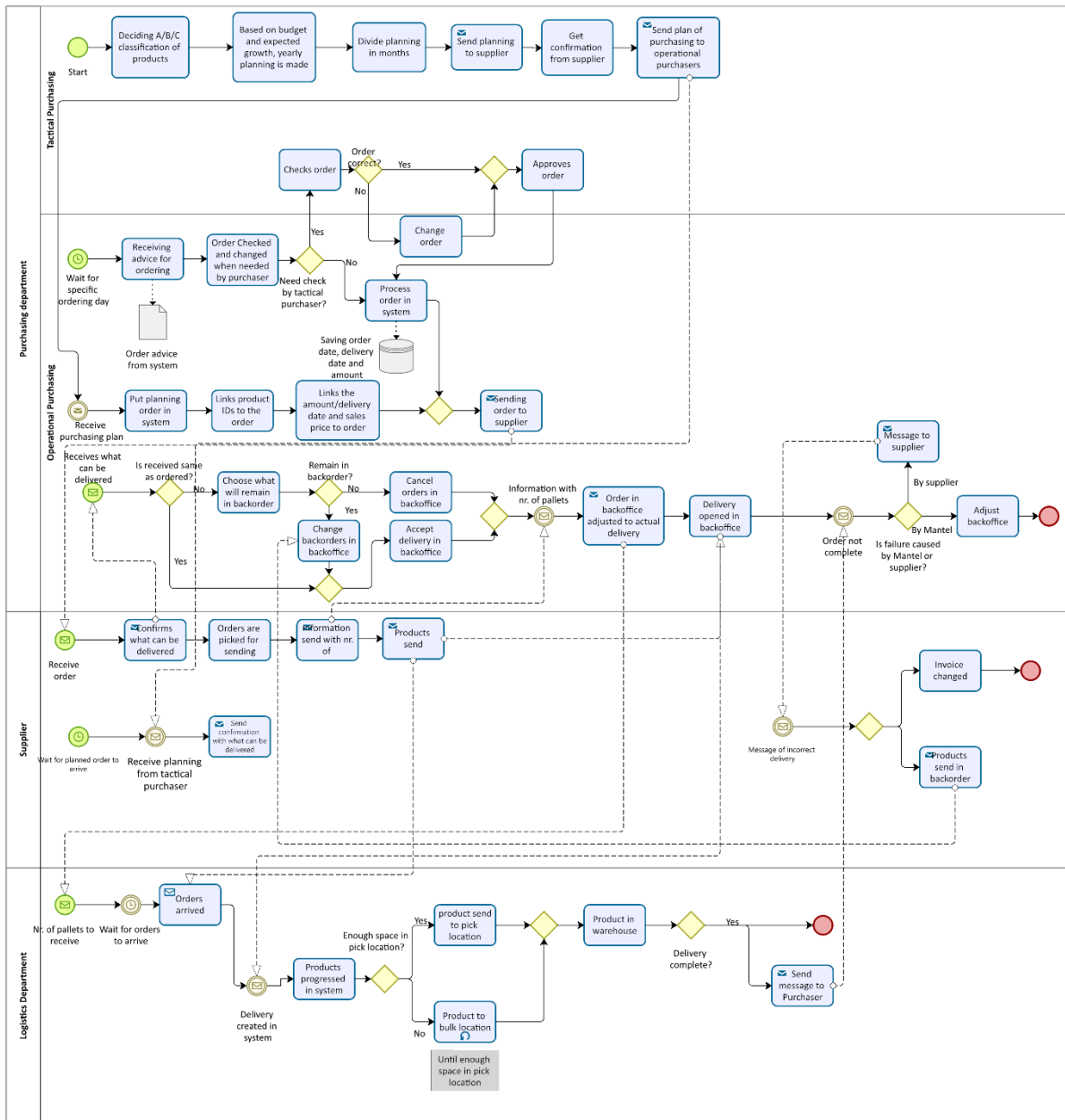


Figure 7: Purchasing process Model

As can be noticed in Figure 7, is that a lot of processes depend on another process at another department. That means, that when the products are ordered, that has impact on suppliers, both purchasing department, and eventually the logistics department. Also, as can be seen in the data analysis, there is a too large variation in the number of orders that arrive in the warehouse. As can be seen in the model in Figure 7, this is caused at the purchasing department, and eventually makes sure that the problem occurs in the warehouse.

By further investigating the planning of the A and B category products, this situation of disruption in the warehouse can be prevented, because with an improved planning, the number of products delivered in the warehouse can be better aligned with the capacity of that warehouse.

In order to do this, further research is needed. First, the forecasting models will be investigated to make sure that the products that are ordered are really necessary to meet demand, and that this forecasted demand is as accurate as possible.

Secondly, the order quantity that should be adapted to, in order to meet demand is investigated in the literature. By having an optimal order quantity, the fluctuations should not be as high as is the case at the moment. The models found in the literature will be applied to the situation in 2021, to be able to measure if the model improved the current situation.

3. Literature study

In this section, an extensive literature study will be done to answer the different knowledge questions as stated in section 1.2. The first question to answer is the forecasting of seasonal demand, and a description of different models and methods that exist. The second will be the analysis of ordering processes of seasonally demanded products.

As described in the previous chapter, at Mantel an ordering process exists consisting of different factors and departments. There are stochastic lead times of the deliveries of products. These products follow a seasonal demand, with higher demand during the months in spring, and lower demand during winter. There are different suppliers to mitigate risk of no-deliveries.

Constraints in the delivery system are the safety inventory and lead times, but also the constraints set by the suppliers in the time between ordering and deliveries. Also, warehouse capacity and delivery dates are constraints to consider. These constraints will be researched in the following literature study, where a framework for uncertainty in demand and inventory replenishment cycles will be investigated.

This literature study will first answer the question on how to forecast seasonally driven demand and will investigate the different policies available to derive an optimal order quantity, where low demand costs and holding costs are incurred.

3.1. Forecasting Seasonal demand

Further back in the supply chain, the uncertainty grows bigger due to the so-called bullwhip effect. The demand variability becomes bigger as one will look further back in the supply chain, further back to the supplier or producer (Costantino et al., 2016). To prevent this, there should be information available for upstream inventory. Seasonality might affect the demand in the supply chain and therefore can be the cause of the bullwhip effect. This bullwhip effect needs to be minimized, and therefore, demand forecasting is important. For Mantel, the forecast is an essential part of the purchasing process. At least one year ahead, a planning is made using a forecast. With this forecast, the planning is made. The more accurate the forecast will be, the more accurate this planning will be, which will reduce the costs.

However, there are many prediction methods. These methods can be scheduled in two categories. The first is the short term and can be used for forecasting up to 12 months. The second type of methods are the long term forecasting methods, which can be used for forecasting further than 1 year. Time series forecasting can be done by machine learning techniques. The Holt Winter method as described below is categorized as a time series analysis, together with the ARIMA technique. Methods using time series analysis are most popular because they are capable to capture trends and seasonality in the behaviour of the demand (Falatouri et al., 2022). Regression based methods can consider both dependent and independent variables, where the independent variable is the time.

3.1.1. Time series

Time series analysis is a forecast approach that uses information of data taken over different periods in time (Noor & Rahman, 2022). There are different time series analysis forecast approaches to consider. Time series forecasting is a process of predicting a future sales value based on past historical data. A time series consists of a trend, seasonality, and noise. This can be additive or multiplicative. Then, $y_t = T_t + S_t + E_t$ or $y_t = T_t \times S_t \times E_T$, where T_t , S_T , and E_T are trend, seasonal and noise variables in period t , respectively (Kotu & Deshpande, 2019).

Trend can be seen as the long-term behaviour of a dataset. The trend consists of a level and a zero-basis trend. The level does not change, while the zero-basis trend does change over time. The

seasonality is the repetitive behaviour in data during a certain period. The cycle consists of long patterns, followed, and preceded by other cycles. Also, there is noise, which is characteristics in the data which is not presented by seasonality, level or trend components and are unpredictable, but ideally follow a normal distribution.

Data can be decomposed into these different parts of trend, seasonality and noise using different steps. There are different variables, such as m , which is the seasonal period.

The first step is to calculate the trend T_t . If m is even, then twice a m moving average is calculated, otherwise, once a m -moving average is calculated. A moving average is calculated by the average of last m data points.

The detrended series is calculated by $y_t - T_t$ for each datapoint in the series, followed by the seasonal component for each m period. This is the average of $(y_t - T_t)$. This can afterwards be normalized in the way that the mean is zero. The noise is $E_t = (Y_t - T_t - S_t)$ for each data point. This information can be used to forecast the data by $y_t = S_t + T_t$ (Kotu & Deshpande, 2019).

3.1.2. Simple forecasting methods

There are many forecasting methods to use, from which some are easy and more basic, and some are more realistic and will yield a better result. The first one is the naive method. In this method, the previous data point is the same as the next.

The seasonal naive method assumes that the next value holds the same value as in the previous season. The average method takes the average of all the data points in the series before the forecasted value. This can be adjusted to the moving average smoothing method, where last k periods are selected to calculate the average. In this way, the average keeps moving forward each time a forecast is calculated and the most recent data is used. The data points can be given a weight, such that one value has more impact on the outcome than other values.

However, these methods are quite simple, and not taking care of the seasonality on the long term or taking account of past errors and outliers in the data. Therefore, these models will likely result in a worse result than more complicated, but also more developed models (Kotu & Deshpande, 2019). Also, for more accurate models, recent data should be considered, which makes it less usable for Mantel for a forecast on the long term.

3.1.3. Regression

Another type of method of forecasting is regression. Regression is a method to analyse the relationship between different variables. Linear regression is represented by the following equation:

$$y = \beta_0 + \beta_1 x$$

This equation takes the linear line between the different data points that has the best fit. By taking the least squares errors, the parameters β_0 and β_1 are found (Montgomery et al, 2021).

3.1.4. Smoothing methods

Another type of forecasting methods are smoothing methods. Smoothing methods make use of observation of past data points. Time periods t , data series y_t and forecasts F_{n+h} with forecast errors e_t are used to explain a time series model. This model can be used with constant time intervals.

Another option is the exponential smoothing method (Noor & Rahman, 2022) by Robert G. Brown, where there are three methods. Simple, double and triple exponential smoothing. The triple exponential smoothing is also called Winter's method and is an approach for handling seasonal data,

while the single approach is used for stationary time series and the double, also called Holt's method, is used for trend patterns.

This smoothing method gives a larger weight to recent observation, and less weight to older observations. The Holt-Winters heuristic (Liu & Wu, 2022) is as follows, with three different formulas and at the end recursive equations.

$$S_t = \alpha \left(\frac{X_t}{I_{t-L}} \right) + (1 - \alpha)X_{t-1}/I_{t-1} \quad (1)$$

$$T_t = \gamma(S_t - S_{t-1}) + (1 - \gamma)T_{t-1} \quad (2)$$

$$I_t = \beta(X_t/S_t) + (1 - \beta)I_{t-L} \quad (3)$$

Where S_t is the level, T_t is the trend and I_t is the seasonality variable.

After calculating these three values, a variable k-step-ahead forecasting is calculated by the next formula:

$$\hat{X}_t(k) = (S_t + kT_t)I_{t-L+k}$$

The variables are explained below

- L : Number of seasons
- I_t : correction coefficient of seasonality
- T_t : trend of the sequence X
- α , β and γ are smoothing parameters corresponding level, trend and seasonality

Initial values are calculated as follows:

$$I_i = \frac{\bar{X}_i}{\bar{X}}, i = 1, 2, \dots, L$$

$$S_{L+1} = X_{L+1}$$

$$T_{L+1} = \frac{(X_{L+1} - X_1 + X_{L+2} - X_2 + X_{L+3} - X_3)}{3L}$$

- Where \bar{X}_i is the average value of the season across different periods and X is the average of all seasons.

3.1.5. ARIMA method

ARIMA, also called Autoregressive Integrated Moving Average is a linear model, which is used for forecasting linear time series. This can also be applied to seasonal data. The main advantage of seasonal ARIMA models is its ability for considering seasonal behaviour in time series.

When using ARIMA and there is demand data of historical periods available, this data can be used to forecast the demand by use of time series analysis. This observes patterns in weekly orders and predict the future demand used by sales and seasonal factors. This method uses regression and the moving average models. This results in a reliable level of forecasting of future demand and can therefore satisfy customers' needs in time (Kim & Jeong, 2018).

ARIMA first takes the correlation of two datasets of two different periods. Autoregressive methods models are models consisting of multiple input variables, with as output the future value point. This model makes use of level I and noise e . α is the coefficient retrieved from the data. If there is no trend

or seasonality, it is called a stationary series. Data should therefore first be made stationary. This can be done by differencing the datapoints. A non-stationary series can be converted into a stationary series, where $y'_t = y_t - y_{t-1}$. Seasonal differencing is the change between the series same periods in different seasons. A season has variable m as period. The stationary time series becomes then: $y'_t = y_t - y_{t-m}$. Then, the moving average of the error can be created to predict the future value. $y_t = l + e_t + \theta_1 e_{t-1} + \dots + \theta_q e_{t-q}$, where e_t is the forecast error and θ is the moving weighted moving average of past forecast errors (Kotu & Deshpande, 2019).

An ARIMA model is a combined model of the above-described models. The following formula describes the formula of ARIMA: $y'_t = I + \alpha_1 y'_{t-1} + \alpha_2 y'_{t-2} + \dots + \alpha_p y'_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots + \theta_q e_{t-q}$.

The ARIMA forecast is the differenced time series data y_t in order d , also noted as ARIMA (p,d,q).

3.1.6. Performance evaluation

The performance of this system can be measured by the MAPE (Chopra, 2019).

$$MAPE_n = \frac{\sum_{t=1}^n \left| \frac{E_t}{D_t} \right| 100}{n} \quad (4)$$

Where $E_t = F_t - D_t$, so the difference between the forecasted demand and the actual demand. If this is measured below 10%, the forecast is said to be highly accurate. The aim for the MAPE is to be better than a naïve forecasting method, which means that there should be an improvement in the method used. Setting another aim is not possible since different datasets can have different kinds of predictability (Gilliland, 2010).

The next table summarizes all the methods as described above.

Method	Forecast method	Formula	Description
Time series analysis – simple forecasting	Naïve method	$F_{n+1} = y_n$	Gives same value as previous period.
	Seasonal method	$F_{n+1} = Y_{n-s}$	Gives same value as in same period in previous season 's'.
	Average method	$F_{n+1} = \frac{y_n + y_{n-1} + \dots + y_1}{n}$	Calculates average over all previous datapoints.
	Moving average method	$F_{n+1} = \frac{y_n + y_{n-1} + \dots + y_{n-k}}{n - k}$	Calculates average over datapoints up to k periods ago, and dynamically changes this.
	Weighted moving average smoothing method	$F_{n+1} = \frac{a \cdot y_n + b \cdot y_{n-1} + c \cdot y_{n-k}}{a + b + c}$	Same principle as moving average, but values from recent datapoints get higher weight than values from datapoints longer in the past.
	Simple Exponential smoothing	$F_{n+1} = \alpha \cdot y_n + \alpha(1 - \alpha)y_{n-1} + \alpha(1 - \alpha)^2 \times y_{n-2} + \dots$ or $F_{n+1} = \alpha \cdot y_n + (1 - \alpha) \cdot F_n$	The forecast smooths every period based on the smoothing factor α for current observations

			and $1-\alpha$ for current forecast.
	Holt's two-parameter exponential smoothing	$\text{Level } S_t = \alpha \left(\frac{X_t}{I_{t-L}} \right) + (1 - \alpha) X_{t-1} / I_{t-1}$ $\text{Trend } T_t = \gamma (S_t - S_{t-1}) + (1 - \gamma) T_{t-1}$ $F_{n+1} = L_n + T_n$	Same as exponential smoothing, but now also takes a variable into account (β) which smoothens the trend.
	Holt-Winters' three parameter exponential smoothing	$\text{Level } S_t = \alpha \left(\frac{X_t}{I_{t-L}} \right) + (1 - \alpha) (X_{t-1} + I_{t-1})$ $\text{Trend } T_t = \beta (S_t - S_{t-1}) + (1 - \beta) T_{t-1}$ $\text{Seasonality } I_t = \gamma (X_t / S_t) + (1 - \gamma) I_{t-L}$ $F_{n+1} = (L_t + T_t) S_{t+L-1}$	Same principle as two-parameter exponential smoothing, but takes into account the seasonality factor by applying a new parameter γ .
Regression based	Regression	$y = \beta_0 + \beta_1 x$	Takes a linear level based on the minimal squared errors, and based on the trend it continues in this way.
	Regression with seasonality	$y_t = (\beta_0 + \beta_1 x) S_t$	Same as normal regression, but now each period gets a seasonal factor.
	ARIMA	$Y_t = l + \alpha_1 \cdot y_{t-1} + \alpha_2 \cdot y_{t-2} + \dots + \alpha_p \cdot y_{t-p} + e$	Focuses on autoregressive, differencing and moving averages, and applies which factor should come first. This results in a (p,d,q)(P,D,Q) model
	Seasonal ARIMA	See ARIMA model	This takes the seasonal factors throughout the year into account.

Table 2: Forecasting models

3.2. Models and methods for order quantities

In the next section, different models and methods for order quantities will be described with their characteristics and constraints, or advantages and disadvantages. To be able to align the inventory with the (forecasted) demand, there should be an optimal order quantity, which is applicable to changes in demand and constraints throughout the year, which is dynamically planned throughout the year, but also meets the different constraints.

There are many different frameworks and methods to analyse which can be applicable for uncertain, seasonal patterned demand. Many heuristics and optimality models exist, which all have their own characteristics and restrictions. There are continuous time scale models with constant demand, and infinite time horizon lot sizing problems. An example of a lot sizing problem is the EOQ model. This is explained below. On the other side there are discrete time scale, dynamic demand, and finite time horizon models for lot sizing optimality. This is often called dynamic lot sizing. Developing a strategy

of purchasing the products should consider the dynamic demand patterns and prices in the market. Both quantity commitments should be negotiable and there should be taken advantage of market prices, by buying the correct quantity at the correct time (Jans & Degraeve, 2007).

In the sections below different planning methods are described, starting with the distinction of static and dynamic planning methods, the EOQ model, choice of suppliers and several other methods, and methods distinguishing between continuous and periodic review.

3.2.1. Timing in procurement planning

There are two different methods as approaching a procurement planning. The first is to make the decision at the latest moment possible, as is a dynamic model, and the second is a static planning, made at the beginning of each year. Both models are not optimal, as in the first, a long-term perspective lacks on total costs and in the second method there is no view in changes throughout the year. Therefore, a combination of these two models can be beneficial to incorporate. There can be used a two-phase scheme, which makes an contract allocation at the beginning of the year, which is based on the requirements of the different contracts at the different suppliers, and a monthly planning at the beginning of the month, when more information is known. Also, seasonality can be considered in this model (Bonser & Wu, 2001).

Replenishment planning is important to keep service levels high, to prevent lost sales and prevent high inventory ordering costs and holding costs of the inventory. For this, an economic order quantity formula is constructed. However, this is too simple to keep track of changes in demand, and is also too basic to consider seasonality. Also, delivery times are not mentioned in this model (Alnahhal et al., 2021).

3.2.2. Basic EOQ model

A lot of systems use the JIT system, the just in time principle. This means, that before a product is sold out, the new replenishment should arrive. This can reduce the inventory level and therefore inventory cost (Rodriguez & Vecchiatti, 2010).

An inventory policy with changing demand should be dynamic, and not static. The demand should be reviewed, and a dynamic planning should be adjusted every week according to this changing demand. In this way, the service levels can be hold up to a desired level and inventory levels and holding costs can be hold low.

Multiple models are based on the JIT principle. JIT considers multiple shipments (Kelle & Silver, 1990), so multiple deliveries throughout the period with just enough products to meet the demand in between different deliveries. This system reduces the inventory level. A simple inventory replenishment system, based on the Just In Time principle, called the Economic order Quantity (EOQ) was set up by Harris (Harris, 1913) and is described by Çalışkan (Çalışkan, 2021). This model is evolved over time. This formula uses the following variables (Chopra, 2019):

- D , items sold per day: a constant demand rate
- Q , items per order: which are fixed each time
- C , average price paid per unit purchased
- S , set up costs
- H , inventory holding cost, h is percentage of C , so $H = hC$.
- Lead time is zero in this model
- Initial inventory = 0, planning horizon is very long or infinite

The average inventory is assumed to be $Q/2$, as the demand rate is constant. There are D/Q cycles per year, and the cycle length is Q/D . Therefore, the total costs per year TC with ordering quantity Q is: $TC(Q) = C*D + S*D/Q + h*C*Q/2$. This formula is derived from:

- cycle stock cost: $hC*Q/2$
- Order cost: $S*D/Q$
- material cost: $C*D$

The EOQ formula can be derived from this total cost formula by taking the first derivative, which will lead to: $EOQ: Q^* = \sqrt{\frac{2SD}{hC}}$. This model is the basic model for inventory replenishment cycles, and many other models exist. However, the EOQ consists of all the basic assumptions for an inventory replenishment policy, which can be reviewed in the remaining of this section.

Often there are situations where multiple suppliers are necessary to attain a high service level or to reduce risk or cost when lead times are uncertain (Sedarage et al., 1999). Therefore, a significant reduction of supplier lead time is expected. This order splitting, where products are divided among different orders from different suppliers, can be done optimally and can be beneficial if the lead time variability is moderate and the order quantity is high in comparison with the expected lead time demand (Kelle & Silver, 1990). A higher service level can be received while at the same time keeping the same safety stock, or the safety stock can be lowered without affecting this service level.

3.2.3. (R,S) policy

The (R, S) policy (Silver et al., 2017), also known as replenishment cycle policy, is one of the most used policies for computing the optimal replenishment level. An order is placed at every R period, and the inventory level will grow to level S then. S is the order-up-to level. This is mostly useful if items are ordered at the same supplier and resource sharing is necessary. When implementing periodic review, an estimation of the workload can be made more realistic. However, when stochastic inventory problems occur, there is no stationary demand processes. Then, the (R, S) Policy can be adjusted to the (R_n, S_n) policy, where n is the variable representing periodically. Every period n the policy is reviewed how many products should be ordered and what the order-up-to level should be (Rossi et al., 2007).

The model uses a period review, with R periods per year, and an order-up-to level of S . R is the review interval, which is the interval in which the current inventory is reviewed. When an order is placed, it will be of high to order level S . Also, it makes use of the forecast of demand, and its uncertainty. \hat{X}_{R+L} is the forecast demand over a review period plus its lead time, while σ_{R+L} is the standard deviation of the forecast errors over this review interval and the lead time in which the order arrives. Both are in units of products.

As derivation of this model, the total costs can be calculated. This consists of expected shortage, and expected costs for having inventory on-hand. This can be calculated as follows.

$$\text{Expected Shortage per replenishment cycle} = \int_S^{\infty} (X_0 - S) \cdot f_x(x_0) dx_0.$$

$$E(OH) \approx S - \hat{x}_{R+L} + \frac{DR}{2}$$

If forecast errors are normally distributed, this can be reduced to

$$\text{Expected Shortage per Replenishment Cycle} = \sigma_{R+L} G_u(k)$$

Where k is the safety factor and G_u is the unit normal variable, with mean 0 and standard deviation 1.

As Mantel makes a planning on yearly based, so at a fixed moment, the periodic review is more useful than the continuous review model. Also, no set-up costs are incurred when ordering the products, only holding costs and ordering costs. Therefore, the stochastic single period model without set-up costs will be reviewed now.

In an optimizing inventory replenishment model for seasonal demand, discrete delivery times are considered. Many studies are neglecting changes in demand or a changing lead time (Alnahhal et al., 2021). Also, many models neglect safety stock. Capacitated replenishment systems assume a minimum size of lot ordering or maximum warehouse capacity. Also, constraints on delivery dates can exist. The demand occurring here is between supplier and retailer, and therefore ordering costs are usually higher, since different partners in the supply chain are not necessarily in the same part of the world, leading to long distances. The periodic order quantity (POQ) is used, which means that periodically an order arrives and per period is viewed what should be ordered and delivered.

This model will give an optimal value for optimal order quantity Y^0 which satisfies demand as good as possible. This model takes into account both the costs for having no stock, and thus lost sales, and the costs for having too many products on stock, which leads to too much costs. As demand is a random variable following a specific distribution, as is described above, the cost that will be incurred is also a random variable.

$$\text{The amount sold in a period is: } \text{Min}(D, y) = \begin{cases} D, & D < y, \\ y, & D \geq y. \end{cases}$$

D is demand and y is the amount on stock. $C(D, y)$ is the total amount of costs incurred when demand is D and amount of inventory is y .

The total cost function then shows: $C(D, y) = \begin{cases} cy + p(d - y), & \text{if } d > y \\ cy + h(y - d), & \text{if } d \leq y. \end{cases}$ The total expected costs is given by $C(y)$:

$$C(y) = E[C(D, y)] = cy + \sum_{d=y}^{\infty} p(d - y) * P_D(d) + \sum_{d=0}^{y-1} h(y - d)P_D(d).$$

In this equation, $P_D(d)$ is the probability function of the demand, c is ordering costs, p is the shortage cost per unit per time unit that a shortage occurs. This equation calculates the total of costs where shortage occurs and where too much inventory is hold.

Often, no distribution description can be found for the demand, and therefore $\phi(a) = \int_0^a \varphi_D(\xi) d\xi$, which is the probability cumulative distribution of the demand D . Then the expected costs are:

$$C(y) = E[C(D, y)] = \int_0^{\infty} C(\xi, y) \varphi_D d\xi$$

The optimal quantity to order is y^0 , which is the value that holds the following formula (Zappone, n.d.):

$$\phi(y^0) = \frac{p-c}{p+h}.$$

3.2.4. Linear programming

An aggregate planning can also be made using linear programming. This planning should decide the number of orders and the safety inventory that should be hold at stock. By using the solver in Excel, an optimal situation can be calculated (Chopra, 2019). By adding constraints on the values, the variables should hold, for example larger than 0, and an optimization in the total costs, the optimal order quantity can be calculated.

As can be concluded out of this literature review, many options exist to evaluate the optimal purchasing strategy, but should be both adaptive throughout the year, but also planned based on forecasted data. The optimality equation can be solved in multiple ways, by linear programming, dynamic programming or differentiating equations, as is the case for the EOQ formula. Also, different constraints can exist, like the uncertainty in demand and lead time, and if seasonality can be applied in the model or not. There are many different scenarios where different models work, with many different heuristics. Also, there are many constraints in modelling the optimal order quantity. The different forecast methods and the method for linear programming are used to analyse the data over 2020 in the next section, which will result in a planning model that is better aligning the orders throughout the year, and thus preventing peaks in deliveries.

4. Data Analysis

In this chapter, a description and analysis of the sales and purchasing data is done. Several models as described in the section above are researched with real life data to check what will be the best forecasting method in this data. A table in this section summarizes all the results of the parameters used in the models and the result of the Mean absolute percentage error.

4.1. Forecasting model

Data from 2017 to 2020 is used to calculate a forecast for 2021. This data contains the sales figures in number of products of all products in the category drivetrain, with brands SRAM and Shimano. With these data per week, an estimation of sales in 2021 per week is made. This forecast is compared with the actual values of the data in 2021, where through the Mean Absolute Percentage Error is calculated. These MAPE values are summarized per model and the results of different valuable parameters in the table that can be found below. Of all models, the results per week can be found in appendix A.

4.1.1. Simple (average) forecasting methods

In this subsection is explained how the average, moving average and weighted moving average methods are analysed. The average method takes the average over all past values and results in a MAPE value of 29.37% on average over a year. However, for a forecast on the long term, this method does not work since the values in advance are not known yet. Therefore, other average methods are analysed.

Another basic forecasting method is the naïve seasonal forecasting, which takes the value of the same period in the previous year. For example, the forecast of week 1 in 2021 will be in this case the same sales value as in week 1 of 2020. This method has resulted in a MAPE of 34.40%.

There are more elaborated average methods, as moving average. This moving average takes the average of a fixed number of past values. For example, the forecast of week 1 in 2021 will be the average of the k past values of week 52 up to week $52 - k$ values. For a moving average of 10 periods in advance this resulted in a MAPE of 24.19%. This method also does not consider the longer period, but only looks 10 weeks in advance.

The other average forecasting method is the weighted moving average, where the most recent values get a higher weight and the values more in the past get less weight. For this method, an average of the five values around the same period in the previous year is calculated and weighted most important. Then the average of the same values in the year before are calculated and this is repeated for all years. The most recent years get the highest weight. The total of the variables will add up to 1, and the weights are optimally distributed, to reduce the MAPE in 2020. This resulted in a MAPE over 2021 in 30,04%.

The weighted moving average method takes both values of past seasonal observations, as the values around that value in previous years, to make it available for long-term forecasting. It weighs more recent values higher than values longer ago. However, the weighted moving average does not react fast on changes or growth. It does not take account for growing trend throughout a year. Linear regression looks at minimal squared errors throughout a period and will therefore be better capable of reacting on these changes.

The more advanced methods as are described in the following subsections should improve the MAPE of the 34.40% of naïve seasonal forecasting method. This is the naïve method that, by implementing another forecasting system, should improve the naïve forecasting method.

4.1.2. Regression

First, the deseasonalised demand is calculated by calculating the average of two moving averages. The first moving average (MA1) is calculated by taking the average between the five previous and six next values. The next value, MA2 is calculated by the six previous and 5 next values. The deseasonalised value per week is the average of MA1 and MA2.

Then, the regression is applied by taking as input variables the weeks and the deseasonalised demand. This results in an output of an intercept of 963.772 and an X variable of 27.577. With this, the demand is calculated by $D_{t,reg} = 963.772 + 27.577 \cdot t$. With this value, the seasonal factor per week is calculated. $S_t = \frac{D_t}{D_{t,reg}}$. Then, per week an average seasonal factor is calculated over the values for all five years. $SI_t = \frac{\sum_{k=1}^5 S_{t+52 \cdot k}}{5}$. With this seasonal value, the expected sales per week is calculated. $E(t) = D_{t,reg} * SI_t$. Over 2021, the MAPE is calculated to review the performance of this linear model, for both $D_{t,reg}$ and $E(t)$ with seasonality. This results in a MAPE of 30.02% and 39.77%. Every value for $E(t)$ and the seasonal index, with errors and MAPE can be found in the appendix.

4.1.3. Smoothing methods

The third model to consider is the Holt-Winter smoothing method. For this method, the input variables are α , β and γ , which are variables for the level, trend and seasonal input. The data is divided in initialization and calculating data, where 2017 is the initialization data in this model. In this case, the seasonal factor is calculated by dividing the sales per period by the average of the total sales per year.

$S_t = \frac{D_t}{\frac{(D_1 + D_2 + \dots + D_{52})}{52}}$. The initial level will then be the sales of the first week of 2018 divided by the seasonal factor of week 1 in 2017. The initial trend will be the difference between the initial level and the sales divided by the seasonal factor of last week of 2017. These are all the initialization values. The next values will be calculated to optimize the variables using eq.1, eq.2 and eq.3 for 2018, 2019 and 2020. The variables alpha, beta and gamma are optimized by the following formula:

Minimize the MAPE over 2018 up to 2020 by changing values for α , β , and γ ,

Subject to:

- α , β , and $\gamma < 1$ and
- α , β , and $\gamma > 0$.

This resulted in the following values for alpha, beta, and gamma.

- $\alpha = 0.621$
- $\beta = 0.267$
- $\gamma = 0.145$

With these values, the forecast for 2021 calculated. These can be found in the appendix. The MAPE will be 106,43%. There can be concluded that this method works better on shorter terms then over a whole year.

4.1.4. ARIMA

The next method is the ARIMA model. This model is calculated by using statistics software R. The code is attached to the appendix.

ARIMA makes use of both Autoregressive and moving average models, where the parameters will apply the order. This resulted after a data analysis in differenced data over trend and thereafter differenced over seasonality, to make the data stationary. The ARIMA model applied is the ARIMA

(1,1,1) (1,0,0) model. The first vector is about which factors to apply, while the second adjusts for seasonality. This results in a MAPE of 47.34%. The ARIMA function generally consists of (p,d,q)(P,D,Q) where *p* is the autoregressive variable, *d* is the number of differences and *q* is the moving average variable. By applying the formula AUTOARIMA, a MAPE of 62.60% was found.

ARIMA makes use of timeseries that are stationary. To achieve this in a data set, differencing is necessary. This is tested, and the output of the R script can be found in the appendix.

For the different ARIMA models around this ARIMA (1,1,1) (1,0,0), alterations on the variables are tried. This resulted in different MAPE values over 2021. The results can be found in the appendix.

The best method will be used to analyse the data. This is in this case linear regression with adjusted variables for seasonality. However, this data has resulted in a larger MAPE than preferred, this is the best model that could be found, while the data is not following the same trend as in previous years, having disruptions due to Covid-19. Also, it remains possible to change the orders up to three months before delivery, which makes it on the longer term less important to have a good MAPE but makes it also possible for Mantel to remain flexible, but also have an estimation on the expected sales over a year ahead. This data will be used as input to the model for calculating the optimal order quantity, as described in the next subsection.

First, the data will be analysed and fitted to a statistical distribution. For overview, the data can be found in appendix B. Also, the results of the different forecast techniques with their respective MAPE can be found in Table 4.1.

Model	Results in parameters	MAPE
Linear regression with seasonality	Level = 963.772; Variable = 25.57722	29.94%
Holt-Winters smoothing method	Alpha = 0.818, beta = 0.134, gamma = 0.401	106.43%
Auto ARIMA	ARIMA(0,1,2)(0,1,1)	62.60%
Naïve seasonal forecasting		34.40%
Holt-Winters two-variable method		30.72%
Moving Average		24.19%
Average		29.37%
Weighted moving average		30.03%

Table 3: Forecasting results

The MAPE of the linear regression with seasonality taken into account is the best for forecasting on the long term. The MAPE however is still 29.94%, which means that the forecasted data is in total 29.94% away from the real sales data. It can be in total 30% too much forecasted, or almost 30% too little products that are forecasted. The MAPE however is better than the MAPE of the Naïve seasonal forecasting, which is 34.40%. This means that the chosen method is better than the naïve forecast, which is an improvement for the forecasting method.

4.2. Optimal Ordering Quantity model

The optimal order quantity model should arrive to an optimal order quantity that minimizes total costs, while also considering expected lost sales based on the forecasted demand in section 5.1. The total costs will consist of holding cost, ordering cost and delivery cost. First, an estimation of these three costs will be made, while also describing or estimating what the costs entail at Mantel. Then, the constraints of the model will be explained. After that, the model will be set up, together with results on what is optimal to order in what week, throughout 2021. This will be reflected to the real sales, where the number of stockouts and lost sales will be estimated, together with the service level.

4.2.1. Costs

The holding costs consist of costs of having products in inventory, but also the costs of having employees handling these costs, as is described in the process description in chapter 3. Besides, the costs of risk and of interest should be taken care off. Therefore, an estimation of this cost is made. The holding cost is estimated by taking a percentage of the product value, this is on average €32.47. This percentage should be higher than the interest rate of the bank.

Holding costs are estimated as the costs for holding one product on stock. Often, the holding costs are between 5 and 45 percent (Durlinger, 2014), but since interest is now low, also the holding costs are estimated lower. For now, the holding costs are estimated on 15%. The average inventory level is 29265.54 products over 2021 for the category drivetrain, with brands Shimano and SRAM. For now, the holding cost will be estimated of 15% of the total costs of a product, so $0.15 * 32.47 = €4.87$ per product. The total holding costs are calculated by taking the average stock hold during a week multiplied by this cost per product.

Therefore, the total holding costs are: $C_{holding} = \left(S - \hat{x}_{R+L} + \frac{DR}{2} \right) * 4.87$, where DR is the same as the order quantity Q.

The ordering costs consists of costs for ordering a product at the supplier. These costs entail the costs for placing an order and sending this product. Moreover, there are delivery costs, which are costs for processing the products between the supplier and the central warehouse, by delivery companies. This is the general cost for sending a product in the Netherlands. These costs will have to be minimized. For calculations for the ordering costs, the costs of ordering a product is taken, which is €32.47. These are denoted as $C_{ordering}$.

Another cost is the shortage cost. This cost is incurred for every sold out that is occurred, for every product that could not be sold. This is the difference between the expected demand that is forecasted by the linear regression method described in the previous section and the actual demand that is met with the inventory on hand, multiplied by the unit cost. S_i is the inventory on hand at a certain period, which is the order up to level, while D_i is the demand that occurs in that period. However, there is a probability that the demand is higher than the forecast has shown, which will lead to expected shortages. This is implemented in the total costs for having a shortage. This means that the expected shortages during a replenishment cycle, in this case 1 week is:

$$ESPRC = \int_S^{\infty} (x_0 - S) \cdot f_x(x_0) dx_0$$

The total shortage costs are:

$$C_{shortage} = ESPRC * C_{ordering}$$

Where C_{shortage} are the ordering costs and therefore the costs that are lost when a shortage occurs. Due to the uncertainty in the forecast, the expected number of shortage is 231 products for every week. This is calculated by the standard deviation of the forecast errors, multiplied by $G_u(k)$. $G_u(k)$ is the unit normal distribution, with mean 0 and standard deviation 1. This safety factor k is assumed to be 0.95. The probability that a shortage occurs with more than 231 products is assumed to be 0, and therefore no costs are incurred for having more product short than 231. Up to 231 products that are higher than demand, shortage costs do occur and are calculated per product that might be short. The total shortage costs therefore is the expected shortage given the forecasted demand, multiplied by the cost of having one product too short to meet actual demand, taken into account the current level of inventory to meet this probability that this demand actually occurs. This level of inventory can also be used to meet demand, and is therefore also incorporated. The total costs of ordering, shortage and holding inventory are added to calculate the total cost. This total cost will be minimized by changing the order quantity.

4.2.2. Constraints

The model should hold to several constraints. To model these constraints, several assumptions are made. First, the capacity of the warehouse should not be exceeded, and the orders should not have too high peaks, as is described in the problem description. To consider this in the model, first a model without this constraint is set up. If the problem still occurs, a cost is considered for too high peaks and too high deviations from the average.

A next constraint is the order and contract constraints. An order should not be too small, that the costs for ordering are higher than the beneficial orders. Therefore, a minimum order quantity is considered. Besides, there are constraints with the suppliers' contracts, where there are made deals about what time should be between ordering and delivery.

At last, the inventory level of one week should be higher than the demand of that week, to prevent lost sales. Therefore, this model assumes that the inventory level at the beginning of the week should be used to meet demand during that next week. Deliveries during the week are not considered that same week but will be considered the next week. This assumption is also realistic, as it takes some time to handle all the incoming goods and to put it in places to make it ready to be sold.

4.2.3. Statistics over forecasted demand

For calculation of the demand uncertainty, the distribution of uncertainty of errors of the forecast of Section 4.1 is analysed. As this is assumed to follow a normal distribution, (Silver et al., 2017). The Chi-squared error test also shows for a normal distribution an error of 6.48, where an error of 14.06 is allowed. This means, that the Normal Distribution will be used for uncertainty in the forecasted demand, and will be used to calculate the shortage costs.

The forecast errors are normally distributed with a mean of -1126 and an estimated standard deviation of 2528. The histogram in Figure 8 shows the distribution of the forecasting errors. Since this is not a perfect normal distribution function, the standard deviation is an estimation of the real standard deviation of the distribution.

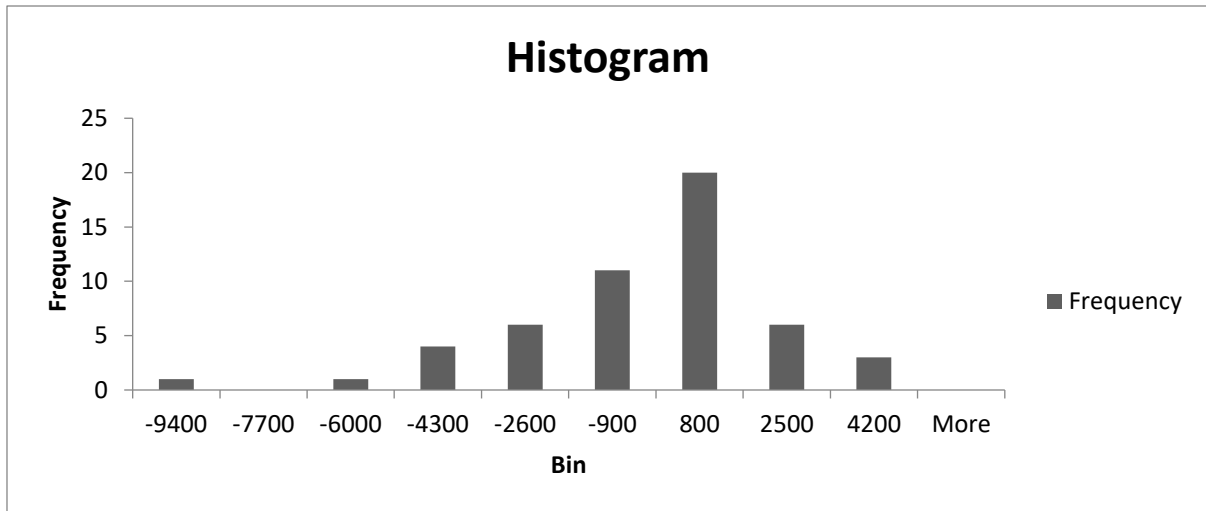


Figure 8: Histogram distribution forecast errors

4.2.4. Model

The model will evaluate the total costs and balance an extra purchase over the extra costs of holding one product more. This means that the model will minimize total costs, given the forecasted demand, with the probability that this is lower than the actual given demand. If this is the case, the shortage costs are incurred, and calculated among the calculation that is given in Subsection 4.2.2.

$$\text{Min } TC(t) = \text{Min } \sum_{t=1}^{52} H_t + \sum_{t=1}^{52} O_t + \sum_{t=1}^{52} C_{short_t} \text{ (eq. 5)}$$

Subject to:

- $Q_i > \text{Min. } Q$, the order quantity should be above the minimum order quantity, to prevent a too low order quantity.
- $\text{All } H_t, O_t, C_{short_t} \geq 0$
- $I(i) > D(i)$, all demand in week i should be met by products that are in stock at the beginning of the week

The model of equation 5 will give a solution based on the starting inventory $I(0)$, and the costs that are given as input, which can be found in Subsection 4.2.2. The $Q(t)$ is an integer, which is the number of products to be purchased. The solution of this model, with the optimal order quantity and the reorder level can be found in appendix C.

In this model, a periodic review period is described, where for every week an order-up-to level OUL is created, by adding the in this model calculated optimal order quantity to the current inventory level. that should be kept in that week. In the order up to level, the safety inventory is also taken into account. This safety inventory is chosen to also decrease the total costs of having shortages and total orders, and to make sure demand can be met at most times. This is affected by the safety factor chosen, which is 0.95. If this will be increased, also the safety inventory will increase, as shortages will occur less.

This safety stock is calculated based on the forecasted demand, and should therefore also each year when the planning is made, be evaluated and changed to the desired numbers, to make sure that the total costs are minimized. When uncertainty in demand is higher, the safety stock will also become higher, to be able to prevent too much lost sales. These lost sales can occur due to too much uncertainty in the market.

4.2.5. Evaluation

The solution in appendix C is visualized in the graph in Figure 12. This graph shows that the number of products ordered, is more fluently divided throughout the year. This is the optimal solution from the above minimization problem. The solution takes lost sales due to the uncertainty in demand. The expected shortage costs are calculated by taking the probability that the actual demand is higher than the forecasted demand. Also, the inventory position is given in a graph in figure 13. In this figure can be seen that the inventory held at the beginning and the end of the year, are lower than in the middle of the year, where the sales are higher throughout the season. This means that the order up to level (OUL) is fluctuating throughout the year. For each week, an order-up-to level is calculated, which should make sure that the expected sales of that week are met, with keeping as low inventory as possible. This should be reviewed each year again by having the forecasted demand and analysing the costs for lost holding an extra product in inventory or having a lost sale. This graph shows that the inventory position should be higher between week 11 and week 35, after and before which a lower inventory can be hold.

In appendix C.2. the analysis is done about how many lost sales this model results in. This is now 334 products in total in this category. This is due to uncertainty and error in the demand forecast. This uncertainty can be taken into account by regular orders, as is described in chapter 3. These regular orders can be ordered just in time and delivered the same week, by having a short term forecast which will yield more reliable solutions. This makes sure that lost sales can be minimized, certainly in products in category B. In category A, these regular orders are not preferred, as there is risk involved in having a too late delivery. This means that for A products, there should be a safety inventory.

This safety inventory should be of a high, such that the lost sales are decreased substantially. Therefore, a safety stock should be able to take on the uncertainty of demand in that period. This uncertainty is the MAPE, which is 30,09%, which is a uncertainty in the forecasted demand. By minimizing the cost, and considering a safety inventory, the safety inventory should on average be 16.27% of the total inventory quantity on hand. This would make sure that the total costs are minimized, with an as low shortage costs as possible. These products can be ordered on regular basis, which is already the case for products in category B. This calculation can be found in appendix C.

The model gives the total products that should be ordered for the category A and B products of Shimano and SRAM. This can be calculated to a budget that should be available for the products, and per product, the total amount of products can be decided on for how much of these to order.

Lost sales could be prevented by having a higher cost for not being able to sell a product to a customer. This means that the costs for lost sales have an higher impact on the total costs, making it more important to decrease this amount of costs.

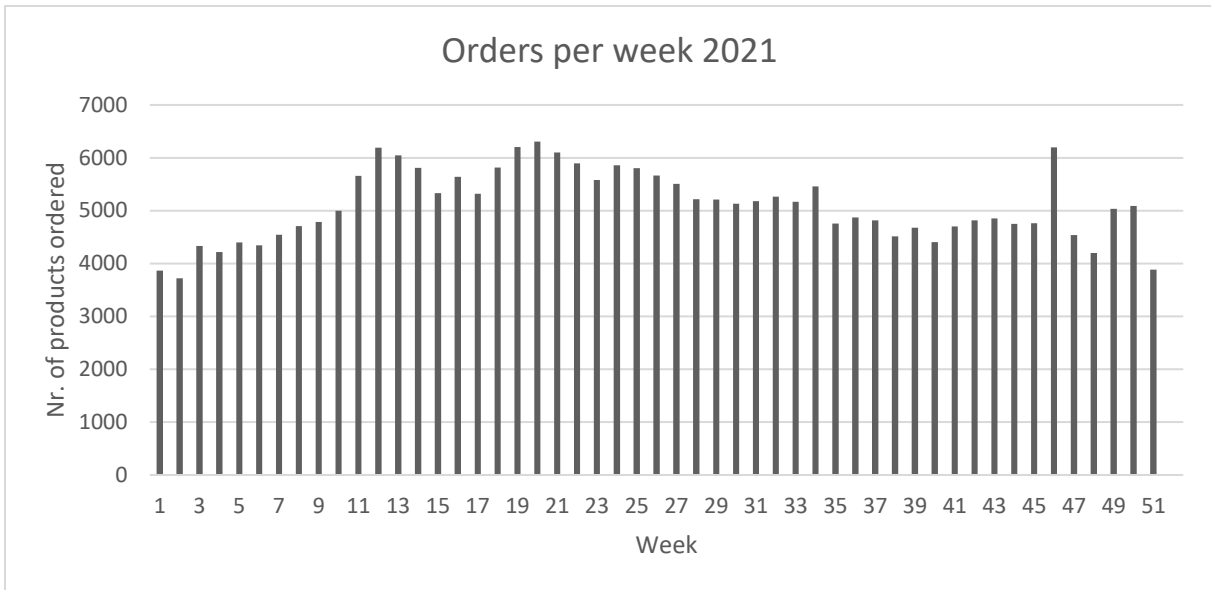


Figure 9: Orders per week forecasted 2021

The inventory position regarding safety inventory and the purchases throughout the year can be seen in figure 10. This inventory position follows a recognizable pattern, where in the beginning and at the end of the year, the inventory is lower, while during the middle of the year, the inventory position should be higher to meet higher demand.

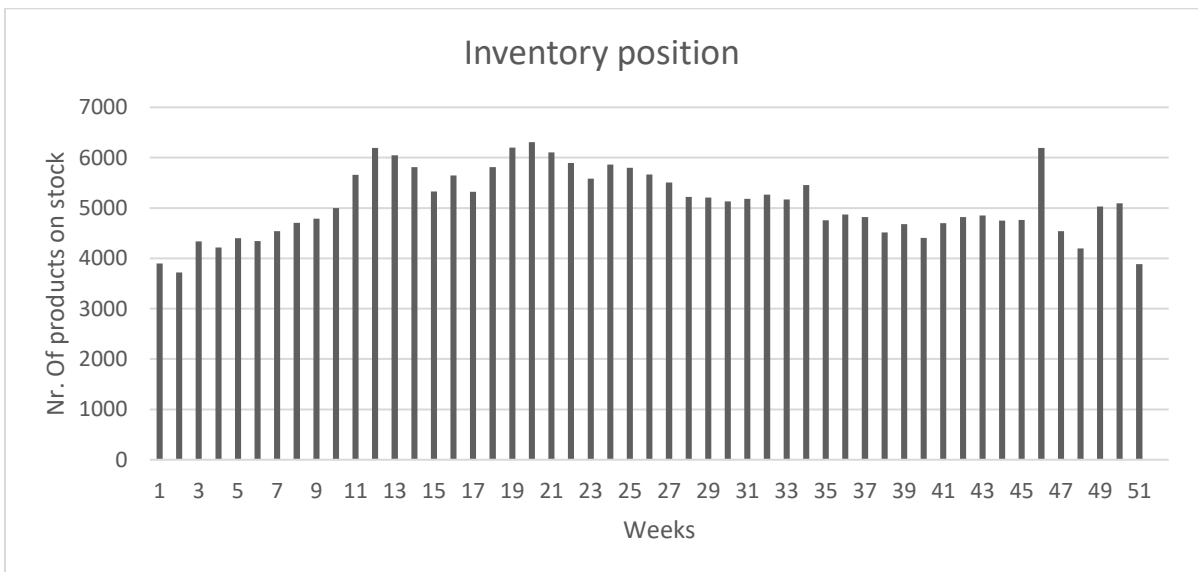


Figure 10: Inventory position forecasted 2021

The orders as are shown in Figure 10 show the smoothening of the total orders per week in 2021. This shows the total number of products that will enter the warehouse per week in 2021. As can be concluded from this, is that the total number of products deviate as maximum amount of 1.35 standard deviations from the total demand. This means, that compared to the current situation, the deviation in orders has changed. Also, the inventory position is now at its max of around 6500 orders per week, while this was around 16000 per week of products that had entered the warehouse. This makes room for the logistics department to have a better spread in deliveries and a better spread of workload throughout the year, also for other product categories.

With this model, Mantel will be able to calculate, eventually for more product categories than only drivetrain, the inventory position that should be held. By calculating the total number of products that can be delivered and should be ordered, a budget planning can be made, and in the way Mantel now plans their orders, it can be divided to the products individually. By this model, the total budget that should be available for the products can be estimated, which can be broken down to the total number of individual products that should be ordered. By implementing the safety stock, per week is available how many products in total should be available to meet the forecasted demand in total. Per product, a safety stock should be kept to make sure every product will be available. However, the safety stock also gives a better insight in how many products can be delivered per day in this situation, and gives an insight in the inventory position that will be held during the year. By implementing the safety stock to the model, the number of products that should be ordered in total is decreased, and will give a more realistic number. This means, that the logistics department can better make a schedule to process all these products.

By implementing the uncertainty costs and holding costs, there automatically is not purchased more products than needed, and in each week, the number of products will lie around the average. This means that, because of the holding costs and shortage costs, the peaks in delivery automatically are lower, as it is always cheaper to delay the purchase, for demand for a next period. However, when the uncertainty becomes higher, the purchase will be higher as well.

5. Conclusions, recommendations and discussion

In this section, a conclusion will be drawn from the research in the chapters above, and a general recommendation about the planning processes will be given. Afterwards, a discussion of the results as described in this thesis is given.

5.1. Conclusions

In this subsection, the main conclusions of the research are described. The main bottleneck at Mantel in the purchasing processes is at the planning of orders. Large orders arrive at once, while at other periods, almost no products are ordered and delivered. This causes a large disruption at the warehouse, where all these products need to be handled. A lot of products are delivered at once, while in other weeks, almost no orders arrive. This leads to high workload in several weeks, while in other weeks this workload is significantly lower.

This process is laid down in several factors, where several stakeholders occur. The stakeholders considered are the suppliers, both purchasing departments and the logistic department. All these stakeholders have influence on or are influenced by the planning of the orders, and failures of this planning when these occur. The main bottleneck therefore is the planning of products and when these products should be delivered. This bottleneck is caused by two subsequent points. At first, there is the global forecast, that is made a year in advance. This forecast creates the planning of products that are expected to sell during the year. Now, this occurs without any basis on historical data, but on feeling and estimation of growth. By not taking historical data into account, the forecast will result in too large errors, which will result in too high inventory positions and no constant stream of incoming products.

From multiple models tested, the linear regression best points out the growth in the trend and the seasonality patterns in each period. This period is in this case a week. For each week, there should be a level, estimation of growth in the trend and seasonal factor be applied. This results in a forecast for demand during a specific week. In this case, demand can be forecasted more accurately and more based on historical data. This has as advantage that per period, the demand can be reviewed and separated on different aspects as trend, level, seasonality, and randomness. This makes it more accurately possible to forecast what will happen in the next periods. With this model, the error in forecasting is lower than the error in a normal naïve forecast, which will lead to an improvement of the forecasted demand. With a better forecast, the stream of orders can be planned better, resulting in less peaks of products that enter the warehouse at once.

This system of forecasting, linear regression works better than other systems, because these models do not consider all these factors, or do not react fast on changes in demand, like in the smoothing method. Also the naïve forecasting methods do not consider that long term forecasting is applicable when trying to make a planning. This makes the linear regression the best forecast method to use, as it has the lowest value of MAPE for long term forecasting methods.

Another aspect that creates bottlenecks is the order quantity. The forecast should be aligned with the order quantity, as this forecast has to deal with uncertainty. As already concluded, the order quantity differs a lot throughout the year. In many weeks, it is high, while at other weeks, almost nothing arrives. This can be changed and altered by having the safety inventory, on a percentage of the estimated demand, giving the starting inventory and calculating at each week what the optimal order quantity for that week should be. By implementing this safety inventory, the uncertainty can be dealt with, and the total products to order can be estimated. This means that a better planning can be made. By implementing the uncertainty of the forecasted demand, the expected shortage costs are taken into account. This means that the shortage costs should be based on the expected demand and the

probability that the demand is higher than the estimated demand. By taking this uncertainty, the safety stock will automatically increase, to take care of this uncertain situation. With this inventory model, based on forecasted demand, most demand can be met, but some demand will remain in shortage. This is caused by the fact that the probability that the demand is higher than forecasted does not outweigh the holding costs of one more product. However, when this is the case, the rest of this demand can be met by regular orders or by increasing safety stock. This means that the inventory can be planned as low as possible. Also, it is possible to review every 3-7 months in advance of delivery the orders, depending on the supplier contract. This means, that up to 3 months in advance, the order can be changed up to the most recent estimation. This leads to the fact that in advance, the supplier gets a global planning, but this will be changed at 3 months before delivery.

5.2. Recommendations

In this section the main recommendations for Mantel are described. By implementing these recommendations, the core problem of having too many peaks should be solved.

The recommendations regarding the planning process is to look at seasonal, trend and normal level patterns in the data while forecasting it on the long term. By having linear regression as forecasting method, these three variables are taken into account, and also the human factor of experience in the demand patterns in the market can be analysed. The linear regression method can take more historical data, and for each new period the most recent data should be used.

The optimal order strategy can be derived by taking the minimum costs of holding costs and shortage costs, together with order costs. By taking the uncertainty in the forecasted demand, as having a probability distribution, the optimal order quantity can be calculated. A recommendation is to calculate the costs of shortage and holding an item on stock precisely, as this is now estimated.

This can be improved by having a good value of safety inventory and the optimal order quantity. In this way, the uncertainty is dealt with, and the shortage costs will be lower than the costs of having one product extra in stock. If this is the case, the optimal order quantity will smoothen out, resulting in less peaks, but will lie around the average value of the forecasted demand, with some uncertainty in the result, resulting in less peaks in delivery, which results in less disruptions in the logistics department.

By implementing the inventory model, the planning of work for the logistics department can be more aligned with the expected deliveries of orders. As the orders are more aligned throughout the year, the planning of the logistics department can also be more aligned, resulting in a more frequent workload over the year.

5.3. Limitations

In this section, the results and conclusion will be discussed, and limitations of the implemented model above are described.

In the results of the data analysis, only data for 2021 is considered. However, the data could be biased due to unforeseen marketing promotions or changes in demand due to the corona crisis that struck the world. This means, that the data could not hold for other years, but need another calculation and run of the parameters, for example the percentage of safety stock. The data visualized sometimes shows a peak or low value, which can be caused by disruption in the supply chain or lockdowns. This means that the historical data is not the optimal data to forecast on, because of market issues due to the coronavirus.

The costs that are used to estimate the optimal order quantity are estimated both on raw data as on an estimation of what is currently used in literature. For example, the holding costs are taken as 15%

of the ordering costs, but can be calculated more accurately, resulting in a more reliable solution, and a more accurate number of costs incurred by holding products on stock or not.

The uncertainty of the inventory model is calculated based on the forecasted demand. This means that the probability that the demand is higher than the forecasted demand throughout the year is small. This can result in less reliable uncertainty and the probability that the demand is higher is very small. This can be solved in a later stadium when over more years data is available and the probability function per week can be calculated. For now, the probability is taken for one year, but with a limited amount of orders from the forecast. This means, that the probability that the demand is higher than the highest forecast is zero. However, with an accurate forecast, this should not be a problem.

As last limitation, the model at the moment is made for the drivetrain category of Shimano and SRAM. This are a lot of products, however, Mantel sells many more items in many more categories. All these categories have their own properties and their own seasonalities, which makes it more difficult to implement this model to this.

5.4. Future work

In this section the points of this research that can be extended to further research are discussed. First, the probability distribution as described in the previous section can be researched per week over multiple years. For this, more historical data is needed to make it more reliable, instead of the four years of data that is available now.

Machine learning techniques are more and more improving to make it able to improve the forecast. This can become a new research item to investigate if these techniques will be able to improve the linear regression method that is described above.

Holding costs and other costs can be estimated more accurately to come to a more optimal solution. Also, the demand is now forecasted at product category, but can be forecasted at individual product level. An analysis of estimation of ABC classes is not considered and can be a goal of a next research.

Next research can also include the other categories and the alignment between the different categories. This research only takes one category into account, but the logistics department has to process all the products of all the product categories. This means, that also the other categories should be aligned to each other, to prevent an overflow of different categories of products enter the warehouse at the same time, and leading to the same problem again.

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A. Appendix Data Analysis

A.1. – Values regression model

Week	E(t)	SI(t)	MAPE	Week	E(t)	SI(t)	MAPE
1	7998.61	1.188958	0.271197	27	7763.27	1.042831	0.347611
2	7201.946	1.066167	0.203101	28	7554.633	1.011106	0.346001
3	6865.616	1.012245	0.176605	29	7466.465	0.995585	0.337527
4	8215.102	1.206304	0.180271	30	7297.111	0.969439	0.330393
5	8284.224	1.211548	0.185042	31	7761.369	1.027353	0.325029
6	7357.503	1.071695	0.205963	32	7759.905	1.023423	0.318646
7	7298.83	1.058895	0.182532	33	7395.285	0.9718	0.312381
8	9546.491	1.379461	0.207702	34	7086.022	0.927798	0.310604
9	8952.373	1.288477	0.212231	35	7460.52	0.973318	0.308437
10	8144.121	1.167514	0.197886	36	7204.475	0.936545	0.304755
11	8370.099	1.195185	0.186329	37	6609.211	0.856094	0.301601
12	8943.438	1.272044	0.194227	38	6400.818	0.82615	0.301662
13	9943.7	1.408788	0.187324	39	6173.017	0.793922	0.299635
14	10045.63	1.41769	0.185517	40	6732.018	0.862756	0.293101
15	8990.721	1.263897	0.178784	41	6419.153	0.819763	0.288322
16	7949.864	1.11326	0.190836	42	6301.703	0.80194	0.286485
17	8995.831	1.254886	0.180111	43	6547.449	0.830299	0.282414
18	8621.09	1.198002	0.175186	44	6360.252	0.803749	0.281163
19	8572.005	1.186634	0.191551	45	6053.764	0.762361	0.280249
20	8700.634	1.199859	0.231615	46	6077.205	0.762664	0.281828
21	8462.589	1.16261	0.287939	47	7695.568	0.962432	0.291087
22	8646.753	1.183428	0.295799	48	6117.919	0.762496	0.287138
23	7979.786	1.088037	0.310951	49	5282.833	0.656161	0.287379
24	7726.558	1.049563	0.314148	50	6121.279	0.757707	0.29195
25	7687.635	1.040379	0.354596	51	6235.163	0.769178	0.301952
26	8384.331	1.130445	0.344138	52	5131.682	0.630905	0.300317

Table A.1: Seasonal regression output per week 2021

A.2. – Holt-Winters smoothing method

Week t	Perc. error	MAPE	Week t	Perc. error	MAPE
1	0.516339	0.516339	27	1.251495	0.710846
2	0.440325	0.478332	28	1.257661	0.730375
3	0.451664	0.469443	29	1.259294	0.748614
4	0.503397	0.477931	30	1.298898	0.766957
5	0.46766	0.475877	31	1.236352	0.782098
6	0.13706	0.419407	32	1.293413	0.798077
7	0.451831	0.424039	33	1.434268	0.817355
8	0.696521	0.4581	34	1.581606	0.839833
9	0.625486	0.476698	35	1.652305	0.863047
10	0.455587	0.474587	36	1.448026	0.879296
11	0.493733	0.476327	37	1.684088	0.901047
12	0.45577	0.474614	38	1.798024	0.924652
13	0.601936	0.484408	39	1.924638	0.950293
14	0.774007	0.505094	40	1.74727	0.970217
15	0.705939	0.518484	41	1.69573	0.987913
16	0.643797	0.526316	42	2.069681	1.013669
17	0.794488	0.542091	43	2.040505	1.037549
18	0.854258	0.559433	44	2.184936	1.063626
19	0.780041	0.571044	45	2.054581	1.085647
20	0.780148	0.581499	46	2.372988	1.113633
21	0.849138	0.594244	47	3.211155	1.158261
22	0.971525	0.611393	48	2.360902	1.183316
23	1.030507	0.629615	49	2.425344	1.208663
24	1.078427	0.648316	50	2.557501	1.23564
25	1.243776	0.672134	51	3.445167	1.278964
26	1.13799	0.690052	52	3.353797	1.318865

Table Error! Use the Home tab to apply 0 to the text that you want to appear here.A.1.2: Holt-Winters smoothing method

A.3. – ARIMA model

A.3.1. R-code

```
1 #Calling libraries and formulas needed
2 library(forecast)
3 library(zoo)
4 library(readxl)
5 library(timeseries)
6 library("fUnitRoots")
7 library(fBasics)
8 library(urca)
9 library(writexl)
10 library(timeseries)
11 library(lmtest)
12
13 #load data
14 data1 <- read_excel("C:\\users\\koenk\\OneDrive\\Documents\\Universiteit Twente\\TBK\\Module 12 - Bachelor Thesis IEM\\Forecasting\\Salesweekly.xlsx")
15
16 #decompose data to timeseries
17 tsData2 = ts(data1, start = c(2017,1), frequency=52)
18 plot(tsData2)
19 diff.comp = decompose(tsData2)
20 plot(diff.comp)
21
22 #test how many differences and whether time series are stationary
23 tsData2 %>% ur.kpss() %>% summary()
24 tsData2 %>% diff() %>% ur.kpss() %>% summary()
25 ndiffs(tsData2)
26
27 Data2stationary = diff(tsData2, differences = 1)
28 plot(Data2stationary)
29
30 acf(Data2stationary, lag.max=4)
31 pacf(Data2stationary, lag.max=4)
32
33 fitARIMA <- arima(tsData2, order =c(1,1,0), seasonal = list(order = c(1,0,0)))
34 coefTest(fitARIMA)
35 fitARIMA
36
37 df3 <- forecast(fitARIMA, h=52, level = c(99.5))
38 plot(df3)
39 df4 <- data.frame(df3)
40 write_xlsx(df4, "c:\\users\\koenk\\OneDrive\\Documents\\Universiteit Twente\\TBK\\Module 12 - Bachelor Thesis IEM\\Forecasting\\Arima_111101.xlsx")
```

Figure 10: R-Code ARIMA Model

A.3.2. Forecast ARIMA

<i>Period</i>	Forecast 2021	Perc. Err	MAPE	<i>Period</i>	Forecast 2021	Perc. Err	MAPE
1	7710.578	0.297442	0.297442	27	8583.096	0.589757	0.391752
2	7803.841	0.062714	0.180078	28	8569.547	0.477508	0.394815
3	7631.282	0.025877	0.128678	29	8357.143	0.231527	0.389184
4	7923.069	0.220017	0.151512	30	8450.394	0.301061	0.386247
5	7823.364	0.248404	0.170891	31	8301.353	0.105939	0.377205
6	7670.32	0.366284	0.203456	32	8138.364	0.07791	0.367852
7	7565.776	0.080054	0.185827	33	8334.827	0.253169	0.364377
8	7501.572	0.515871	0.227083	34	8300.157	0.466459	0.367379
9	7765.369	0.348105	0.24053	35	8612.187	0.425387	0.369036
10	7917.195	0.039002	0.220377	36	8325.263	0.047671	0.36011
11	8094.529	0.035503	0.20357	37	8269.871	0.486585	0.363528
12	8358.738	0.197355	0.203052	38	8264.69	0.683579	0.37195
13	8549.224	0.050403	0.19131	39	8015.225	0.587488	0.377477
14	8867.63	0.260291	0.196237	40	8067.828	0.152547	0.371854
15	8985.189	0.083859	0.188745	41	7907.629	0.112184	0.36552
16	8448.8	0.457695	0.205555	42	8261.104	0.587758	0.370812
17	8485.861	0.04867	0.196326	43	8438.04	0.432361	0.372243
18	8287.405	0.12663	0.192454	44	8565.164	0.652868	0.378621
19	8293.781	0.437895	0.205372	45	8716.197	0.785374	0.38766
20	8566.359	0.962061	0.243207	46	8647.256	0.925035	0.399342
21	8556.397	1.441197	0.300254	47	9363.371	1.089106	0.414018
22	8673.956	0.465443	0.307762	48	8265.089	0.488133	0.415562
23	8881.179	0.830039	0.33047	49	8353.557	1.053985	0.428591
24	8838.539	0.587381	0.341175	50	8826.584	1.18588	0.443737
25	8773.981	1.653957	0.393686	51	8419.31	1.433327	0.46314
26	8870.021	0.145406	0.384137	52	8418.912	0.996422	0.473396

Table A.2.3: Forecast ARIMA

A.3.3. – Different ARIMA models and results

ARIMA Model	MAPE 2021
(1,1,1)(1,0,0)	47.34%
(1,1,0)(1,0,0)	45.98%
(1,0,1)(1,0,0)	34.3%
(2,1,1)(1,0,0)	46.15%
(1,1,1)(1,1,0)	68%
(1,1,1)(1,1,1)	58%
(0,1,1)(1,0,0)	45.81%
(1,1,1)(0,0,0)	31.59%
(1,1,1)(1,0,1)	31.59%

Table A.3: ARIMA variations and MAPE values

B. Appendix results of forecast

B.1. – Results of demand forecast Linear regression

Week	Demand	Week	Demand
1	3969.42	27	5664.287
2	3895.835	28	5508.508
3	3720.897	29	5218.249
4	4333.708	30	5209.403
5	4217.089	31	5131.356
6	4399.458	32	5181.7
7	4345.546	33	5264.575
8	4541.81	34	5168.854
9	4706.258	35	5457.519
10	4787.217	36	4756.654
11	5000.37	37	4870.464
12	5656.423	38	4819.502
13	6192.851	39	4515.062
14	6044.036	40	4680.323
15	5811.599	41	4407.324
16	5329.183	42	4698.795
17	5643.149	43	4817.226
18	5322.013	44	4852.039
19	5814.791	45	4749.606
20	6202.294	46	4760.944
21	6309.097	47	6195.801
22	6102.638	48	4539.236
23	5891.806	49	4197.304
24	5579.612	50	5032.343
25	5860.123	51	5091.745
26	5801.963	52	3882.835

Table B.1: Forecasting results

C. Appendix Results OOQ-model

C.1. – Results of OOQ model including safety inventory

Week	D(t)	Q	S	Total Costs
1	3969.4204	3865.255	7865.25521	€ 156,850.14
2	3895.8348	3720.897	7616.732116	€ 308,160.95
3	3720.8973	4333.708	8054.605037	€ 482,354.40
4	4333.7077	4217.089	8550.796318	€ 652,193.24
5	4217.0886	4399.458	8616.546281	€ 828,841.83
6	4399.4577	4345.546	8745.003541	€ 1,003,477.33
7	4345.5458	4541.81	8887.356211	€ 1,185,441.44
8	4541.8104	4706.258	9248.068574	€ 1,373,546.11
9	4706.2582	4787.217	9493.475386	€ 1,564,673.84
10	4787.2172	5000.37	9787.58708	€ 1,763,760.79
11	5000.3699	5656.423	10656.79322	€ 1,987,345.11
12	5656.4233	6192.851	11849.27383	€ 2,230,959.88
13	6192.8505	6044.036	12236.88642	€ 2,469,017.84
14	6044.0359	5811.599	11855.63502	€ 2,698,396.50
15	5811.5991	5329.183	11140.7826	€ 2,909,761.52
16	5329.1835	5643.149	10972.33226	€ 3,132,850.16
17	5643.1488	5322.013	10965.1622	€ 3,343,947.44
18	5322.0134	5814.791	11136.80445	€ 3,573,445.28
19	5814.791	6202.294	12017.08511	€ 3,817,412.69
20	6202.2941	6309.097	12511.391	€ 4,065,368.16
21	6309.0969	6102.638	12411.73471	€ 4,305,614.35
22	6102.6378	5891.806	11994.44335	€ 4,537,987.96
23	5891.8055	5579.612	11471.41732	€ 4,758,704.09
24	5579.6118	5860.123	11439.73446	€ 4,989,894.64
25	5860.1227	5801.963	11662.08529	€ 5,218,913.47
26	5801.9626	5664.287	11466.24913	€ 5,442,791.40
27	5664.2865	5508.508	11172.79411	€ 5,660,852.47
28	5508.5076	5218.249	10726.75653	€ 5,868,075.13
29	5218.2489	5209.403	10427.65174	€ 6,074,967.48
30	5209.4028	5131.356	10340.75885	€ 6,278,945.52
31	5131.3561	5181.7	10313.0558	€ 6,484,803.42
32	5181.6997	5264.575	10446.27516	€ 6,693,755.94
33	5264.5754	5168.854	10433.42931	€ 6,899,134.17
34	5168.8539	5457.519	10626.37335	€ 7,115,291.32
35	5457.5195	4756.654	10214.1736	€ 7,305,277.80
36	4756.6541	4870.464	9627.117925	€ 7,499,514.00
37	4870.4638	4819.502	9689.965371	€ 7,691,847.23
38	4819.5016	4515.062	9334.563496	€ 7,872,812.55
39	4515.0619	4680.323	9195.384548	€ 8,059,948.77
40	4680.3226	4407.324	9087.646382	€ 8,236,891.09
41	4407.3238	4698.795	9106.118331	€ 8,424,717.07
42	4698.7946	4817.226	9516.020319	€ 8,616,965.33
43	4817.2257	4852.039	9669.264448	€ 8,810,513.52

44	4852.0387	4749.606	9601.644375	€	9,000,236.81
45	4749.6057	4760.944	9510.549908	€	9,190,383.49
46	4760.9442	6195.801	10956.74556	€	9,434,108.45
47	6195.8013	4539.236	10735.03738	€	9,615,976.43
48	4539.2361	4197.304	8736.540425	€	9,785,076.52
49	4197.3044	5032.343	9229.647245	€	9,985,357.36
50	5032.3429	5091.745	10124.0878	€	10,187,856.30
51	5091.7449	3882.835	8974.580406	€	10,345,213.96
52	3882.8355	0	3882.83549	€	10,366,603.61

Table 2: Inventory and order quantities 2021