MASTER

Optimization of the inventory levels at an infrastructure and installation wholesaler with smooth, erratic and lumpy demand

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Optimization of the inventory levels at an infrastructure and installation wholesaler with smooth, erratic and lumpy demand.

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Abstract

This research is conducted at Van Walraven N.V., a wholesaler in construction and installation materials. The focus is on minimizing the inventory of products with smooth, erratic or lumpy demand, while maintaining the service level of these products. The inventory management model in this study is a periodic review multi-item inventory system with backordering and lot-sizes. The products follow a normal distribution. Inventory can be reduced by using the correct forecasting method and by applying service level differentiation with an aggregated service constraint. This study also investigated the use of quotations and call-off orders as advance demand information. However, only a very small part of the total turnover appears to come from call-off orders and also the conversion rate from offers to orders is low. The products with a lumpy demand can best be forecasted by the Syntetos Boylan Approximation (SBA), because this method works good for products with a large standard deviation. The Teunter Syntetos Babai (TSB) method can be used for forecasting smooth and erratic demand, because the TSB methode works well for products with a high average. Finally, a simplified version of the service level differentiation model of Donselaar, Broekmeulen and Kok (2021) was applied to determine the reorder level by using an aggregate service constraint. The aggregate fill rate is a weighted average of all fill rates, where the weights are based on the average demand (volume-based) or the average turnover (turnover-based). Using these weights reduces the inventory with an improved aggregate service compared to the current situation, especially if the weights are volume-based. The company has to choose between low inventory costs due to low fill rates for expensive products and more backorders (volume-based weights), or on the other hand, a higher fill rate for expensive products, fewer backorders and higher inventory costs (turnover-based weights).

Preface

This thesis is the result of my graduation project for the Master of Science in Operations Management and Logistics at Eindhoven University of Technology. This graduation project has been conducted at Van Walraven N.V..

With great pleasure I look back on a good study time in Eindhoven and student time in Utrecht. But with even more pleasure I look forward for what civilian life will bring me.

First of all, I want to thank Karel van Donselaar for sharing his expertise and enthusiasm about the topics of my project. He was always supportive and gives helpful feedback during my project. Second, I would like to thank my second supervisor Tarkan Tan. We did not meet very often, but your critical view and valuable feedback was much appreciated.

Of course, I also want to thank Henk Pastor for providing me the opportunity to conduct my thesis at Van Walraven. All pleasant colleagues at Van Walraven have certainly ensured that I came to the office with pleasure. Although I could work less in the office because of corona, I really enjoyed the time at Van Walraven. It was always fun, even when the football results were not good for me. Everyone was always open to answer my question and it was possible to ask everything. I really enjoyed working at the office despite the fact that I was working on my challenging thesis.

Finally, I want to thank my family, friends and especially my boyfriend Viktor for all the support. The discussions about several topics of my thesis with Viktor contributed to this final version of my Thesis.

Esther van Leeuwen

Executive summary

Introduction

In this master thesis, performed at the inventory management department of Van Walraven, it is investigated how the inventory levels can be optimized while maintaining service. Van Walraven is a wholesaler in construction and installation materials, which means there is high regular demand, but also lumpy demand from projects. This uncertain lumpy project requires a lot of inventory. When the customer has a project, the customer can request a call-off order for their products. This is an order that can be purchased in parts form a certain date. A call-off order is immediately placed in stock, so that if the customers need the order earlier than the announced date, the call-off order is available. Van Walraven is struggling with a high stock level for various reasons. Therefore, the aim of this research is to optimize stock levels, which has led to the following research question:

How can an infrastructure and installation wholesaler minimize the inventory, while maintaining the service level?

Item classification

The answer on this research question is divided into four parts. The first stage of this research was to find the best item classification procedure. The chosen item classification of Slim4 and Syntetos (2001) gives a good overview of which product groups have most inventory value. The frequent and normal products (Slim4 classification) with a smooth and erratic demand pattern (Syntetos categorization) provide 48% of the current inventory value and 72% of the turnover. The irregular (Slim4 classification) with a lumpy demand pattern (Syntetos categorization) provide 25% of the current inventory value.

Advanced demand information (ADI)

The second stage of this research is to study when and what information is needed to improve the inventory management. Therefore, the use of quotations and call-off orders as advance demand information (ADI) has been studied. For perfect ADI, the use of ADI is only useful if all or no customers share ADI with the wholesaler. The value of all requested quotations is 20% of the total turnover in that period and the conversion rate from quotation to order is 12%. In addition, only 2.6% of the irregular products with a lumpy demand pattern have had call-off orders and these call-off orders account for 2.2% of the total turnover of the irregular products with a lumpy demand pattern. For the frequent and normal products with a smooth and erratic demand pattern, 14% of the products had a delivered call-off order that only account for 1.1% of the total turnover of the frequent and normal products with a smooth and erratic demand pattern. It can be concluded that a large part of the customers does not provide ADI by requesting quotations or ordering call-off orders, so it is a high risk to include quotations or call-off orders as perfect or imperfect ADI. However, the call-off orders can be placed in stock 7 days before the date of the first delivery, which results in a reduction of the average inventory value per day. Another advantage of placing a call-off order line in stock at a later moment is that a cancelled call-off order line may not have been placed in stock yet. This reduces the excess stock of cancelled call-off order lines.

Forecasting method

The third stage was to investigate which forecasting method is most suitable for forecasting irregular products with a lumpy demand pattern and frequent and normal products with a smooth or erratic demand pattern. The Teunter Syntetos Babai (TSB) method performs best with the frequent and normal products with a smooth or erratic demand pattern, because the TSB method provides good forecasts for products with a high average demand. The SBA method performs better in forecasting irregular products with a lumpy demand pattern. It turns out that the SBA method performs better when the standard deviation of the demand is large.

	IR/LU ($\sum \mathbf{Demand} = \mathbf{29,035\ pcs}$) *Number of items: 2680*				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	20,414,282	69,492	8,271	26,866	49,860
TSB	22,880,019	74,638	268	24,925	54,990
EXP	23,902,898	77,721	2,526	26,334	56,512
EXP 0.2	19,287,214	72,925	3,249	28,454	53,581
	FR&NO/SM&ER ($\sum \mathbf{Demand} = \mathbf{1,084,953\ pcs}$) *Number of items: 5286*				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	552,748,928	601,089	128,569	234,263	483,895
TSB	531,919,233	591,551	35,114	193,304	480,961
EXP	650,965,515	655,700	18,802	297,809	537,860
EXP 0.2	587,606,457	627,449	20,315	264,892	509,812
	Total				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	573,163,210	670,582	136,841	261,129	533,755
TSB	554,799,252	666,188	35,382	218,229	535,952
EXP	674,868,413	733,421	21,328	324,143	594,373
EXP 0.2	606,893,670	700,374	23,564	293,346	563,393

Service level differentiation

The last stage of this research was the application of the simplified version of the service level differentiation model of Donselaar, Broekmeulen and Kok (2021). Service level differentiation is applied to the inventory-drive products with a periodic review system. Service level differentiation can be applied to determine the reorder level by using an aggregate service constraint. The aggregate fill rate is a weighted average of all fill rates, where the weights are based on the average demand (volume-based) of the average turnover (turnover-based). The use of service level differentiation with both volume-based and turnover-based weights results in a decrease of the inventory compared the current situations for both product groups. This is mainly because the ready rates for turnover-based weights are the same for all products and for volume-based weights the ready rates vary due to the difference in the purchase price (needed for the calculation of the holding costs). Therefore, it is important that a company should consider whether the target aggregate fill rate is well defined so that the objective function of the company can be achieved. The company has to choose between low inventory costs due to low fill rates for expensive products and more backorders (volume-based weights), or on the other hand, a higher fill rate for expensive products, fewer backorders and higher inventory costs (turnover-based weights).

The largest reduction in inventory is realized with volume-based weights and is therefore recommended in situations such as Van Walraven. The aim can be a P_2^* that is equal to the current situation, or a $P_2^* = 0.99$ for both product groups. This results in a total reduction of the inventory value and an improvement of the aggregated service level.

	Volume-based weights				Turnover-based weights			
Current situation	**FR&NO/SM&ER**		**IR/LU**		**FR&NO/SM&ER**		**IR/LU**	
Number of items	3397		2414		3397		2414	
Aggr. Fill Rate	0.95		0.84		0.95		0.87	
Value $E[I^{OH}]$	€ 314,527		€ 129,738		€ 314,527		€ 129,738	
Service level differentiation	**Lagrange**	**Value $E[I^{OH}]$**	**Lagrange**	**Value $E[I^{OH}]$**	**Lagrange**	**Value $E[I^{OH}]$**	**Lagrange**	**Value $E[I^{OH}]$**
Aggregated Fill Rate								
0.84	-	-	2.1	€ 45,335	-	-	-	-
0.87	-	-	-	-	-	-	4.05	€ 89,840
0.90	0.6	€ 130,366	3.8	€ 57,866	1.8	€ 243,818	5.15	€ 95,105
0.95	1.2	€ 174,919	8.15	€ 75,352	3.3	€ 286,552	9.7	€ 107,973
0.97	1.9	€ 204,845	13.3	€ 86,286	4.95	€ 311,339	14.7	€ 115,970
0.98	2.65	€ 226,268	18.95	€ 93,984	6.65	€ 327,984	20.2	€ 121,628
0.99	4.4	€ 258,694	31.9	€ 104,541	10.5	€ 352,070	32.8	€ 129,724

Recommendations

The studies in these four parts resulted in the following recommendations for Van Walraven:

1. Place the call-off orders in stock 7 days in advance. This reduces the current inventory value per day of the call-off orders, and it reduces the chance that a cancelled call-off order is already in stock.
2. Reduce the products with a surplus buffer. The surplus buffers are mainly allocated to products with low sales and a surplus buffer increases the change of excess stock.
3. Forecast the irregular products with a lumpy demand pattern with the SBA forecasting method and the frequent and normal products with a smooth or erratic demand pattern with the TSB method. Update the forecast monthly.
4. Implement service level differentiation for products with an (R, s, nQ)-inventory management model with an aggregate volume-based fill rate of 0.99. It is important to indicate that a company should consider whether this target aggregate fill rate is well defined so that the objective function of the company can be achieved.

Future research

Service level differentiation is in this research only applied to products with a (R, s, nQ)-inventory control model. The model applied in this research could be adapted so that it is also suitable for the (R, s, S) and the (R, s, S, nQ)-inventory control model. In addition, the current corona crisis may influence this research. Further research can be conducted into the effects of the corona crisis on management inventory control policies and demand forecasting, but also whether demand patterns will change over time due to the corona crisis. Mapping the effect of the corona crisis on sales data will help in the future to determine which data is suitable for further investigations, and which data has been influenced too much by the corona crisis and therefore cannot provide a good picture of the future.

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List of abbreviations

A-ADI	Aggregated Advance Demand Information
ADI	Advance Demand Information
AiDI	Average inter-Demand Interval
CV^2	Square Coefficient of Variation
D-ADI	Detailed Advance Demand Information
DoBr	Model designed by Donselaar and Broekmeulen (2015, 2020)
EOQ	Economic Order Quantity
ERP	Enterprise Resource Planning
EWMA	Exponentially Weighted Moving Average (Holt, 2004)
EXP	Exponential smoothing with an optimal α
EXP 0.2	Exponential smoothing with $\alpha = 0.2$
FR	Fill Rate
FR&NO/SM&ER	Frequent and normal products with a smooth and erratic demand pattern
IC-Order	Intercompany Order
IOQ	Incremental Order Quantity
IP	Inventory Position
IR/LU	Irregular products with a lumpy demand pattern
KPI	Key Performance Indicator
K-S test	Kolmogorov-Smirnov test
LTD	Lead Time Demand distribution
MAD	Mean Absolute Deviation
MOQ	Minimum Order Quantity
MSE	Mean Squared Error
NBD	Negative Binomial Distribution
PDA	Periodic Demand Approach
pcs	Pieces
RMSE	Root Mean Squared Error
SKU	Stock Keeping Unit
SBA	Syntetos Boylan Approximation (2001)
SDA	Single Demand Approach
SMA	Single Moving Average method
TFR	Target Fill Rate
TSB	Teunter-Syntetos-Babai method (2011)
WSS	Willemain, Smart, Schwarz Method (2004)

1. Introduction

This research is a master project of the study Operational Management and Logistics at Eindhoven University of Technology. The research is conducted for the inventory management department of Van Walraven B.V. in Mijdrecht. It is an investigation into optimizing the inventory, by better forecasting and controlling the intermittent (project) demand. This investigation takes into account the complaints from management and the sales, the complaints are:

"The inventory is too high and must decrease. It cost way too much money." – Management

"The inventory must increase because there is never enough. Therefore, we grab miss and have backorders" – Sales

Inventory management is constantly looking for a stable balance between these statements, in which both parties can agree. In this study, it will be examined whether the inventory can be reduced while maintaining the service level.

1.1. Company introduction

Van Walraven is a wholesaler in construction and installation materials and supplies a wide range of products to companies that work in residential and non-residential construction, civil engineering, installation technology and industry. Van Walraven was founded in 1968 as a trading company Gebroeders Van Walraven N.V.. The head office is located in Mijdrecht with a storage area of 40,000 m^2. After many acquisitions, Van Walraven has created national coverage with their 12 affiliates. Van Walraven is an internationally operating company with turnover in the Netherlands and the former Netherlands Antilles.

Van Walraven has a wide range of products in their assortment, for example sewage, drainage, sanitary and work clothing. The range consist of over 57000 products. Quality of the products is most important. Van Walraven focuses on customer intimacy: this means that they continuously adapt the products and services to the wishes and requirements of the customers. Investments are made in customer loyalty and building a strong relationship with customers.

1.2. Problem introduction

The big problem that Van Walraven is facing is having a lot of (unnecessary) stock. This has two reasons: stocking call-of orders and having a high safety stock for products with irregular or lumpy demand. It is important to know that Van Walraven would like to offer a good service to the customer to keep them satisfied.

First of all, call-of orders are fully stocked when they are entered into the system. A call-of order is an order to supply a certain quantity of different products to a certain customer, in which the price is discussed in advance for the entire order. This order can then be called up in parts by the customer, for which the purchase dates are not known. The customers have several reasons to order a call-off order, the price is fixed, they do not miss out when they need the product and the customers often have little space to store their materials. As a result, products of a call-off order can be in stock for months and are sometimes not fully purchased due to different reasons. This results in excess stock. Call-off orders create a conflict between both the inventory management that wants to decrease the inventory and the provision of good service to the customers.

Second, Van Walraven experiences irregular demand for certain products, possibly due to project demand. The customers do not have a constant demand for products, but just what is needed for that project at that moment. 3% of the products have a lumpy demand pattern and 15% have an irregular demand pattern, see Figure 1.1. Figure 1.2 shows that the lumpy products provide 6% of the total stock value and the irregular products 21%. The service level-driven inventory management system used by Van Walraven (Slim4) calculates a high safety stock for lumpy and irregular stock-controlled products due to the high demand uncertainty. The inventory management system Slim4 uses exponential smoothing to forecast demand. However, the accuracy decreases with exponential smoothing if there is a high variability in the demand size (Ghobbar & Friend, 2003). The demand uncertainty of irregular demand is partly compensated by adding a surplus buffer. A surplus buffer is manually added to the reorder level of a product. The amount of this surplus is not bounded by rules. Examples for adding a surplus buffer are: a surplus buffer is added because a (large) customer had complained that he misses out, or because Van Walraven expect a lot from some new products, but the inventory management system Slim4 does not yet calculate a safety stock because there is still not enough historical data available. If a new product does not meet those expectations, Van Walraven will be left with excess stock and high inventory costs.

At the moment, the products are categorized per ABC/XYZ classification. Each ABC/XYZ category is assigned a target service level. The ABC/XYZ-classification reduces the number of different service levels, but it is difficult to determine the value of the service level per category and what the appropriate classification criteria are ((Donselaar, Broekmeulen, & Kok, 2021). Teunter, Syntetos and Babai (2017) have shown that an ABC-classification leads to unnecessarily high inventory costs.

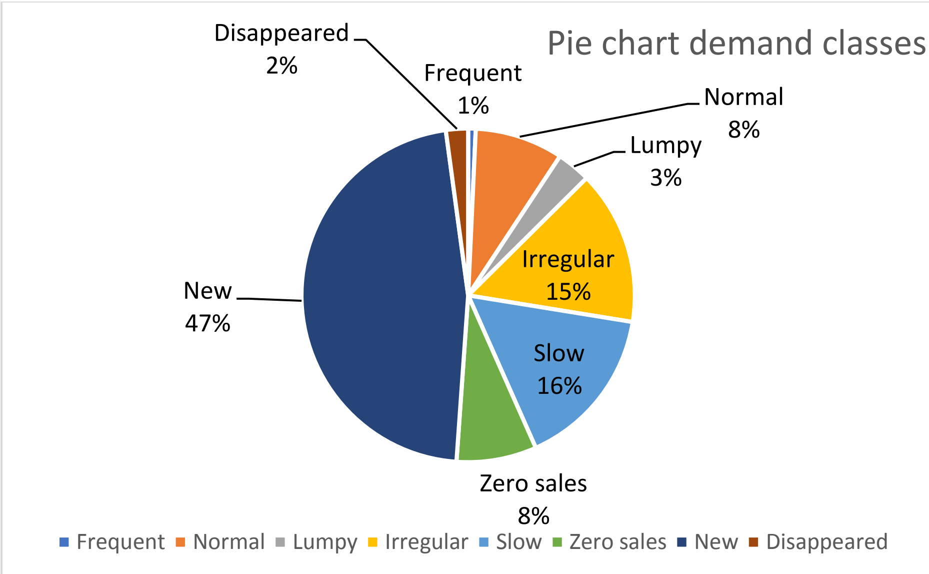

Figure 1.1: Pie chart demand classes according to Slim4

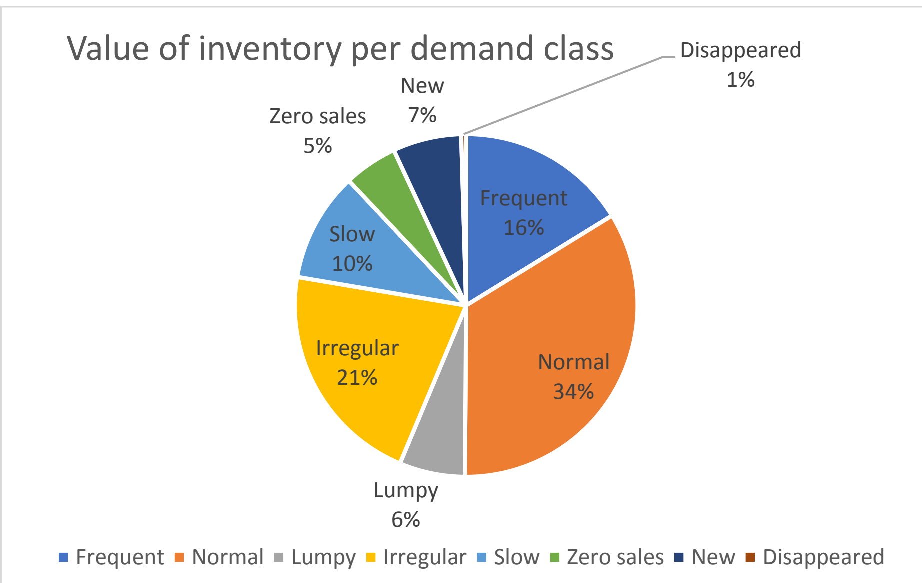

Figure 1.2: Pie chart of the value of the inventory per demand class

1.3. Problem definition

The problem definition presented in this section is based upon the problem introduction in section 1.2. Furthermore, discussions were held with the managers of the purchase department and the inventory management department to define their experiences and opinions about the high inventory. The problem is defined as:

Uncertain, irregular demand and limited capacity at construction sites leads to high inventory at infrastructure and installation wholesalers.

1.4. Research questions

In this section, the research question and sub-questions are discussed. This research has the goal to minimize the inventory at an infrastructure and installation wholesaler, while maintaining the service level. The research questions and sub-questions will help to achieve the goal. The main question of this research is formulated as follows:

How can an infrastructure and installation wholesaler minimize the inventory, while maintaining the service level?

The research starts by classifying the items, so that the focus of the type of products in this research is known. The item classification can be used to determine a suitable forecast method. The use of advance demand information (ADI) influences the inventory management. Therefore, it is studied how ADI can be best used. Both the item classification and the use of ADI are necessary to determine an appropriate inventory forecasting method and an inventory control model. Finally, other possible improvements for minimizing inventory at an infrastructure and installation wholesaler are discussed. The sub-questions are formulated as follows:

1. *Which item classification can be used?*

Item classification is crucial for forecasting and managing inventory (Rego & Mesquita, 2011; Syntetos, 2001). A product classification helps to determine which products need the most managerial attention. In addition, demand characteristics influence the choice of a forecast method and inventory management method. The performance targets and service levels are also determined at item category level. The sales history of the past 24 months can be used for this.

2. *How can perfect or imperfect advance demand information be used in inventory management?*

Receiving ADI can be advantageous, so that the wholesaler knows in advance what the possible demand is. The effect of information sharing depends on the moment and the amount of information that is given. The goal is to determine at which moment and which information is needed to improve the inventory management. The data of the currently call-off orders and quotations are used for this sub-question.

3. *What is the best demand forecasting method considering the item classification?*

Demand forecasts are important for an inventory control system because the lead time, the prevention of out-of-stock moments and ordering costs must always be considered. The method shall take into account the item classification as this will affect the ordering and managing of the products.

4. Which inventory control model should be used?

An inventory control model is used to track and manage inventory. An inventory control model are inventory rules or algorithms that determine how many units the optimal order quantity consists of, the review frequency, the desired service level, the reorder levels and the reorder points. These inventory rules are optimized in this sub-question. Service level differentiation can be applied to determine the reorder level by using an aggregate service constraint (Donselaar et al., 2021). This is an aggregate fill rate, in which the fill rate of each stock keeping unit (SKU) is weighted. The aggregate service can have a major effect on the performance of the system, so it is important to define the aggregate service properly. There are three weighting options: 1. Generic weights, 2. Volume-based weights, which uses the average demand of a SKU and 3. Turnover-based weights, which is the price multiplied by the average demand of a SKU. The heuristics introduced by Donselaar et al. (2021) are used for the service level differentiation. A sensitivity analysis is performed to determine the influence of the different parameter settings in the inventory control model.

5. What improvements can be recommended based on the gained insights?

Forecasting and inventory management models are not the only possible solution to reduce inventory, but there may be other opportunities that can improve the inventory situation of certain products with the possible use of ADI. It will be analysed whether these improvements result in inventory reduction and whether the improvement is feasible.

1.5. Research gap

The literature on ADI has focused on ongoing demand from small orders. Donselaar, Kopczak and Wouters (2001) distinguished their research by explicitly focusing on ADI in project environments. In that study, the demand is regarded as a lumpy project-based demand. The ADI is provided at item-level through proposals. The research for this master thesis will elaborate on this, because there is little literature on ADI in project environments available. In this study, quotations and call-off orders are used as ADI. Since only 1.5% of the total turnover is sold by call-off orders, the impact of using call-off orders like ADI seems very small. That is why this study also looked at other options for reducing the stock of demand orders.

In addition, different forecasting methods are applied to products with smooth, erratic and lumpy demand pattern. Much research has already been done into the most suitable forecasting method for these products. This research contributes to the results of previous studies, but also reveals differences with previous studies. The characteristics of the demand are used to substantiate these differences. Finally, a simplified version of the service level differentiation model of Donselaar, Broekmeulen and Kok (2021) is applied to determine the reorder level. This is a recent study in which no distinction has yet been made between products of different demand patterns. The research in this master's thesis does make this distinction and is therefore an addition to the previous research. Another difference is that the demand is gamma distributed in the research of Donselaar et al. (2021). However, in this study, the demand for all products is normally distributed.

1.6. Scope

This research only includes the inventory management at Van Walraven Mijdrecht. This means that orders from the affiliates to their customers are not included. But the orders that are executed by Mijdrecht for an affiliate are included, because they are included in the sales data of Mijdrecht. The Inter-Company orders (IC-orders) from Mijdrecht to an affiliate is seen as a customer order, and IC-orders vice versa as a supplier order. The return of obsolete stock from an affiliate can be seen as a supplier order from an affiliate.

In the beginning of December 2020, 59252 items are in the ERP system of Van Walraven, but the final data selection consist of 20961 items. For this research, the sales per month from 12-2018 to 11-2020 are used. The sales consist of all products sold from Mijdrecht. This means that negative sales in a month is possible if more products have been returned than have been sold. Products were not included in the data selection for the following reasons:

- Products created for an affiliate for single use.
- Products created for a single project. 37 products are project products and these products are sold to one customer in a specific period. These products are only included in the assortment for this project and will expire at the end of the project. This is a service that is offered so that the customer can buy all products for the project at Van Walraven. Products are placed in stock in consultation with the customer. The products are order-driven products, so the products do not have a forecast and are only purchased from the supplier when an order of the customer is placed.
- Stopping products. These products are withdrawn from sale when the inventory on hand of all locations is zero, e.g. the supplier stops making the product, a new version of the product is coming, or the product is poorly sold.
- Deposit for the rental of products. This deposit does not result in income or expenses.
- Products that have not had sales in the past year (12-2019 to 11-2020) are disregarded.
- Products that only had one or two months of sales in the past two years. Sufficient historical data is required for data-driven inventory control. Therefore, at least three demand events must occur in the measured period (Rego & Mesquita, 2015). This means that products that only had one or two months of sales in the past two years are excluded.
- Products whose returns in a month result in less than three months of sales. In addition, a product is also excluded from the selection if the returns in a month result in less than three months of sales. So, a product has had three or four demand events, but one or more months has negative sales. The product was sold in a month with positive sales and returned in the following month. This means that in the end nothing was sold. Therefore, this type of product is also excluded from the data selection.

The 38032 products that have been excluded from the selection have a current inventory value of 22% of the total inventory value and the turnover of these excluded products are 6% of the total turnover. This high inventory value is caused by products that are placed in stock because Van Walraven expects a lot of sales for these products. But also, the products that only have 1 to 4 months of sales have high current inventory value. The Minimum Order Quantity (MOQ) of these products is higher than the total sales, so there is a lot of stock left. The items that are not included in the data selection are not suitable for the data analyses performed in this research, because the products are poorly sold and therefore do not have suitable data. The sales of these products must be stimulated in order to decrease the current inventory value. Table 1.1 provides an overview of the total inventory value and the turnover based on the purchase price of all items, the data selection and the products that are out of scope. The share of the turnover and inventory value of the data selection and the items that are out of scope are also given in Table 1.1.

	All items	**Data selection**	**Out of scope**
Number of items	58993	20961	38032
Current inventory value	€ 2,897,079	€ 2,259,923 (78%)	€ 637,156 (22%)
Turnover based on purchase price	€ 21,366,619	€ 20,052,041 (94%)	€ 1,314,579 (6%)

Table 1.1: An overview of all items, the data selection and the products that are out of scope.

The data selection includes both stocked products and order-driven products. The order-driven products have sold less than 7 order lines in the past year. The inventory management system, Slim4, used by Van Walraven does not calculate with these order-driven products, which means that these products do not have a forecast and reorder level. These products are only purchased when there is an order form a customer. 6046 products in the data selection are order-driven.

1.7. Research design

The study is designed based on the model of Mitroff, Betz, Pondy and Sagasti (1974). This model is shown in Figure 1.3. The operations management problem is solved in four phases, namely conceptualization, modelling, model solving and implementation. The arrows show that these phases do not follow a clearly defined path for solving the problem. The research provides room for feedback, validation and repair work between the various phases. The model helps to complete all steps in this study.

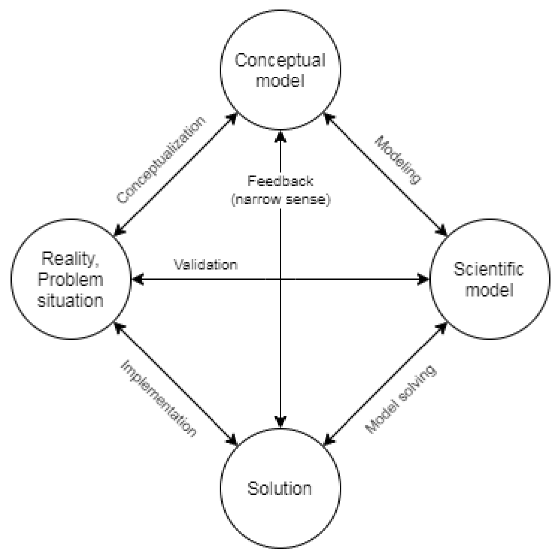

Figure 1.3: Quantitative research model (Mitroff et al., 1974)

This research follows these steps. First, the problem and the AS-IS situation is described in sections 3, 4 and 5 . In the AS-IS situation two sub-questions can be answered. Subsequently, the conceptual model can be worked out in section 6. Sub-questions 3 and 4 can then be answered by presenting the scientific model for the forecasting method and the inventory control model. This scientific model can be solved and implemented. The scientific model is made with the aim to reduce the inventory by forecasting the demand with an appropriate method and to reduce the inventory value with the same service by service level differentiation. The model with service level differentiation is implemented in the VBA-based DoBr tool from Donselaar and Broekmeulen (2015). Finally, a sensitivity analysis is performed to determine the influence of the different parameter settings in the inventory control model. The scientific model is presented in sections 7 and section 8. Section 9 provides other possible improvements for reducing the inventory. In this section is sub-question 5 answered. Finally the conclusion to the main research question, the recommendations for Van Walraven, contribution to the literature and the limitations and future research possibilities are given in section 10

2. Literature study

2.1. Item classification

A product classification helps to determine which products should receive the most attention from management (Rego & Mesquita, 2011; Syntetos, 2001). The framework of Syntetos (2001) makes an item classification based on the demand patterns of the products. These characteristics of the demand patterns influence the use of a forecasting method and inventory management method. Syntetos (2001) uses two parameters to determine the irregularity of the demand:

- Average inter-Demand Interval (AiDI, normally called ADI in literature, but in this study, ADI is used for Advance Demand Information): This is the average interval between two demand moments of item i.

$$AiDI = \frac{Total\ number\ of\ demand\ periods}{Number\ of\ periods\ with\ non-zero\ demand} \quad (1)$$

- The Square Coefficient of Variation (CV^2): The standard deviation of the demand of item i, divided by the average demand of item i.

$$CV^2 = \left(\frac{Standard\ deviation}{Mean}\right)^2 \quad (2)$$

These parameters must be calculated per product. The use of monthly aggregated data for item classification provides good results according to Syntetos, Boylan and Croston (2005). A requirement for calculating the AiDI is that there must be at least three periods of non-zero demand per product. The total number of demand periods is the maximum possible periods between the first and last period with non-zero demand. This means that if demand occurs between January and November 2019, the total number of demand periods equals 11. The number of periods with non-zero demand is measured as the periods where demand occurs. The standard deviation and mean of the demand are calculated over the periods with demand, this means that the periods without demand are excluded for the calculation of CV^2.

These parameters are used by Syntetos (2001) to classify the demand pattern into four different categories:

- Smooth demand: regular demand over a period of time with a limited variation in the quantity. (AiDI < 1.32 and $CV^2 < 0.49$)
- Erratic demand: regular demand over a period of time, but large variation in quantity. (AiDI < 1.32 and $CV^2 \geq 0.49$)
- Intermittent demand: extremely sporadic demand, with little variability in the quantity per demand moment. (AiDI ≥ 1.32 and $CV^2 < 0.49$)
- Lumpy demand: extremely sporadic demand, with many periods without demand and large variation in the quantity. (AiDI ≥ 1.32 and $CV^2 \geq 0.49$)

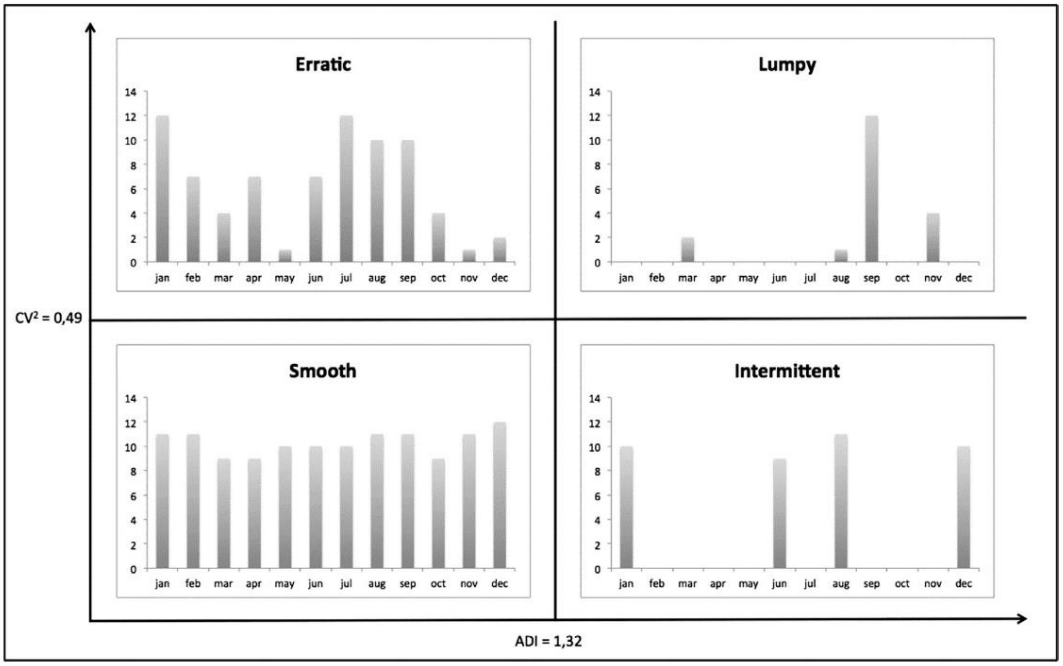

Figure 2.1: Framework of demand patterns by Syntetos (2001). *Source: Constantino, Di Gravio, Patriarca and Petrella* (2018)

The cut-off values of the parameters, 1.32 for AiDI and 0.49 for CV^2, are the result of a numerical analysis performed on theoretical results (Syntetos, 2001). Figure 2.1 shows the four categories with possible demand histories. The categorization rules were established after algebraic comparisons of the mean square error expressions, and later strictly checked via a large sample of empirical data and via simulation on theoretically generated demand data (Ghobbar & Friend, 2002, 2003; Syntetos, 2001).

In other studies, the demand patterns of products are often presented with the normal distribution, especially the smooth products with a low variation in the demand size. There is more discussion about determining a demand distribution that fits well with products with an irregular or lumpy demand pattern. According to Syntetos, Babai, Lengu and Altay (2011), there is little empirical support for using the normal distribution for these irregular products because the irregular demand skewed strongly to the right. Because irregular demand is ordered at irregular times and the demand sizes also differ, the preference is for compound theoretical distributions. For example, the Stuttering Poisson or the Negative Binomial Distribution (NBD) performs very well for describing the lumpy demand according to Syntetos, Babai and Altay (2012) and Syntetos et al. (2011). In stuttering Poisson, the AiDI is Poisson distributed and the demand size has a geometric distribution. Also, demand size is often described as a logarithmic distribution, so that the total demand follows a NBD over time. Irregular demand can also follow the gamma distribution. The gamma distribution is the continuous analogue of the NBD. The advantage of the gamma distribution is that only positive values are possible, which is often the case with inventory control, but it also covers a wide range of distribution forms. Thus, different demand distributions are used for modelling irregular demand.

Syntetos et al. (2011) performed a goodness-of-fit test so that the demand distributions could be classified on the AiDI and the CV^2. This classification scheme is shown in Figure 2.2. For example, the gamma distribution appears to work best when the CV^2 is very large, but the NBD and stuttering Poisson distribution also work well when the variation in demand is large. The normal distribution also appears from this classification scheme very suitable for smooth products.

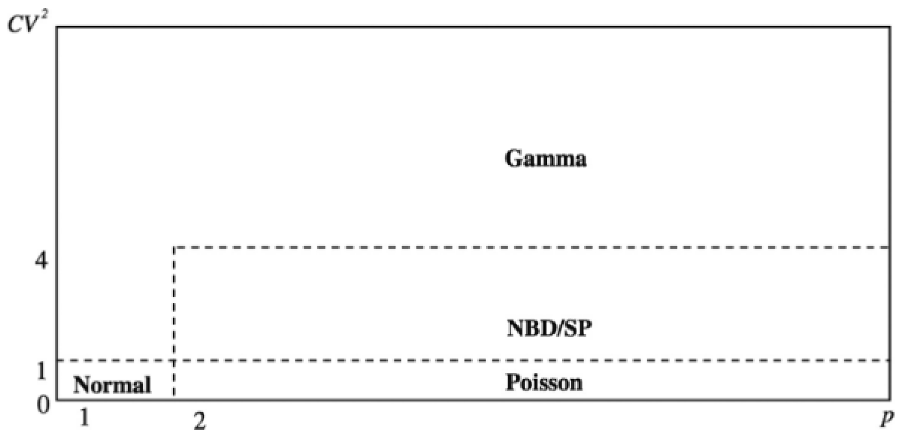

Figure 2.2: Classification scheme of the demand distribution based on the AiDI (p) and CV^2 (Syntetos et al., 2012)

2.2. ABC/XYZ classification

Inventory control requires a split in goods of lower and higher strategic importance for the company (Buliński, Waszkiewicz, & Buraczewski, 2013). Not all stock rules are in fact applicable to all products and it is inefficient to establish an inventory control policy for each individual product. Dickie (1951) was one of the first that develop a classification to determine the purchasing policy, production planning and store management. The ABC/XYZ analysis aims to make this division. This analysis is a combination of an ABC-analysis and an XYZ-classification. The ABC-analysis divides products into groups based on a given criterion. In the service and maintenance industry, criticality for the functioning of a spare part is used as criteria (Naylor, 1996). However, in other situations these criteria are often the demand value, demand volume or rotation (Teunter, Babai, & Syntetos, 2010). The groups are classified according to the Pareto principle: 20% of the items causes 80% of the result (Buliński et al., 2013), e.g. 80% of the total turnover. This is shown graphically in Figure 2.3 as a Lorenz curve. A-products are very valuable to a company and the inventory of those products is closely monitored. Therefore, A-products have a high service level to ensure that there are no stockouts (Teunter, Syntetos, & Babai, 2010). An advantage of using one criterion is the simplicity and it is also sufficient for achieving cost-optimal solutions (Teunter, Babai, et al., 2010). But the use of one criterion only provides information about one criterion, this is often the monetary value. This has the effect for example, that a slow product with a high selling price is an A-product, and a fast-moving product with a low price is a C-product. The ABC-analysis also provides limited information about the demand, which is necessary for determining the required stock (Stojanović & Regodić, 2017). Therefore, the demand frequency of an item is added as XYZ-classification (Aktunc, Basaran, Ari, Irican, & Gungor, 2019). For example, Aktunc et al. (2019) classifies the items by annual costs (ABC-analysis) and by the frequency of variation of the demand (XYZ-classification). The frequency of the demand is expressed in the inter-demand interval. This interval is also used in the item classification in section 2.1. The XYZ-classification provides a good overview of which goods are in stock and which of these goods are used. X-products have little variation in demand, which makes the future demand forecast very reliable. Z-items have irregular demand and is therefore difficult to forecast. Nowotyńska (2013) recommends choosing a supplier with a short delivery time for Z-items, so the company can quickly purchase these irregular products. In contrast, Aktunc et al. (2019) recommend maintaining a high safety stock for items with irregular demand in CZ- and BZ-classes of the ABC/XYZ analysis.

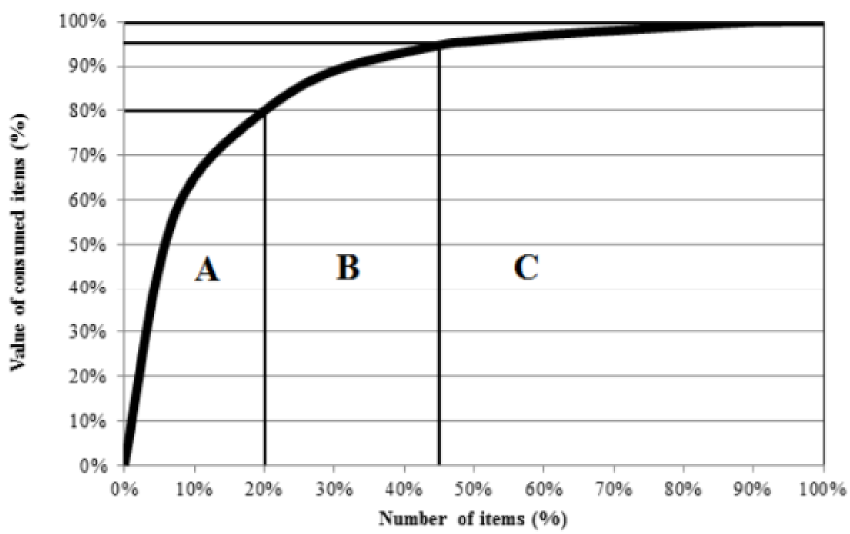

Figure 2.3: Graphical representation of the ABC-analysis. Source: Kučera and Dastych (2018, p. 961)

2.3. Service level differentiation

Several definitions of the service level are used in the literature. A commonly used definition is the fill rate, whereby for each product must be determined which percentage of demand can be supplied directly from stock (Silver, Pyke, & Peterson, 1998). The fill rate reflects how customers experience the service of a company (Teunter, Babai, et al., 2010). Inventory managers try to maximize the service level while minimizing costs. A high service level ensures a large safety stock to cover demand uncertainty, delivery time and supply uncertainty. The ABC/XYZ-classification shows that not every product is equally important and profitable for the company. Therefore, not every product gets the same service level. The standard approach of ABC-applications is to set the same service level for all products in a class. An important question for setting fixed service levels per class is which values the service levels should have. For example, the A-products can have the highest service level, because they generate the highest turnover (Armstrong, 1985; Stock & Lambert, 2001). But C-products can also get a high service level, because it is not valuable to deal with stockouts of these items (Knod & Schonberger, 2001).

Teunter, Syntetos and Babai (2017) showed that setting a target service level per ABC-class can lead to suboptimal solutions. They recommended setting a service level for each SKU so that it is possible to achieve the target system service level at minimal cost. This individual approach yields a cost advantage compared to the determination of service level per ABC/XYZ-class. Setting a service level for each SKU while achieving the target system service level is called service level differentiation. Donselaar, Broekmeulen and Kok (2021) experienced that the inventory value can be minimalized with a minimum aggregate service constraint. The products have an (R, s, nQ)-inventory policy. The aggregate fill rate is a weighted average of all products in the assortment. Three different weights are used for the fill rate: generic weights, volume-based weights and turnover-based weights. The volume-based weights are calculated with the average demand and the turnover-based weights with the average turnover, which is the price times the demand. Which weight is used for the aggregate service constraint has a major influence on inventory costs. Volume-based weights, for example, lead to significantly less inventory than the use of turnover-based weights. This is because volume-based weights give a lower service level to expensive products, because the holding costs of the products are taken into account when determining the service level with volume-based weights. Holding costs are a percentage of the purchase price. Because turnover-based weights do not include the price in the calculation of the reorder level and service level per product, the turnover-based service levels have less variation between the products. The use of service level differentiation by setting a separate service level for each product that meets the aggregated service level is used in this research. Donselaar et al. (2021) also developed several heuristics for calculating the optimal reorder level. One heuristic proved to be very efficient and close to the optimum. Volume-based and turnover-based weights are also considered when calculating the reorder level in this heuristic.

2.4. Advance demand information (ADI) in a project environment

Van Walraven's customers work in a project environment. This means that demand for individual products is lumpy and very irregular, several companies propose to win the bid of a project, companies apply to multiple wholesalers and the information becomes more detailed and accurate as time goes by (Donselaar et al., 2001; Thonemann, 2002). According to Donselaar et al. (2001), manufacturers operating in a project environment are confronted with both regular small demand and very irregular, lumpy demand from often large orders. A lot of stock is needed to serve this irregular demand. The correct use of ADI can reduce stock for this project demand. Customers can share perfect or imperfect ADI. Perfect ADI contains exact information about orders in the next period and these orders will not change. In contrast, imperfect ADI provides information about future orders, but these are subject to changes (Tan, 2008). Customers prefer to wait as long as possible before sharing demand information with manufacturers or wholesalers, in order to minimize the risk of demand and product changing. In a project environment, the customer provides order information in advance, but the customer does not yet know if he will win the bid of the project. Unfortunately, ADI is very uncertain, because decisions about which bid will get the order and which wholesaler gets the order has not yet been made. In addition, it is also not clear which products the customer exactly needs. Thonemann (2002) distinguishes between aggregated (A-ADI) and detailed ADI (D-ADI). At A-ADI, a customer provides information about whether an order will be placed in the next period, but it is not known whether other wholesalers may receive the order or which products they will order. The aggregation level depends on the situation. For example, there are studies that share their quantities of a certain product family, because these products contain the same expensive component or come from the same supplier (Donselaar, 1990; Heijden, Diks, & Kok, 1997; Lee & Tang, 1997; Thonemann, 2002). At D-ADI, customers indicate which products they will order, but it is not clear which wholesaler receives the order.

A-ADI and D-ADI are most useful when the order probability is low and the information quality is high, because this reduces demand uncertainties. A low order probability means that the product is not ordered each period. D-ADI is desirable over A-ADI if the wholesaler has several products in range and if the demand rates of all the products are the same. The use of ADI in a project environment is especially useful if the proposals have a high probability of changing in an order, and if these proposals have a lumpy demand pattern (Donselaar et al., 2001). Sharing ADI unfortunately also has disadvantages. One of them is that sharing ADI increases the bullwhip effect. Therefore, it is recommended to either receive ADI from all customers or from no customers. Another disadvantage of ADI is the variation in the base-stock levels and the increase in variation in the order sizes.

2.5. Inventory control model

Inventory control systems can be a single-period inventory model as well as a multi-period inventory model. With a single-period inventory model, only one order can be placed for an item to meet the demand, such as Christmas trees or newspapers. The well-known Newsboy problem is used to determine the order size to maximize the expected profit (Dutta, Chakraborty, & Roy, 2005). In multi-period inventory models can multiple orders for the same product be placed, because a product is in the assortment for a longer period. This research uses a multi-period inventory model. Multi-period inventory models aim to optimize the amount of inventory and orders sizes per period. According to Donselaar and Broekmeulen (2015), inventory control models are divided into four categories based on the review frequency and the replenishment quantity. The system can be periodically or continuously reviewed, and the order size can have a fixed quantity or a variable quantity. With continuous reviewing, the inventory position (IP) is continuously monitored and the inventory can be replenished at any time, these are the (s, Q) and (s, S)-systems. Where s is the reorder level and S is the order up to level. With periodic reviewing, the IP is monitored every R periods and orders can only be placed at fixed times. Periodic reviewing takes place on the (R, s, nQ) and (R, s, S)-systems. Q is the order size. Figure 2.5 shows a (R, s, nQ)-inventory control model with n=1. If the IP is lower than reorder level s, a quantity of Q is ordered. Figure 2.4 shows an (R, s, S)-inventory control model.

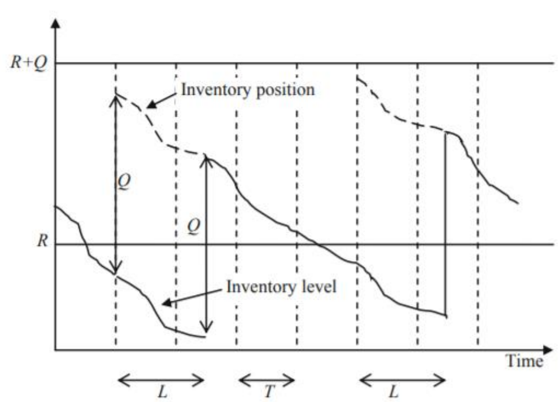

Figure 2.5: (R, s, nQ)- inventory control model (Axsäter, 2015)

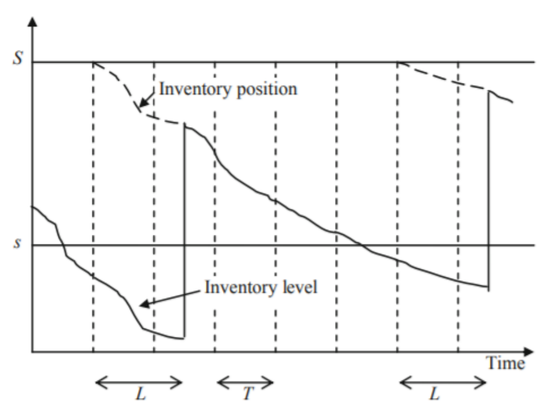

Figure 2.4: (R, s, S)- inventory control model (Axsäter, 2015)

The MOQ and the Incremental Order Quantity (IOQ) determine whether the inventory control model has a fixed or variable order size. An overview of the inventory control systems with the associated MOQ and

IOQ boundaries is shown in Table 2.1. An exception is if the MOQ and IOQ are both greater than one, then it is a (R, s, S, nQ)-inventory control model. Hill (2006) describes an (R, s, S, nQ)-inventory control model as a system that periodically reviewed whether the IP is less than or equal to reorder level s, then an order is placed for the largest multiple of Q items so that the IP does not exceed the order up to level S. If a system has an order up to level S, it is assumed that $S = s - 1 - MOQ$.

		Review frequency	
		Periodic review	**Continuous review**
Replenishment quantity	**Fixed base quantity** *Boundaries:* *IOQ ≥ 1* *MOQ ≤ IOQ*	(R, s, nQ): Review inventory every R period. Whenever the IP drops below s, order nQ units to bring IP ≥ s.	(s, nQ): Review inventory continuously, if IP drops below s, order nQ units to bring IP ≥ s.
	Variable quantity *Boundaries:* *IOQ = 1* *MOQ > 1*	(R, s, S): Review inventory every R period, whenever IP drops below s, order up to level S. (R, S): Review inventory every R period, if IP < S then order up to level S.	(s, S): Review inventory continuously, if IP drops below s, order up to level S.

Table 2.1: Classification of multi-period inventory control models (Donselaar & Broekmeulen, 2015)

The advantage of a (s, S)-system compared to a (s, nQ)-system is that the optimal reorder level s and the order up to level S can be determined, this reduces inventory costs. Continuous reviewing often result in a better customer system (Purnomo, Wee, & Praharsi, 2012). Continuous reviewing is not manageable for a company with thousands of SKUs because it leads to many orders in a relatively short period of time (Rego & Mesquita, 2015). This is one of the reasons that periodic reviewing of the IP is recommended. Another advantage of periodic reviewing is the convenience of regular order days.

2.6. Forecast models

By accurately forecasting the demand for products, the required inventory can also be reduced. In this section, it is determined which forecasting methods are commonly used to smooth products and for products with irregular or lumpy demand. Rego and Mesquita (2015) have conducted a simulation study in which they make recommendations per demand categorization class of Syntetos (2001). These recommendations include the use of a forecast method, a time bucket and a Lead-Time Demand (LTD) distribution. Three different forecast methods are studied: Simple Moving Average (SMA), the Syntetos Boylan Approximation (SBA) and bootstrapping. The company in the study of Rego and Mesquita (2015) sells spare parts for the automotive industry and uses a (s, nQ)-inventory control model. The parameters of the reorder level s and the order size Q can be determined using TFR as a performance measure an under six different LTD distributions. In addition, three different time buckets are used for the simulations: Single demand approach (SDA) and weekly or monthly periodic demand approach (weekly PDA and monthly PDA). SDA or weekly PDA are more suitable for forecasting highly irregular demand. However, many companies only have the monthly data available for forecasting demand. The recommendations per demand categorization are shown in Figure 2.6. SBA and bootstrapping are used for forecasting irregular demand and smooth demand, so these two forecasting methods will be explained in this section.

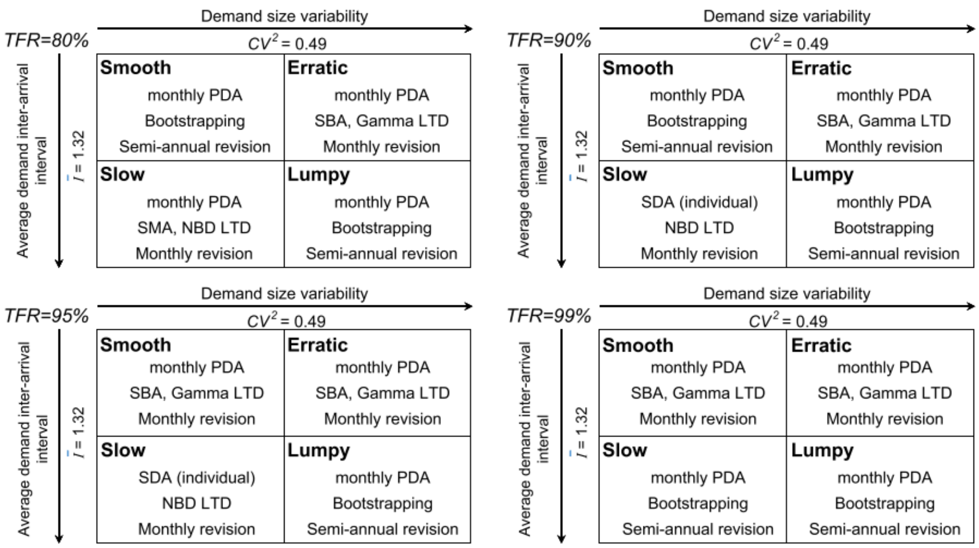

Figure 2.6: Recommendations per demand categorization under each TFR (Rego & Mesquita, 2015)

2.6.1. Croston's method, Syntetos Boylan Approximation (SBA) and Teunter Syntetos Babai (TSB)

Before explaining the SBA, Croston's forecast method will be explained first. Croston (1972) was the first that developed a traditional time-series method for products with irregular demand. Many other forecasting methods have continuoud with Croston's basic method such as SBA and Teunter-Syntetos-Babai (TSB) forecasting method. The Croston method (1972) and the single exponential smoothing are most commonly used in forecasting intermittent and low demand. Willemain, Smart, Shockor & DeSautels (1994) discovered that the Croston method is significantly better than single exponential smoothing under intermittent demand. However, the accuracy decreases with both methods if there is a high variability in the inter-demand interval and demand size (Ghobbar & Friend, 2003). The Exponentially Weighted Moving Average (EWMA) method of Holt (2004) is also widely used for forecasting irregular demand. Croston (1972) noted that using EWMA is not appropriate for this irregular demand. Therefore, Croston's method uses the average interval between two demand moments and the average demand size. Two smoothing constants are used for the calculation of the smoothing estimates (Axsäter, 2015). The smoothing estimates are only adjusted in periods with positive demand. Syntetos and Boylan (2001) noted that Croston's method is biased. They found an error in the mathematical derivation of the expected demand. This error provides a small advantage if the method is applied in practice. Syntetos and Boylan (2001) eliminate this bias in SBA forecasting method. The smoothing estimates in SBA are calculated in the same way as with Croston (1972). A disadvantage of the Croston method and SBA is that the obsolescence of products is not considered. These methods are only updated if the demand in a period is positive. It is important for a wholesaler of infrastructure and installation materials to stay up to date with these products. Therefore Teunter, Syntetos and Babai (2011) developed a forecasting method that is based on Croston's method, which updates the demand probability. The use of the demand probability instead of the demand interval is a small adjustment, because the demand interval is the inverse of the demand probability. The advantage of the demand probability as a smoothing estimate is that it can be updated each period, even if there is no demand in a period.

2.6.2. Bootstrapping

For products with an irregular demand, a non-parametric approach can also be used for forecasting demand. Bootstrapping is a non-parametric approach that reconstructs the empirical distribution of the data, making distribution assumptions obsolete (Syntetos, Babai, & Gardner Jr., 2015). Bootstrapping takes random samples from a larger sample, and these random samples differ from each other and from the population. A histogram of the demand distribution during lead time is built from the samples. The mean and standard deviation of the LTD can be calculated from this histogram. One assumption of bootstrapping is that the historical demand pattern will continue in the future. The most robust bootstrapping method was developed by Willemain, Smart and Schwarz and is further referred to as the WSS method.

Efron (1979) introduced bootstrapping as a continuous sampling with data set replacement. The WSS method tackled one of the drawbacks of the bootstrapping method of Efron (1979): the values of the empirical distribution can be the same as the original sample. The WSS method reflects the autocorrelation between the demand moments and generate values that have not yet occurred. The method uses Markov chain and jittering. Jittering adds variation to the simulated values. As a result, the simulated values obtained differ from the observed values. Jittering adds greater variation when the demand is large.

Zhou and Viswanathan (2011) have improved the WSS method. They use the inter-demand interval distribution for the demand moments instead of the Markov chain in the WSS method. Jittering is not used. Rego and Mesquita (2015) use the model of Zhou and Viswanathan (2011) to forecast the demand of products with a lumpy demand pattern. Rego and Mesquita (2015) have made an adjustment by using probabilistic lead times, so it comes closer to reality by using uncertain lead times.

Bootstrapping methods is not be used to forecast demand in this study. Viswanathan and Zhou (2011) compared their bootstrapping model with parametric methods and concluded that the parametric methods are more accurate. They attribute the poorer performance of bootstrapping method to the short demand history available. Syntetos et al. (2015) conclude that parametric methods are simpler and perform well. In addition, parametric methods require less time and computer power for calculating the forecast of many SKUs. Therefore, it has been concluded that this study use the parametric forecast methods, SBA and TSB, for forecasting demand. The TSB method is used in this study because it is an adjustment to the SBA method, as the TSB method also calculates the demand in months with zero demand.

3. Supply chain

3.1. Van Walraven's supply chain

This section explains how the purchasing at suppliers, sales to customers and mutual exchange of goods takes place between the head office in Mijdrecht and the affiliates. In addition, it is explained at what level decisions are made and how the information exchange takes place. This is shown in Figure 3.1.

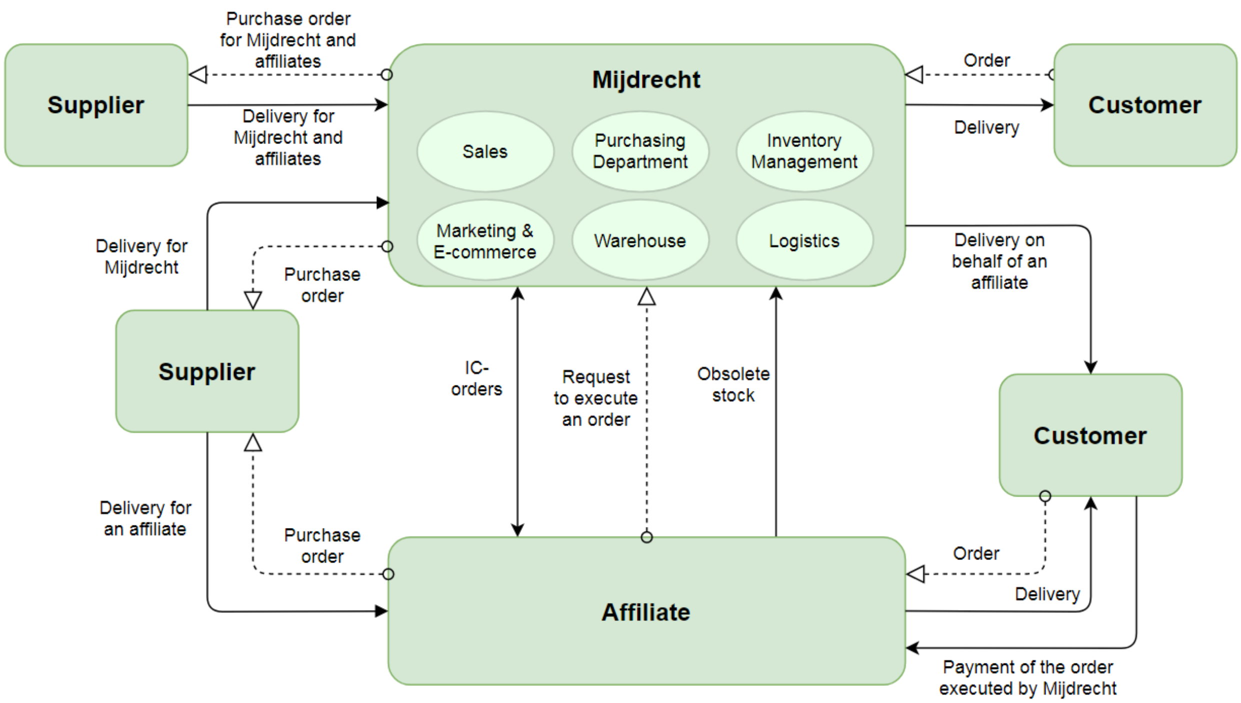

Figure 3.1: Supply chain and information flow of Van Walraven

All departments and the management are represented at the head office in Mijdrecht. Decision-making takes place centrally in Mijdrecht, but decisions about inventory management take place locally. In Mijdrecht, it is decided which suppliers are included in the overall range of Van Walraven, but the affiliate manager determines which products and quantities they have in stock. This depends on the demand of their customers and the available space at their affiliate. In order to achieve economies of scale or because a supplier only wants to deliver to one address, the purchase of products from a few suppliers for all Van Walraven affiliates is done from the head office. The purchasing department in Mijdrecht determines from which suppliers an affiliate can purchase directly.

Intercompany orders (IC-order) take place between Mijdrecht and the affiliates and vice versa. Approximately 35% of the range of an affiliate is ordered from suppliers and the other 65% becomes an IC-order from Mijdrecht. If a product on order turns out to be a backorder, the sales employee can choose whether the product should come from the supplier or an affiliate. The seller can see in the ERP-system when the next delivery will be from the supplier of the product. This option is chosen if the delivery by the supplier is feasible in terms of the order deadline of the customer. The sales employee can also check whether the product is still sufficiently in stock at an affiliate. The purchasing department ultimately determines at which affiliate the products are collected. This decision considers which transport will take place between the affiliate and Mijdrecht.

Each affiliate has a small sales department, which maintains contact with the customer, makes quotations and enters orders. Customers can request a quotation or place an order by email, telephone, website or via their account manager. These orders are entered in the ERP system at the sales department. Each affiliate takes care of processing the order, this means entering the order in the ERP system, the delivery to and contact with the customer. In addition, all affiliates, including Mijdrecht, have a shop where customers can buy their products six days a week. When all products of an order are present in the affiliate, the affiliate delivers the products to the customer. However, the management in Mijdrecht has decided that Mijdrecht will take care of the delivery of an order from an affiliate, if not all products of an order are in stock at an affiliate. This decision was made to reduce the transport between the affiliates and to be able to serve the customer quickly. An order that Mijdrecht executes for an affiliate is seen as a normal order in the inventory control system in Mijdrecht. Therefore, the order is also paid to Mijdrecht. At a later point in time, the turnover of this order is attributed to the affiliate that won the order.

3.2. Current inventory control system

All departments at Van Walraven work with Unit4 Wholesale (Agresso) as ERP system. In addition to this ERP system, a service level-driven inventory management system from Slimstock B.V. is used for purchasing goods from suppliers and inventory management, called Slim4. Van Walraven Mijdrecht has been using Slim4 since 2011. The other affiliates have their own inventory management system. They have chosen for Slim4's software to get a better overview of the stock and they can respond more quickly to fluctuations in demand. Slim4 calculates the reorder level based on the history data and the pre-set target service levels, with the aim to minimize the on-hand inventory. The order and handling costs are not included in the calculation.

3.2.1. Inventory control model and order quantities

Slim4's inventory management system used by Van Walraven has periodic review moments and is designed as a (R, s, S)-system with backordering. Many suppliers require batch ordering, so the inventory management system can be better described as a (R, s, nQ)-system. However, the MOQ and Incremental Order Quantity (IOQ) of several products are not equal. This means that an (R, s, nQ)-system is not suitable for those products, but they also use a (R, s, S, nQ)-system. The value of the IOQ and MOQ determine the type of inventory management system, the limits per inventory management system are shown in Table 3.1. Van Walraven's products are divided into types of inventory management systems based on these boundaries. Order-driven products do not have an inventory control model in Slim4. If those products sell enough order lines, 7 order lines in 1 year, order-driven products will be converted into stocked products. Table 3.1 shows which inventory control system is used for order-driven products when it becomes a stocked product, based on the boundaries of the MOQ and IOQ. Table 3.1 shows that more than 50% of the inventory-driven products have a (R, s, nQ)-system and the other products have either a (R, s, S)-system or a (R, s, S, nQ)-system. Due to the agreements with the suppliers about their order sizes and the use of the Economic Order Quantity (EOQ) for the calculation of the MOQ and IOQ in Slim4, the products have different inventory control models. How the EOQ is used to determine the MOQ and IOQ in Slim4, is described below.

Inventory control model	Boundaries	Number of items
(R, s, nQ)-system	IOQ ≥ 1 and MOQ ≤ IOQ	11435
(R, s, S)-system	IOQ = 1 and MOQ > 1	1195
(R, s, S, nQ)-system	IOQ > 1 and MOQ > IOQ	2286
No inventory control system	IOQ ≥ 1 and MOQ ≤ IOQ	5822
	IOQ = 1 and MOQ > 1	168
	IOQ > 1 and MOQ > IOQ	56

Table 3.1: Boundaries and number of items per inventory control model

The Economic Order Quantity (EOQ) is calculated with formula (3) for a period of one year after the lead time. The EOQ may be in stock for a maximum of 6 weeks. The inventory costs h are 25% of the purchase price p. The ordering cost A are 10 euros for each product.

$$EOQ = \sqrt{\frac{2\ A\ d}{h}} \qquad (3)$$

$h\ =\ Holding\ cost\ per\ unit\ and\ time\ unit\ =\ 25\% * p$
$p\ =\ Purchase\ price$
$A\ =\ Order\ cost\ =\ 10\ euro$
$d\ =\ Demand\ per\ time\ unit$

In addition, an EOQ bandwidth is added to the EOQ formula and this bandwidth is calculated using the cost sensitivity percentage. Van Walraven has set this cost sensitivity at 30%. For example, at a cost sensitivity of 30%, a range of order quantities higher and lower than the EOQ can be ordered, resulting in a maximum cost increase of 30% above the optimal EOQ. Based on this cost sensitivity and the requirement that the EOQ must meet demand for a maximum of 6 weeks, the MOQ and IOQ are calculated. The supplier provides their MOQ and IOQ. Slim4's calculated MOQ and IOQ takes into account the MOQ and the IOQ of the supplier. This means that the MOQ in Slim4 is the suppliers MOQ or a multiple of the suppliers MOQ. This is EOQ calculation for MOQ and IOQ is one of the reasons why multiple inventory control models are used. Another reason is that the MOQ and IOQ of the suppliers do not meet one of the boundaries of the inventory control model, but the products meet one of the three boundaries.

There may be a conflict between the limits of the cost sensitivity and that the MOQ should not exceed the EOQ of 6 weeks. The minimum limit of the cost sensitivity is then higher than the maximum limit, which is in case of the conflict the 6 weeks EOQ limit. Since the minimum limit is higher than the maximum limit, Slim4 determines that these products get the MOQ and IOQ from the supplier. The order behaviour of these products has been analysed and the order sizes of these products are the MOQ or the MOQ plus a multiple of the IOQ. Depending on the size of the customers' orders and the reorder level, the MOQ or MOQ plus a multiple of IOQ are ordered.

3.2.2. Review period and lead time

Van Walraven have an agreement with suppliers about fixed order and delivery times. The review periods and lead times are set as deterministic. The period between a particular review moment and the moment the next order is delivered is defined by Slimstock as the cover period, i.e. the cover period is equal to the review period plus the lead time.

3.2.3. Demand classes and item classification

The demand classes in which SKUs are categorized in Slim4 are normal, lumpy, frequent, irregular, slow, zero sales, new, disappeared and user determined. The SKUs classified as normal have a demand pattern corresponding to the normal distribution. A relatively new demand class at Slim4 is frequent. Products that have more than 20 order lines per month are assigned to this class. This means that the SKU has on average one order line per working day. Lumpy SKUs are characterized by a relatively low demand average, and a high safety stock in order to deal with increased demand or uncertainty. Irregular SKUs are characterized by periods of zero demand and periods of high peaks. Slim4 tries to recognize a pattern in the demand moments and the corresponding volumes of irregular SKUs. This pattern is extrapolated as a forecast. Slow SKUs are ordered in small quantities with a relatively low frequency. If items have had no sales in the past 24 months, they are categorized as zero sales. The item must have had positive sales in the past, because if an item has never had positive sales than it is a new SKU. The forecast and safety stock of zero sales and new items are set to zero. There will only be an order advice if an order has been entered or if there are backorders. Disappeared items no longer appear in the import file from Unit4 to Slim4 and are removed after 3 months. SKUs can also be manually forecasted, which make it a User Specified SKU.

The SKUs are also classified in an ABC/XYZ-category. The data from last year is used for the ABC/XYZ-classification and in this thesis the classification from the beginning of December 2020 is used. The ABC-analysis is based on the turnover based on the purchase price and the XYZ-classification is based on the number of order lines.

3.2.4. Forecast

A seasonal pattern must first be established to forecast the demand for a product. This seasonal pattern will be included in the forecast. The Fisher test compares the demand pattern from two years ago with the demand pattern from one year ago. There is a seasonal pattern as the F-test is higher than 2.82.

Each month, a demand forecast is made per product for the next 12 months. This forecast included historical demand data from the past 24 months. This historical demand data also included the products sold on a call-off order. Call-off orders can cause outliers in demand and therefore these call-off orders are often excluded from the forecast calculation. It is therefore important to note that Slim4 includes the call-off orders in the forecast calculation. Exponential smoothing is used for forecasting all product categories. A monthly demand forecast for the coming year is calculated based on these categories and trends. Slim4 makes no statement about how exactly the product categories are included in forecasting demand. The final demand forecast has a smoothing factor of 20%, which means that last month's sales count 20% in the final demand forecast. The other 80% is the regular monthly forecast.

3.2.5. Safety stock and surplus buffer

A safety stock per SKU is determined to cope with the peaks in demand (e.g. lumpy and irregular products). The safety stock calculation includes the standard deviation of demand, service level, review period, lead time and the MOQ. It is also possible to include the reliability of the supplier in determining the safety stock. However, Van Walraven manually adjusts the lead time in their ERP-system if an order proves to have a longer lead time. Therefore, this function is not reliable in Slim4 for Van Walraven. Van Walraven has determined service levels per ABC/XYZ-category. These service levels are designed in such a way that Van Walraven can achieve their overall order (line) fill rate (OFR) of 98%. The formula of the total buffer of a product is:

$$Buffer = Safety\ stock + Surplus\ buffer \qquad (4)$$

This surplus buffer can be entered manually. For several SKUs, the surplus buffer is used to be able to supply the expected extra demand from projects.

3.2.6. Call-off order and reorder level

To determine how many products have to be ordered, a reorder level is calculated per product in order to meet expected demand. The reorder level depends on the total buffer of formula (4) and the forecasted demand during the cover period. The forecasted demand during the cover period and the safety stock include the call-off orders in the historical demand data. The current open call-off orders are added to the reorder level, so that these call-off orders are in stock for the customer on time. The reorder level of a product is increased by the number of items of the call-off order. The formula for the reorder level is:

$$\begin{aligned} Reorder\ level = {} & Forecasted\ demand\ during\ cover\ period \\ & + Total\ buffer + Call\ of\ order \end{aligned} \qquad (5)$$

3.2.7. Order advice

If at a review moment the current inventory position of a SKU is lower than the reorder level, an order advice is given in which the total inventory is minimized. The purchasing department will order items where necessary. The order advice is the number of products that is needed to bring the inventory position back to or above the reorder level. The order advice is rounded up to the MOQ, or to the MOQ added by a multiple of the Incremental Order Quantity (IOQ).

3.2.8. Connection between Unit4 and Slim4

All departments of Van Walraven work daily with Unit4 Wholesale, such as the financial administration, but also new products and purchase orders are processed. Daily communication takes place between the ERP-system and Slim4, so that Slim4 has the necessary data to provide an order advice. For example, Slim4 receives a product list, data from purchases at suppliers and sales to customers and adjustments to the surplus buffer. Slim4 uses this information to forecast the demand, determine the total buffer and order level, which resulted in generating an order advice. Figure 3.1 shows this data exchange between Unit4 and Slim4.

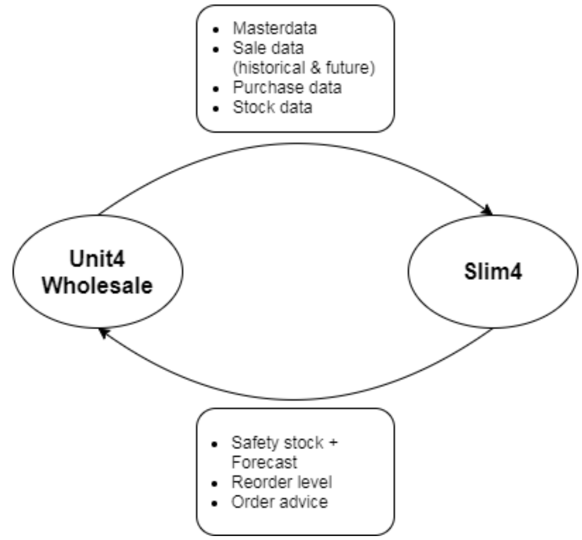

Figure 3.1: Data exchange between ERP-system and Slim4

4. Demand analysis

4.1. Item classification

In this section the products are divided into classes, which can help determine where most inventory is. These classes can also be used to determine service levels, forecasting methods of the demand and the inventory control model. Three different item classification methods are explained in this section: demand categorization of Syntetos (2001), the classification used in Slim4 and the ABC classification. The monthly sales data from December 2018 to November 2020 of the data selection of section 1.6 has been used to classify the products in different categories.

The demand categorization of Syntetos (2001) is described in section 2.1. For this demand categorization, the average inter-demand interval and the square coefficient of variation of the demand size are calculated with formula (1) and (2). Products can be divided into different categories based on these formulas. Customers are divided into different discount categories or have made price agreements for large projects. This means that the turnover based on the sales price gives an unclear picture. That is why the turnover is expressed in sales times the purchase price.

The classification of the products by demand pattern used in Slim4 is not known. Slim4's demand categorization uses more categories than that of Syntetos (2001). Table 4.1 shows which demand categorization a product is assigned in Slim4 and according to Syntetos' theory (2001). The total row in Table 4.1 gives an overview of the demand categorization of Syntetos (2001) and the total column is the summary of the classification of Slim4. The percentages are relative to the total number of items, total turnover and total current inventory value. The products in normal, lumpy, irregular and slow categories of Slim4 are largely divided into two demand categories of Syntetos (2001). This shows that Slim4 does not use the demand categorization method of Syntetos (2001).

		Smooth	Erratic	Intermittent	Lumpy	Total
Frequent	*Number of items*	445	30	1	1	477 (2%)
	Current inventory value	12.26%	0.85%	0.01%	0.01%	13%
	Turnover	23.30%	0.76%	0.00%	0.00%	24%
Normal	*Number of items*	2178	2749	46	177	5150 (25%)
	Current inventory value	16.43%	17.20%	0.41%	1.14%	35%
	Turnover	25.96%	20.76%	0.23%	0.79%	48%
Lumpy	*Number of items*	212	919	168	633	1932 (9%)
	Current inventory value	0.55%	3.86%	0.74%	2.08%	7%
	Turnover	0.72%	3.12%	0.47%	1.73%	6%
Irregular	*Number of items*	89	248	2353	4403	7093 (34%)
	Current inventory value	0.55%	2.09%	5.78%	16.14%	25%
	Turnover	0.39%	0.82%	2.69%	7.54%	11%
Slow	*Number of items*	334	311	3375	2222	6242 (30%)
	Current inventory value	1.26%	1.81%	8.51%	7.41%	19%
	Turnover	1.37%	1.07%	4.27%	3.27%	10%
Zero sales	*Number of items*	3	1	0	11	15 (0.07%)
	Current inventory value	0.01%	0%	0%	0.41%	0.42%
	Turnover	0.02%	0%	0%	0.53%	0.55%
New	*Number of items*	23	4	0	1	28 (0.13%)
	Current inventory value	0.45%	0%	0%	0.05%	0.50%
	Turnover	0.03%	0.03%	0.00%	0.00%	0.06%
Disappeared	*Number of items*	3	3	12	7	25 (0.12%)
	Current inventory value	0 %	0%	0%	0%	0%
	Turnover	0.05%	0.02%	0%	0.04%	0.12%
Total	*Number of items*	3286 (16%)	4265 (20%)	5955 (28%)	7455 (36%)	20962
	Current inventory value	32%	26%	15%	27%	100%
	Turnover	52%	26%	8%	14%	100%

Table 4.1: Comparison of the distribution of products according to Slim4 and Syntetos (2001)

The demand categorization formulas (1) and (2) do not take into account the turnover of the products. For example, the fast-moving smooth products can still have a low turnover because of a low selling price. Therefore, the ABC-analysis include the turnover based on the purchase price in the product classification. 8% of the products have not been assigned to an ABC-class, because these products have sold less than 7 order lines so far. These products provide 3% of the current inventory value and 2% of the sales.

The ABC-analysis has been expanded with the XYZ-classification. This expansion ensures that products are not only classified by turnover, but also how many times products are sold. The criterion of the XYZ-classification is the number of order lines. Slim4's ABC/XYZ classification is used for the ABC/XYZ-classification in this thesis, this is explained in section 3.2.3. Due to the data selection in the scope and the use of the ABC/XYZ-classification of Slim4, the A-products no longer consist of 20% of the products. The A-class of this data selection consists of 14% of the total products, and they provide 72% of the turnover.

This is shown in Table 4.2. The number and percentage of products and the turnover based on the purchase price per ABC/XYZ-class are shown in Table 4.2. The percentages are again compared with the total column in Table 4.2.

The service level is determined per ABC/XYZ-class at Van Walraven. Slim4 uses this set service level for each SKU separately when calculating the safety stock. These service levels are designed and adjusted in such a way that Van Walraven's overall OFR can be met. The current service levels at Van Walraven are also given in Table 4.2. The service level for products that do not have a class have a service level of 50%.

Turnover based on purchase price

Order line					
	ABC/XYZ-class	**AX**	**AY**	**AZ**	**Total A-Class**
	Number of items	2148 (10%)	640 (3%)	186 (1%)	2974 (14%)
	Current inventory value	38%	12%	5%	55%
	Turnover	60%	9%	3%	72%
	Service level	95%	93%	80%	-
	ABC/XYZ-class	**BX**	**BY**	**BZ**	**Total B-class**
	Number of items	1675 (8%)	1682 (8%)	927 (4%)	4284 (20%)
	Current inventory value	6%	9%	7%	22%
	Turnover	7%	6%	3%	17%
	Service level	93%	90%	80%	-
	ABC/XYZ-class	**CX**	**CY**	**CZ**	**Total C-class**
	Number of items	948 (4%)	3061 (15%)	7942 (38%)	11952 (57%)
	Current inventory value	1%	4%	14%	19%
	Turnover	1%	3%	5%	9%
	Service level	94%	80%	50%	-

Table 4.2: ABC/XYZ-classification with the number of items, the turnover based on the purchase price and the service level per class

Table 4.1 shows that the smooth products have the highest current inventory value and the highest turnover. In addition, Table 4.2 shows that the A-class provides 57% of the current inventory value, of which the AX-class has the largest inventory value, see Table 4.2. Appendix A provides an overview of the combination of the demand categorization of Syntetos (2001) and the ABC/XYZ classification. The most important findings in this comparison is that the smooth products in the A-class account for more than 1/4th of the total inventory value and almost half of the total turnover. Due to the high turnover, these A-products are very valuable for Van Walraven. Therefore, the A-products have been assigned a high service level to not record stockouts. This is one of the reasons why these A-products have a high inventory value.

Table 4.1 shows that the frequent and normal products according to Slim4 have a lot of inventory. These products largely follow Syntetos' (2001) smooth and erratic demand pattern. 27% of the products belong to these categories of Slim4 and Syntetos (2001) and together these products provide 48% of the current inventory value and 72% of the turnover. Products with an erratic and smooth demand pattern are both regularly sold, but erratic products have a large variation in quantity per demand moment. Due to the large share in the current inventory value, this research will focus on frequent and normal products with a smooth and erratic demand pattern (FR&NO/SM&ER). Products with a smooth and erratic demand pattern can use the same forecasting methods. This will be explained in detail later in this research.

Another important finding is that intermittent and lumpy products have twice as much share in the current inventory value as in the turnover, see Table 4.1. The high inventory value is partly due to a high safety stock for the intermittent and lumpy demand pattern of the irregular products. Table 4.1 shows that the irregular products of Slim4 provide 25% of the current inventory value, of which especially the products with a lumpy demand pattern provide the largest stock. This means that these irregular products with a lumpy demand pattern (IR/LU) also have a large share in the total current inventory value of Van Walraven Mijdrecht. This research will be extended with these IR/LU. Later in this study it will be investigated whether ADI is available for these products, such as quotations and call-off orders. ADI can help to minimize the inventory value of these products.

At this moment, Van Walraven determine the service level per ABC/XYZ-class. Teunter, Syntetos and Babai (2017) showed that setting a target service level per ABC-class can lead to suboptimal solutions. They recommended setting a service level for each SKU so that it is possible to achieve the target system service level at minimal cost. This individual approach yields a cost advantage compared to the determination of service level per ABC/XYZ-class. Van Donselaar et al. (2021) experienced that the inventory value can be minimalized with a minimum aggregate service constraint. This aggregate fill rate is a weighted average of all products in the assortment. The heuristics used by Van Donselaar et al. (2021) is used to reduce the inventory value of the FR&NO/SM&ER and IR/LU products.

4.2. Comparison current inventory with expected inventory on hand

This research focus on the FR&NO/SM&ER and IR/LU products, because these products have a high current inventory value. This section examines the characteristics of the products with the most physical stock. The current physical inventory is compared with the required expected inventory on hand ($E[I^{OH}]$) according to the theory. The DoBr tool has been used to calculate the reorder level and the $E[I^{OH}]$ for all FR&NO/SM&ER and IR/LU products. This tool was developed by Van Donselaar and Broekmeulen (2020) in Excel for calculating different KPIs for the (R, s, nQ), (R, s, S) and (R, s, S, nQ)-inventory control model. The definitions and expressions for the KPIs of Van Donselaar and Broekmeulen (2015) are used for the DoBr tool. The input parameters required for the calculation of the reorder level per SKU based on the Target Fill Rate (TFR) are: average forecasted demand per period, standard deviation per period, lead time, review period, TFR, IOQ and MOQ. This research uses monthly time buckets for the analyses. The lead time is on average 9 days and the review period is 7 days for all products.

The reorder level calculated with the DoBr tool is used for the calculation of the $E[I^{OH}]$ .The inventory on hand is the highest just after a potential delivery and lowest just before a potential delivery (Donselaar & Broekmeulen, 2015). Therefore, the average of the expected inventory on hand at the beginning and at the end of a potential delivery cycle is taken as value for the physical inventory based on the theory and these are also calculated with the DoBr tool. The input parameters required for the calculation of the $E[I^{OH}]$ begin and end are lead time, review period, average forecasted demand per period, standard deviation per period, the calculated reorder level, IOQ and MOQ.

For the comparison in this section, the surplus buffer and the open call-off orders are excluded from the reorder level calculation in Slim4. The results of this comparison are shown in Table 4.3. The calculated reorder levels of the DoBr tool have a higher value than the reorder levels of Slim4. With the FR&NO/SM&ER products, this is mainly caused by products whose standard deviation is at least 1,5 times the average forecasted demand. On the other hand, the current inventory value is much higher than the $E[I^{OH}]$ that is necessary according to the theory, see Table 4.3. The FR&NO/SM&ER products have more than 64,635 euros of call-off orders in stock. There are 62 FR&NO/SM&ER products with a difference of more than 1293 euros between $E[I^{OH}]$ and the current inventory value. These 62 products provide 192,385 euros of the difference. The ten products with the largest difference were analyzed. One product has a difference between $E[I^{OH}]$ and the current inventory value of almost 32,317 euros. This product has had sales of about 25,000 pieces per month for a year, mainly from one customer. An annual order at the supplier is placed for this product due to price agreements. Just after making the annual order, the demand dropped to about 5500 pieces per month because the big customer no longer buys the product. As a result, the annual order was much larger compared to the sales. Furthermore, 5 products had a large order from the supplier because of a favorable low price at that moment, or because there is a price advantage if a large batch is ordered. High demand was expected for two products, which is why a large batch of these products was ordered. Ultimately, the demand was disappointing. All in all, it means that there are several reasons for the big difference between $E[I^{OH}]$ and the current inventory value.

1445 IR/LU are order-driven products and therefore have no reorder level. The DoBr tool do not calculate the $E[I^{OH}]$] for these order-driven products. However, these order-driven products have a physical stock for €87,365. Products with a (R, s, nQ)-inventory control model account for the largest difference between the physical stock and the $E[I^{OH}]$. The 3397 FR&NO/SM&ER products with a (R, s, nQ)-policy provide 159,232 euros of the difference and the 2414 inventory-driven IR/LU with a (R, s, nQ)-policy for 87,365 euros of the difference between the current inventory value and the $E[I^{OH}]$ value. This is not caused by a difference in reorder level values, because the reorder level values calculated by the DoBr tool are higher than with Slim4. Van Walraven could reduce the current inventory value of products with a (R, s, nQ)-inventory control model.

	Irregular products with lumpy demand pattern	**Frequent and normal products with smooth and erratic demand pattern**
Number of items	4403	5402
Reorder level value DoBr	€ 164,323	€ 600,925
Reorder level value Slim4	€ 141,196	€ 510,242
$E[I^{OH}]$ value DoBr	€ 185,442	€ 743,526
Current inventory value	€ 369,926	€ 1,050,389

Table 4.3: Comparison current inventory value with the required $E[I^{OH}]$ based on the theory

4.3. Conclusion sub-question 1

This section gives the answer to sub-question 1:

Sub-question 1: Which item classification can be used?

Three different classifications have been studied to gain insight into which type of products should receive attention in this study: Slim4's classification, the demand categorization of Syntetos (2001) and the ABC/XYZ classification. The combination of Slim4's classification and the demand categorization of Syntetos (2001) made it clear which type of products have the highest inventory. The frequent and normal products (Slim4 classification) with a smooth and erratic demand pattern (Syntetos categorization) provide 48% of the current inventory value and 72% of the turnover. 27% of all products are FR&NO/SM&ER products. The irregular (Slim4 classification) with a lumpy demand pattern (Syntetos categorization) provide 25% of the current inventory value. These product groups also have a big difference between the $E[I^{OH}]$ according to the theory and DoBr tool and the current inventory value. This difference has several causes: favourable price agreements with the supplier for purchasing a large batch, unexpected drop in the demand or a product cannot meet the expectations. The chosen item classification of Slim4 and Syntetos (2001) gives a good overview of which product groups have most inventory value and therefore where the inventory must be reduced.

4.4. Trend/Seasonality

When forecasting the demand in Slim4, a trend or seasonal pattern is taken into account. This section examines whether the FR&NO/SM&ER and IR/LU products have a trend or seasonal pattern according to Slim4. Determining a trend or seasonal pattern is only possible if a product has at least 24 months of sales history. As indicated earlier, a Fisher test is used to determine a seasonal pattern. According to Slim4, the IR/LU products do not have a seasonal pattern or trend. 80% of the FR&NO/SM&ER products have a trend or a seasonal pattern. However, it appears that only 1.7% of the FR&NO/SM&ER products have a seasonal pattern. Slim4 expresses the trend in a decrease or increase in sales in units. On average, the trend is less than 1% of the monthly sales of a product. Because so few products have a seasonal pattern and the trend is only a very small percentage of the monthly sales, it is assumed for simplicity that there is no trend or seasonal pattern. Demand is therefore stationary.

4.5. Demand structure

The previous section concluded that there is no trend or seasonal pattern present with the FR&NO/SM&ER and IR/LU products. This simplifies the demand analysis to determine the demand structure, because all data is suitable for the understanding of the structure. The demand data from the past two years is used to determine the distribution of the demand size. The demand distribution is studied separately for the FR&NO/SM&ER and the IR/LU products. Outliers in the data are treated as actual demand and are not treated particularly.

	FR&NO/SM&ER Syntetos et al. (2011)	K-S Test (α=0.05)	K-S Test (α=0.01)	IR/LU Syntetos et al. (2011)	K-S Test (α=0.05)	K-S Test (α=0.01)
Normal (CV<1, AiDI <1.75)	4642 (86%)	5229 (97%)	5352 (99%)	756 (17%)	1199 (27%)	2343 (53%)
Poisson (CV<1, AiDI >1.75)	-	-	-	1580 (36%)	-	-
NBD/SP (1<CV<4, AiDI >1.75)	-	-	-	1280 (29%)	-	-
Gamma (CV>1, AiDI <1.75 & CV>4, AiDi>1.75)	760 (14%)	4451 (82%)	4518 (84%)	787 (18%)	135 (3%)	265 (6%)

Table 4.4: Demand distribution according to Syntetos et al. (2011) and the K-S test

In Figure 2.2 in section 2.1 is the classification scheme of Syntetos et al. (2011) given, in which the different distributions are classified based on the inter-demand interval and the square coefficient of variation of the demand sizes. According to this schema, products with a smooth demand pattern follow the normal distribution. Of the FR&NO/SM&ER products, 86% of the products meet the limit values to be able to follow the normal distribution. The goodness-of-fit of the FR&NO/SM&ER products with the normal distribution will be tested with the Kolmogorov-Smirnov test (K-s test). The K-S test is based on the empirical distribution function and the fit is determined by comparing the empirical distribution function with the assumed distribution function. The null hypothesis is that the product demand follows a normal distribution. If the calculated p-value of the K-S test is higher than the significance level of $\alpha = 0.05$, the null hypothesis is not rejected, and the product follows the normal distribution. The K-S test shows that 97% of the FR&NO/SM&ER products have a good fit with the normal distribution. The products that do not have a good fit mainly fall into the normal category with an erratic demand pattern. It is remarkable that the products that do not have a good fit have an average CV^2 of 4, while the products that do follow a normal distribution according to the K-S test have an average CV^2 of 1.07.

The demand of 14% of the FR&NO/SM&ER products follows a gamma distribution according to the schema of Syntetos et al. (2011). Therefore, also a K-S test is conducted to test the goodness-of-fit with the gamma distribution. In order to estimate the gamma distribution, the mean and the variation of the demand must first be determined. With the mean and de variation of the demand, the parameters a and b for the gamma distribution can be estimated with the following formulas:

$$a = \frac{\mu^2}{\sigma^2} \; and \; b = \frac{\sigma^2}{\mu}$$

The K-S test shows that 82% of the products follow the gamma distribution. Fewer products follow the gamma distribution according to the K-S test than the normal distribution, partly because the gamma distribution cannot have negative values. 14% of the FR&NO/SM&ER products have negative demand in the history because these products returned in a month more items than sold.

According to several studies, the normal distribution performs worse for products with an irregular demand, because irregular demand skewed to the right (Syntetos et al., 2012; Turrini & Meissner, 2019). The IR/LU products in this study have different demand distributions according to the classification scheme of Syntetos et al. (2011). According to the K-S test, 27% of the IR/LU products have a good fit with the normal distribution ($\alpha = 0.05$) and only 3% with the gamma distribution. At a $\alpha = 0.01$, 53% of the IR/LU products have a fit with the normal distribution. If only the inventory driven products are considered, 78% of the IR/LU products have a good fit with the normal distribution at a $\alpha = 0.01$. The fit with the gamma distribution is very low, partly 25% of the IR/LU products have negative sales in the data history. The Poisson distribution, NBD and Stuttering Poisson distribution also experience problem when looking for a fit for products with negative sales. Because with an $\alpha = 0.01$ in the K-S test more than half of the IR/LU products have a fit with the normal distribution, more than 3.4$^{\text{th}}$ of the inventory driven products have a fit with the normal distribution and the normal distribution responds good to negative sales in history, the IR/LU products will follow the normal distribution in this study. This means that the product groups in this scope, the FR&NO/SM&ER and the IR/LU products, both follow the normal distribution.

5. Advanced demand information

This section investigates whether Van Walraven has suitable ADI that can be included in the inventory control model so that the current inventory can be reduced. The use of ADI is useful according to section 2.4 when the probability that a proposal will be converted into an order is high. Van Walraven does not have access to data whether there are proposals (bids) for construction projects in the next period, or the probability that a customer will win the bid. Account managers have consultations with customers about upcoming project, but which products are exactly needed for the project becomes clear in a quotation for the project. No data is available of these consultations about how many times the consultation is converted into a quotation and that quotation into an order. However, it is investigated in section 5.1 how many customers converted quotations into orders and whether certain customers have high conversion rates.

As mentioned before in the problem introduction, Van Walraven has to deal with call-off orders. Customers request call-off orders because they want to be sure that they can purchase the products on a specific date. But also, because the customer does not have enough space to store the product, Van Walraven stock this product for the customer with a call-off order. Call-off orders can be used as ADI. Call-off orders are information of high quality, because it is known how much will be purchased of a product and the date of delivery. Unfortunately, call-off orders are regularly cancelled by the customer. The effect of call-off orders on the demand pattern, current inventory level and reorder level is investigated in section 5.2. Call-off orders are fully stocked when the call-off order is entered in the ERP-system. Only 1.5% of the total turnover was sold through call-off orders. This means that the share of call-off orders in the turnover is very small, but the cancelled call-off orders do have a large impact on the inventory value. That is why this section examines the possibilities of reducing the inventory value of the demand orders, for example by putting them in stock at a later time. In addition, it is more likely that a call-off order is not yet in stock if it is cancelled. This is examined in section 5.2.4.

Another form that can be seen as ADI are project products. These products are only included in the assortment for this project and will expire at the end of the project. This is a service that is offered so that the customer can buy all products for the project at Van Walraven. Project products have been excluded from the data selection in section 1.6, but the project products are used for the investigation of ADI. The use of project products is discussed in section 5.3.

5.1. Quotations

The sales department prepares quotations for Van Walraven's customers. From January 2020 to June 2020, 39% of the quotations were converted into an order, see Table 5.1. Quotations change regularly. Sometimes the quotations changes immediately after it has been offered, because a customer wants to have something else offered or wants to add products to the quotation. For some quotations, the sales departments know in advance that there is a big chance that the quotation will become an order. This is due to the account manager's communication with the customer and the sales department.

	Quotation has become an order	**Total**
Number of quotations	1426 (39%)	3701
Value of quotations	€ 1,134,798 (11%)	€ 10,605,697

Table 5.1: Overview of number and value of the quotations from January till June 2020

Several major customers have been studied for this study. These are customers with the most requests for quotations, customers who convert the most quotations into orders, and customers with the largest amount of quotations and orders. Based on the data analysis, these major customers convert almost 50% of their quotations into orders. However, it appears that they mainly convert the smaller quotations into an order, because on average a customer converts 26% of the quotation value into an order. Figure 5.1 shows these conversion percentages of the major customers, in which the blue bars are the percentage of the number of quotations that are converted into an order and the orange bar is the percentage of the total quotation value of the customer that is converted into an order. The orange bars are below 20% for more than half of the customers, this shows that these customers mainly order small orders.

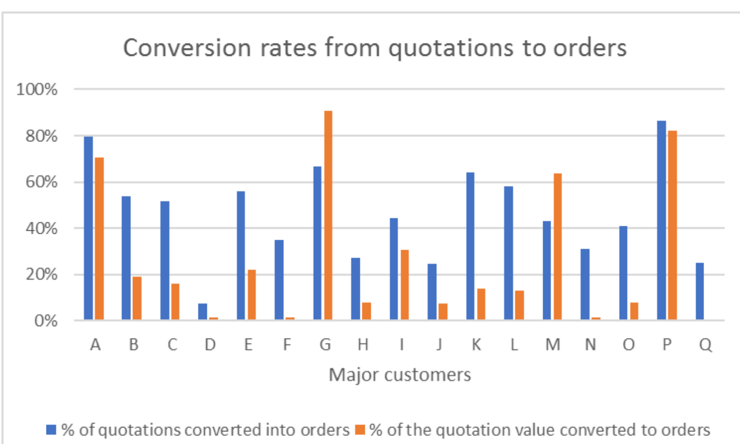

Figure 5.1: Conversion rates from quotations to orders of the major customers

283 customers (of the 1173 customers who have requested a quotation) convert more than 75% of their quotations into an order, of which 216 customers have only submitted 1 request and converted it into an order. Only seven customers have converted five quotations or more into an order and are among the customers who have converted more than 75% into orders. Because many customers have only requested one quotation, the average and median of the number of quotations, of the customers who convert more than 75% of their quotations, that have become an order are 1 and 1.6 respectively. This is shown in Table 5.2.

Thonemann (2002) indicated that the use of ADI is only useful if all or no customers share ADI with the manufacturer or wholesaler. Imperfect ADI provides information about future orders but is subject to changes. The value of all requested quotations is 20% of the total turnover in that period. This means that a large proportion of customers do not provide ADI by requesting quotations. Moreover, it can be concluded from the analysis in this section that the conversion rate from quotation to order is very low and there are few customers who convert a high percentage of quotations into an order. As a result, quotations are not suitable for use as perfect or imperfect ADI

	Number of quotations that have become order	**Value of quotations that have become order**
Minimum	1	€ 1
Maximum	27	€ 23,822
Average	1,6	€ 994
Median	1	€ 232
Sum	452	€ 281,458
% of total	12%	3%

Table 5.2: Overview of the customers who convert 75% of the quotations into orders

5.2. Call-off orders

232 call-off orders that were delivered or cancelled between December 2018 and November 2020 and only the call-off orders from products that are included in the data selection, see section 1.6, are included in this section. These call-off orders consist of 1359 products with a total of 3195 call-off order lines. A call-off order line is the demand of a product in a specific time window. One call-off order can consist of one or more products and a product can have multiple call-off order lines per call-off order because the delivery dates of these call-off order lines differ. Table 5.3 shows what percentage of the ordered call-off orders have actually been delivered or cancelled. The percentages in the table are relative to the total number of delivered and cancelled call-off order lines. This means that 39% of the call-off order lines with FR&NO/SM&ER products have been delivered to the customer. The delivered call-off order lines only have a 1.5% share in Van Walraven's total turnover.

Despite the low share in total turnover of these call-off order lines, an analysis has been made of the influence of the call-off orders on the demand pattern and the turnover of IR/LU and FR&NO/SM&ER. The FR&NO/SM&ER have a 57% share in the total value of the call-off order lines that have been ordered. The IR/LU only have a 11% share in the value of all ordered call-off order lines. A quarter of the value of all call-off order lines are cancelled, of which the cancellations for the FR&NO/SM&ER have the largest share. An analysis of cancellations is discussed in section 0.

	Irregular products with lumpy demand pattern	Frequent and normal products with smooth and erratic demand pattern	Total of all call-off orders
Number of products	152	831	1359
Delivered	8%	39%	73%
Cancelled	4%	17%	27%
Delivered + Cancelled	11%	57%	100%

Table 5.3: Overview of the values of call-off order lines (number of items times the purchase price)

An important note for this section is that call-off order lines are added to the reorder level, so the call-off order line is almost instantly available. This is shown in formula (5). It is immediately added to the reorder level because Van Walraven wants to be able to serve the customer when the customer needs the products. The customer may need these products earlier.

5.2.1. Call-off order lines of irregular products with a lumpy demand pattern

To check whether call-off orders have a major impact on the demand pattern of the products, five IR/LU with the largest turnover are studied. The demand patterns of these five products are given in Figure 5.2. These products have had no call-off orders in the period from December 2018 to November 2020. One product (71868) has a surplus buffer of 10 pieces since February 2020. A customer has indicated that he will need product 71868 during 2020, but the customer does not exactly know how many he will need. For several reasons, this product has received a surplus buffer instead of a call-off order. Because the customer does not know the exact amount that he is going to purchase, the customer can request too many in a call-off order, which leads to cancellations. A call-off order is added to the reorder level in Slim4, so a cancellation results in obsolete stock of the product. In addition, it is an expensive product with a purchase price of 686 euros. This means that obsolete stock results in a high inventory value. Because the customer would like to have the products immediately when he needs them and does not want to wait for the lead time of three days, 10 pieces of product 71868 is added as a surplus buffer. This is an exception, because it is the only product in the assortment where a surplus buffer is set for a customer instead of a call-off order. A surplus buffer is more often added to products in the assortment because the customer indicates that he wants to buy the product. The data shows that the customer often does not buy the product after having indicated this.

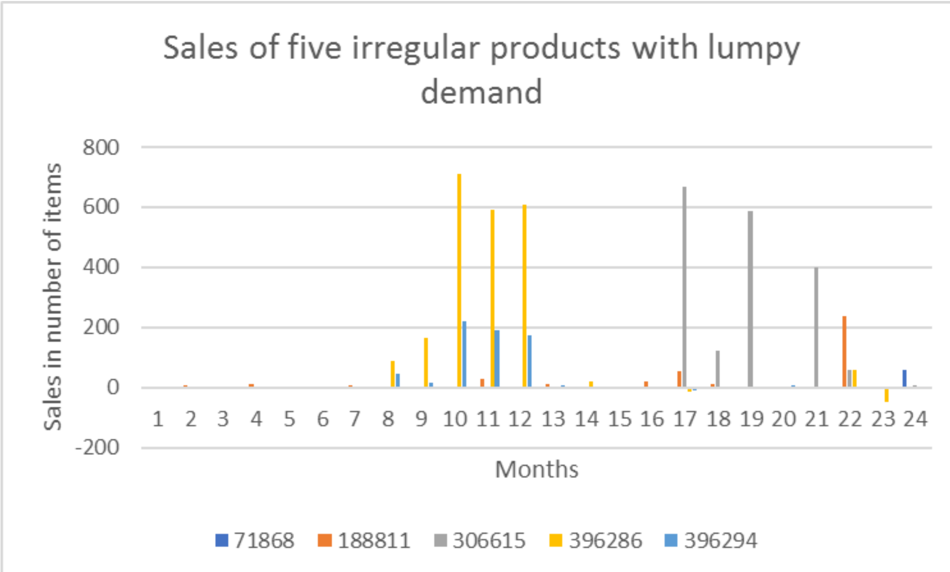

Figure 5.2: Demand pattern of five irregular products with lumpy demand pattern with the largest turnover

Only 116 IR/LU products (2.6%) have had a delivered call-off order between December 2018 and November 2020 and these call-off orders account for 2.2% of the total turnover of IR/LU products. Figure 5.3 shows the demand pattern of an irregular product with a lumpy demand pattern. In months 14 to 18 there is a call-off orders of 51 items, the reason of the peak at month 7 is unknown. The call-off orders change the demand pattern significantly, but the call-off orders for IR/LU products have little share in the total turnover of irregular products.

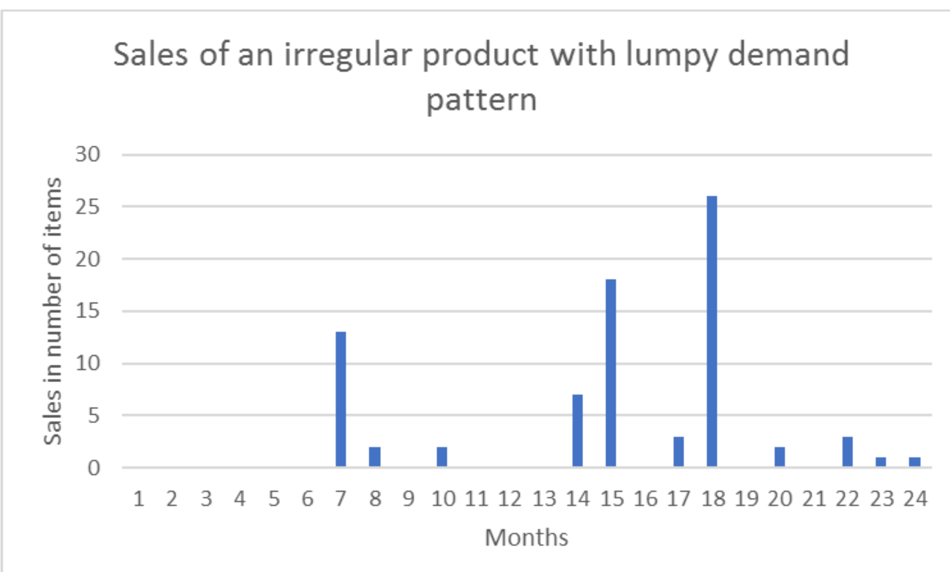

Figure 5.3: Sales of an irregular product with a lumpy demand pattern

5.2.2. Call-off order lines of frequent/normal products with a smooth/erratic demand pattern

14% of the FR&NO/SM&ER have had a delivered call-off order and these call-off orders only account for 1.3% of the total turnover of FR&NO/SM&ER. Figure 5.4 shows the demand pattern of a normal product with an erratic demand pattern. The peak in month 10 is not caused by call-off orders, multiple customers order large quantities in normal orders in this month. The peak at month 15 is due to a call-off orders of 2 different customers. In the months 18-21, one customer had a call-off order of 438 items.

The share of call-off orders in the total turnover of IR/LU and FR&NO/SM&ER is small, 1 to 2% respectively. The products highlighted in Figure 5.2, Figure 5.3 and Figure 5.4 have peaks in demand due to call-off orders as well as normal orders that have not been announced in advance.

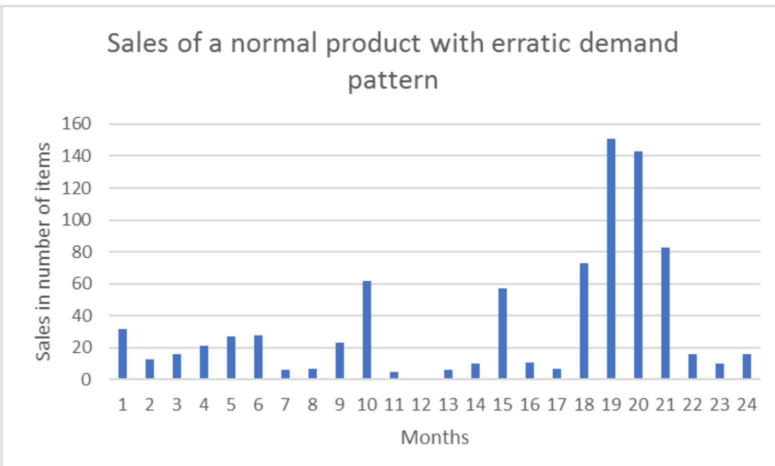

Figure 5.4: Sales of a normal product with an erratic demand pattern

5.2.3. Analysis of reduction in the duration of call-off orders in stock

On average, there are 85 days between the entry of the call-off order line and the date that the first delivery is expected, with a median of 45 days. Table 5.4 shows that the lead time of the products is on average nine days. As indicated earlier, the call-off order line is added to the reorder level of a product, so the call-off order line is immediately in stock after the delivery of the call-off order line by the supplier. Table 5.4 and Figure 5.5 show that a call-off order is often placed in stock too early, which results in a temporarily high inventory value.

(in days)	Lead time of the call-off order line	Time between entry of call-off order line and the first delivery
Mean	9	85
Median	8	45
Minimum	1	1
Maximum	121	922

Table 5.4: Comparison of the lead time and the time between the entry and first delivery of a call-off order line

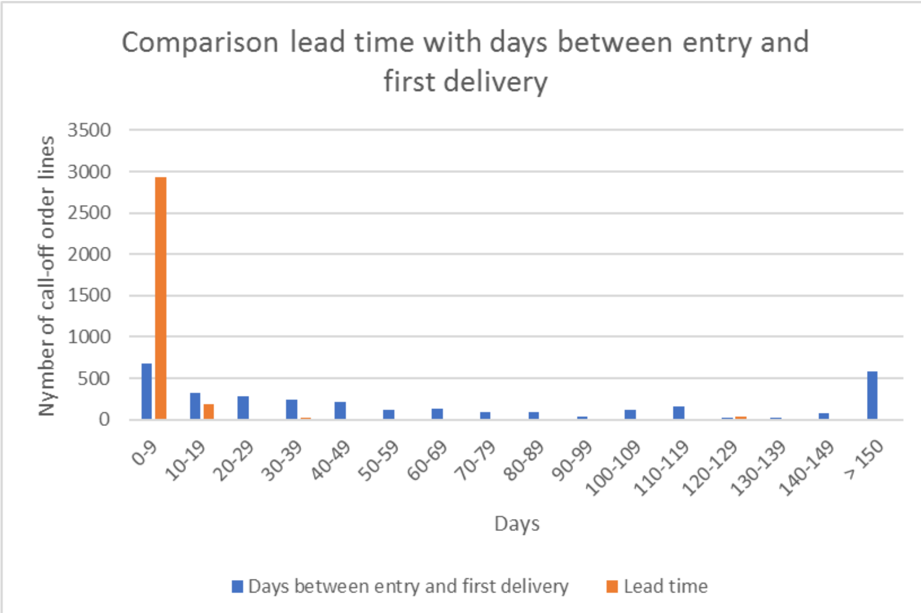

Figure 5.5: Comparison of the lead time with days between entry and first delivery of call-off order

First, it is checked how many days a call-off order lines will be entirely or partially removed from stock for the first delivery. 77% of all call-off order lines are removed from stock one working day before the date of the first delivery. It is assumed that the date of the first delivery is not adjusted in the meantime. One working day means that the actual days between the withdrawal of the call-off order line and the first delivery can be more than one day due to a weekend or one or more holidays. 52% of the call-off order lines are removed from stock one days in advance, 0.01% 2 days, 20% 3 days, 3% 4 days and 2% 5 days. Because 21% of the call-off order lines are cancelled in its entirety, it means that almost all call-off order lines are removed from stock one working day in advance. Only 2% will be removed from stock later than the date of the first delivery or more than 5 days in advance, of which only 7 call-off order lines were withdrawn from stock more than 5 days in advance. Because a large part of the call-off order lines is taken from stock 1 working day in advance of the date of the first delivery, the call-off order can be taken from stock at a later time. As a result, there is also a change that the call-off order line that is cancelled, have not yet been placed in stock. There is no data available about when the call-off order lines were cancelled. It must be ensured that the call-off order lines are in stock 1 working day in advance, which can mean 5 normal days due to holidays and weekends. If a call-off order line is ordered from the supplier, a minimum of one day of processing time is also required within Van Walraven. A safe margin It is therefore safe to stock a call-off order line 7 days in advance.

The shortening of the time that a call-off order line is in stock to 7 days is compared to the current situation in which a call-off order is immediately put in stock. For each product *i*, the time in days between entering the call-off order line *c* and the first delivery is now indicated with $W_{i,c}$. The lead time in days of product *i* is indicated with L_i. Call-off order lines with $L_i > W_{i,c}$ are excluded from the comparison in this section, because it is assumed that these call-off orders must be delivered directly from stock of Van Walraven. In addition, call-off order lines that have not been delivered to the customer are not included. For this comparison it is assumed that each call-off order line must be ordered from the supplier, this means that a call-off order line is in stock for a maximum of $W_{i,c} - L_i$ time. A summary of the comparison made in this section is shown in Table 5.5. The average inventory value per day is used to show how much value these call-off order lines have per day. The average inventory value is calculated using the following formula:

$$Average\ inventory\ value\ per\ day = \frac{Number\ of\ items * purchase\ price * days\ in\ stock}{365}$$

The number of items in the formula are the number of items of the whole call-off order line. It is not known in advance whether the customer purchases the entire call-off order at once. The first column in Table 5.5 shows the decrease in the number of days in stock and the average inventory value per day if call-off orders are placed in stock 7 days in advance. The last column shows the totals of all call-off order lines where at least one piece was sold and with $W_{i,c} > L_i$. The average inventory value per day of call-off orders is reduced by 90%. However, this means that if the call-off order lines are put in stock 7 days in advance, 6 call-off order lines will not be in stock if the customer wants the call-off order line earlier. This is only 0.003% of the total call-off order lines. This means that the inventory value of call-off orders can be significantly reduced by placing a call-off order in stock 7 days in advance of the announced first day of delivery while maintaining the service. This can be given as advice to Van Walraven.

	Call-off order lines with $W_{i,c} - L_i > 7$	**Total call-off order lines with $W_{i,c} > L_i$**
Number of call-off order lines	1698	2180
Reduction days in stock	102,263 (89%)	115,498
Reduction of average inventory value per day	€44,809 (90%)	€ 49,531

Table 5.5: Comparison of days in stock of call-off order lines

5.2.4. Cancelled call-off orders

In two years, almost 3/4th of all call-off order lines have been sold. The cancelled call-off orders remain as stock. The cancelled call-off orders are 5% of the total current inventory value. Multiple large call-off orders have been cancelled and these are responsible for most of the value of the cancelled call-off order. As indicated earlier, no further information is available about the time of cancellation and the reasons for this. The exact reasons for cancelling call-off orders are unknown. The type of customer who cancels the most call-off order lines are installers. This is also reflected in the type of product that is cancelled the most: pipe systems for both supply and drainage. 6% of the supply pipe system products have a call-off order line, of which 38% of these products have a full or partial cancellation. Of these supply pipe system products with cancellations, 52% fall into the FR&NO/SM&ER category. In addition, 11% of the drainage pipe system products have a call-off order line and 43% of these lines have been cancelled. Of these drainage pipe system products with cancellations, 80% fall into the FR&NO/SM&ER category. Because the FR&NO/SM&ER products have a large sales volume, it can be assumed that cancelled call-off order lines are sold to another customer and no excess stock remains. The two product groups with the greatest number of products in the assortment of Van Walraven are also the piping system for supply and drainage, besides they also have the highest turnover and current inventory value. Many products increase the likelihood of applications of call-off orders, which also increases the likelihood of cancellations. This may be the reason that call-off order lines of pipe systems products ordered by installers have the most cancellations. It is possible that the impact of the cancellations on the current inventory can be reduced by putting the call-off order line in stock at a later moment. This means that there is a chance that the call-off order line is not yet in stock when it is cancelled.

5.3. Project products

Due to the consultation of Van Walraven's account manager with the customer about specific project, special project products are placed in stock for the project, which only the customer of that project can use. These products are only included in the assortment for this project and will expire at the end of the project. This is a service that is offered so that the customer can buy all products for the project at Van Walraven. Otherwise, a customer must buy this product from a competitor. In addition, Van Walraven takes care of the storage of the products for that project, because there is often little storage space on the construction site. Several current project products are for a customer of an affiliate of Van Walraven. The affiliates also have less space for large storage of products, therefore Van Walraven Mijdrecht serves as storage for the affiliate.

At this moment, 37 project products are in the assortment. The project products have no forecast and are order-driven. The stock is either replenished by consultation of the account manager and the customer or call-off order lines are entered for the products that are ordered immediately. As a result, project products are not used as ADI, because these order-driven products do not have a reorder level.

5.4. Conclusion sub-question 2

This section gives the answer to sub-question 2:

Sub-question 2: How can perfect or imperfect advance demand information be used in inventory management?

The use of quotations and call-off orders as advance demand information has been studied. For perfect ADI, the use of ADI is only useful if all or no customers share ADI with the wholesaler. The value of all requested quotations is 20% of the total turnover in that period. This means that few customers request a quotation, which means that there is no perfect ADI. Moreover, the conversion rate from quotation to order is very low (12%) and there are few customers who convert a high percentage of quotations into an order. Only 2.6% of the IR/LU products have had call-off orders and these call-off orders account for 2.2% of the total turnover of the IR/LU products. For the FR&NO/SM&ER products, 14% of the products had a delivered call-off order that only account for 1.1% of the total turnover of FR&NO/SM&ER products. All in all, call-off orders account for 1.5% of the total turnover between December 2018 and November 2020.

It can be concluded that a large part of the customers does not provide ADI by requesting quotations or ordering call-off orders. In addition, the conversion rate from quotation to order (12%) is very low and 27% of the call-off order lines are cancelled, the risk of including quotations and call-off orders as perfect or imperfect ADI is very high. Therefore, it is not appropriate to include quotations and call-off orders as ADI in the inventory control model.

Nevertheless, the inventory can be reduced by placing call-off orders in stock at a later moment. At this moment, call-off orders are directly added to the reorder level in Slim4. It appears that 76% of the call-off order lines are removed from stock one working day before that date of the first delivery (which is known at the moment that the call-off order is ordered). In order to reduce the risk that a call-off order must be delivered earlier than one working day in advance, it was investigated what the effect is of putting the call-off orders in stock 7 days in advance. The average inventory value per day of the call-off orders can be reduced by 90% if call-off orders are put in stock 7 days in advance. An additional advantage of placing a call-off order line in stock at a later moment is that a cancelled call-off order line may not have been placed in stock yet. This reduces the excess stock of cancelled call-off order lines.

6. Conceptual model

In this section the conceptual model of the forecasting method and the inventory control model is discussed. The conceptual model discusses the different steps, and in which order these steps are taken so that the inventory value of Van Walraven is minimized while maintaining the service level. In section 4 is concluded that the FR&NO/SM&ER and IR/LU products have a large share in the total current inventory value. The products with an order-driven inventory management is not included in this conceptual model, because these products do not have a forecast and a reorder level in the current system. This means that 2958 IR/LU and 5402 FR&NO/SM&ER products are included in this conceptual model. An overview of the conceptual model is given in
Figure 6.1.

First of all, the demand will be forecasted. Exponential smoothing is currently used at Van Walraven as forecast method with a smoothing factor of 20%. A detailed explanation of the forecast method used at Van Walraven is given in section 3.2.4. According to the analysis in section 4.4, the IR/LU products have no seasonal pattern or trend and with the FR&NO/SM&ER products the trend is only 1% on average of the expected demand per period. Therefore, a trend and seasonal pattern is not taken into account when forecasting demand. According to Rego and Mesquita (2015) the Syntetos Boylan Approximation (SBA) (2001) can be used for products with a smooth and erratic demand pattern and bootstrapping for products with a lumpy demand pattern. However, bootstrapping is not used to forecast lumpy demand in this study. Viswanathan and Zhou (2011) concluded that bootstrapping yields less accurate results than SBA. These results are due to the short demand history available. Syntetos et al. (2015) indicated that the SBA method performs well for products with lumpy demand pattern, as well as that the SBA method is simpler, which means that the method need less time and computer power to calculate the forecast. This means that bootstrapping is not used for calculating the forecast, but the SBA method also forecast the products with a lumpy demand pattern. As indicated earlier, the SBA only makes a new forecast of the demand if a product has in a period positive demand. The Teunter-Syntetos-Babai forecast method (TSB)

(2011) has made an adjustment to the SBA so that the forecast is made every period, this prevents the obsolescence process. Both methods are used as forecasting method in this research.
Subsequently, the inventory control model is developed, so that inventory costs are minimized. Continuous review is not manageable at a wholesaler with thousands of SKUs. Continuous review leads to many orders is a short period of time, and this results in too much work at the purchasing department. Therefore, the inventory position IP will be reviewed weekly. At the moment, Van Walraven uses a review period of one week. The order size Q and reorder level of the products are updated monthly (Rego & Mesquita, 2015). So, a (R, s, nQ)-inventory management model is used. Most products in the scope have a (R, s, nQ)-inventory model, which means that if only these products are included in the conceptual model, a clear picture of the current situation is sketched. In addition, the calculations made with a (R, s, nQ)-inventory model require little computer power, so the results can be calculated quickly. This means that only the 2414 IR/LU and 3397 FR&NO/SM&ER products with a (R, s, nQ)-policy are included in the development of the inventory management model. All these products are inventory driven. The demand follows the normal distribution according to the K-S test in the data analysis. When determining the reorder level, an aggregate service constraint is added. In the current situation, the products per ABC/XYZ class have been assigned a service level. The inventory management model developed in this study involve service level differentiation. This means that each product is assigned its own fill rate and this fill rate satisfies an aggregate fill rate constraint. The aggregate fill rate is the weighted average of all products. The weights are based on volume or turnover. A slightly simplified version of the service level differentiation heuristic from Donselaar et al. (2021) is used to determine the reorder level.

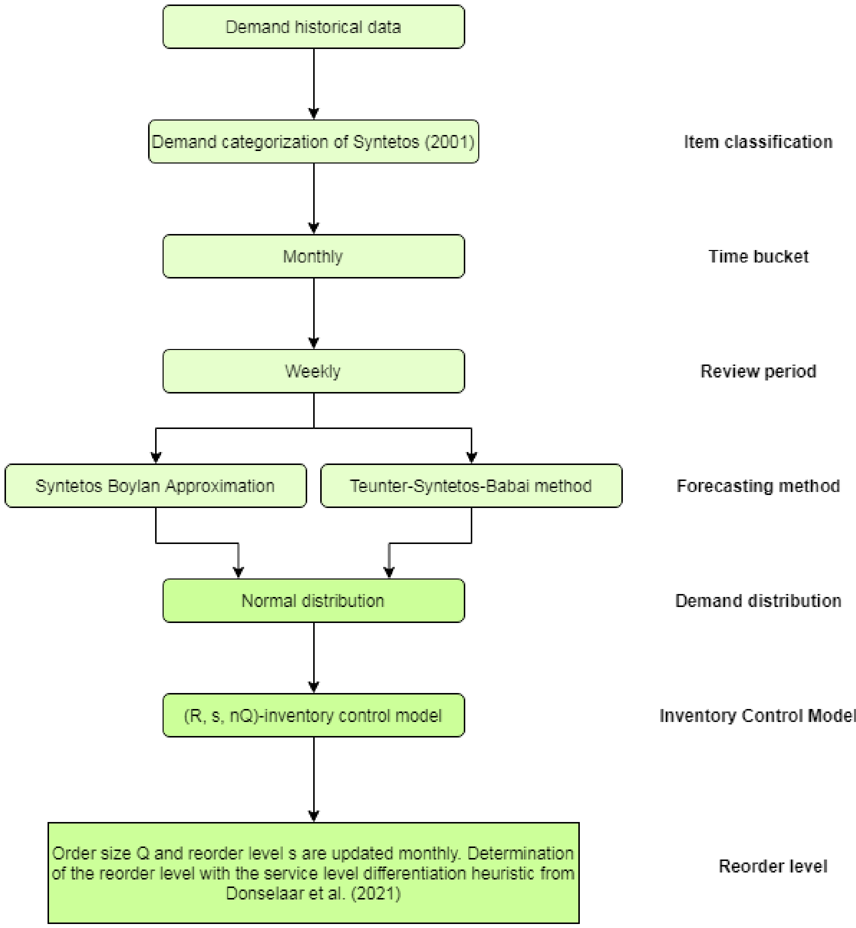

Figure 6.1: Overview of the conceptual model

7. Forecast model

The operation of the SBA and TSB forecasting methods are described in this section and then the performance of these methods is tested. The performance of these methods is compared with the current forecast method used at Slim4. When forecasting the demand in Slim4, exponential smoothing is used with a smoothing constant of 0.2. The current forecasting method is explained in detail in section 3.2.4. This states that the trend and seasonal pattern are also included in the forecast of the demand. However, in section 4.4 it has been shown that the influence of a trend and seasonal pattern is very small. Therefore, it is assumed that there is no trend or seasonal pattern. Finally, the performance is also compared with exponential smoothing in which the smoothing constant α is optimized. This method has been added to the comparison to examine if a variable (optimized) α performs better than a fixed α. The SBA and TSB methods are an extension of the exponential smoothing, because two smoothing estimates and therefore two smoothing constants are used. The mathematical model using the smoothing estimates and constants of the SBA and TSB forecasting methods are explained in section 7.1. Subsequently, the smoothing estimates are initialized in section 7.2, after which the smoothing constants are optimized in section 7.3 The performance of the four methods, SBA, TSB, exponential smoothing with $\alpha = 0.2$ and exponential smoothing with an optimized α, are discussed in section 7.4.

7.1. SBA and TSB method

The SBA has two smoothing estimates: the average interval between two demand moments I_t and the average demand size S_t. The smoothing estimates are only adjusted in periods with positive demand. Two smoothing constants are used for the calculation of the smoothing estimates: α and β (Axsäter, 2015). The two smoothing constants must satisfy the condition that 0 ≤ α and β ≤ 1. The SBA can be described in mathematical terms as formula (6). The SBA method is an extended version of exponential smoothing if the demand is always positive; then $\beta = 0$ and $I_t = 1$, the formula of the SBA method is equal to the formula of exponential smoothing.

$$F_{t,t+1} = \left(1 - \frac{\beta}{2}\right)\frac{S_t}{I_t} \tag{6}$$

$$If\ D_t = 0 \begin{cases} S_t = S_{t-1} \\ I_t = I_{t-1} \end{cases}$$

$$If\ D_t > 0 \begin{cases} S_t = \ \alpha D_t + (1-\alpha)\, S_{t-1} \\ I_t = \ \beta x + (1-\beta)\, I_{t-1} \end{cases}$$

The TSB method (2011) is comparable to the SBA method, except that the TSB also includes the risk of obsolescence in the calculation of the forecasted demand. This means that the demand interval I_t is replaced by the demand probability C_t, because the demand probability can also be updated in periods without demand. The use of the demand probability instead of the demand interval is a small adjustment, because the demand interval is the inverse of the demand probability. The TSB is defined in mathematical terms in formula (7). As can be seen in TSB's formula, the forecast is updated downwards in periods with zero demand. If the demand remains zero for several consecutive periods, the forecast will also slowly go to zero. The size of β determines the rate at which the forecast goes to zero. The greater β, the faster the forecast will reach zero.

$$F_{t,t+1} = \ C_t * S_t \tag{7}$$

$$If\ D_t = 0 \begin{cases} S_t = S_{t-1} \\ C_t = C_{t-1} + \ \beta(0 - C_{t-1}) \end{cases}$$

$$If\ D_t > 0 \begin{cases} S_t = \ \alpha D_t + (1-\alpha)\, S_{t-1} \\ C_t = \ C_{t-1} + \beta(1 - \ C_{t-1}) \end{cases}$$

The parameters used for SBA and TSB in formulas (6) and (7) are defined as:

$F_{t,t+1}$:	Forecast of the demand mate in period t for period t+1
I_t:	Estimate of average interval between two positive demand at the end of period t
S_t:	Estimate of the size of a positive demand at the end of period t
C_t:	Estimate of the demand probability at the end of period t
D_t:	Demand in period t
x:	Number of periods since the preceding positive demand
∝:	Smoothing constant for demand size

β: Smoothing constant for demand occurrence

7.2. Initialization smoothing estimates

In this section the smoothing estimates are calculated from the SBA method: S_t and I_t, and from the TSB method: S_t and C_t. The S_t for exponential smoothing is calculated in the same ways as for the SBA and TSB methods (Makridakis & Hibon, 1991). The formula of the SBA method with $\beta = 0$ and $I_t = 1$ can be used for exponential smoothing if the demand is always positive. The initialization procedure of (Romeijnders, Teunter, & Van Jaarsveld, 2012) and the data selection from the scope from December 2018 and November 2020 are used. The period between December 2018 and July 2019 is used to initialize the smoothing estimates and the period between August 2019 and March 2020 are used in the next section for the optimization of the smoothing constants. An initialization period and optimization period of 8 months has been chosen. The item classification is based on the categories of Slim4 and Syntetos (2001). Slim4 calculates this category over the demand data of the past year. Syntetos (2001) takes into account the period between the first and last moment of demand in the past two years. This means that the first year (December 2018-November 2019) of demand data can differ for products belonging to the same category. That is why it has been decided to include 4 months of the first year of demand data in the calculation for the optimization of the smoothing constants in section 7.3.

With $|T|$ as number of months in the initialization period with a positive demand, the mathematical formulas for the smoothing estimates in period 0 are (Romeijnders et al., 2012):

$$I_0 = \frac{8}{|T|}$$

$$S_0 = \frac{1}{|T|} \sum_{t \in T} D_t$$

$$C_0 = \frac{|T|}{8}$$

7.3. Optimization smoothing constants

A sensitivity analysis is needed to calculate the optimal smoothing constants α and β for the SBA and TSB methods. These methods assume that both α and β are between 0 and 1. The higher the smoothing constant α, the more value is placed on the recent positive demand. In addition, a high β means that more value is attached to the last interval between two positive demand moments. At the TSB, if the demand is positive in all months, C_t is equal to one for all forecasts. In that case the TSB method is equal to exponential smoothing, because the β no longer has any influence on the forecast of the TSB method due to $C_t = 1$, only the α has an effect.

Romeijnders et al. (2012) developed a sensitivity analysis and calculated one optimal α and one optimal β as a constant for all spare parts. In the sensitivity analysis in this section, the optimal smoothing constants per SKU are calculated separately, this is due to the difference in demand of SKUs per item classification because the first year of the demand data may differ, this is explained in section 7.2. The demand data of 8 months, August 2019 to March 2020, are used for this optimization. The Mean Squared Error (MSE) has been used as an empirical optimization for calculation the optimal α and β. It is a suitable performance measure because the MSE contains both the variance of the estimator and the bias (average estimation error). Unfortunately, the MSE is sensitive for outliers. The MSE is calculated by formula (8).

$$MSE = \frac{1}{8}\sum_{t=0}^{7}\left(D_{t+1} - F_{t,t+1}\right)^2 \tag{8}$$

For each SKU, the optimal α and β for the SBA and TSB method have been calculated by selecting 20 values between 0.05 and 1 for each smoothing constant. The demand forecast of 8 months is calculated with these smoothing constant values. Subsequently, the MSE is calculated per α and β combination, this means that 400 MSE values have been calculated for each product. Finally, the optimal α and β have been chosen which, in combination, has the lowest MSE value and thus has the smallest difference between the forecasted demand and the actual demand. Figure 7.1 provides a graphical overview of the forecast of SBA and TSB relate to the actual demand of an IR/LU product. The calculations of the demand forecasts of the SBA and TSB of this product are shown in appendices B and C. The optimization of the smoothing constants with the MSE is also shown in these appendices.

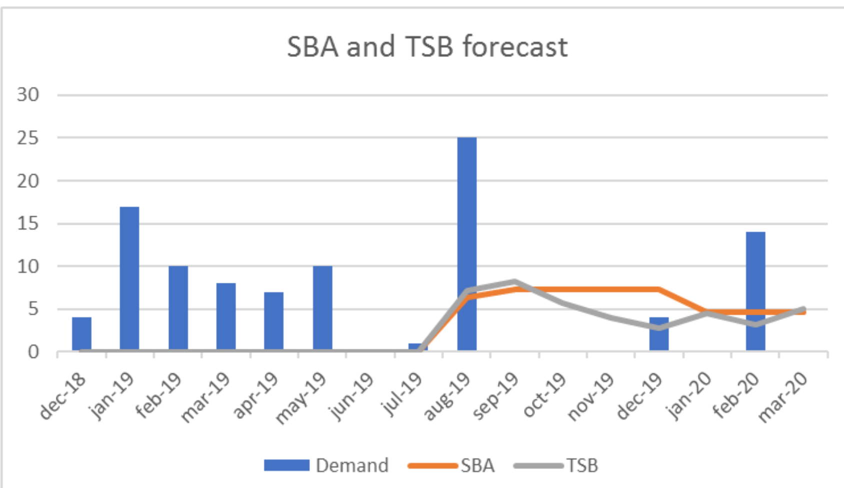

Figure 7.1: SBA and TSB forecast with the actual demand

7.4. Performance of the forecast methods

The performance of the SBA, TSB, exponential smoothing with $\alpha = 0.2$ (EXP 0.2) and exponential smoothing with an optimized alpha (EXP) are compared in this section. For the exponential smoothing with an optimized alpha, the alpha per product with the lowest MSE value is used. Forecasts are only made for inventory-driven products. 117 FR&NO/SM&ER and 278 IR/LU products are not included in this performance comparison. These products have no sales during the initialization period, which means that no estimates can be calculated and therefore no optimization can be made. A test set of the sales of 8 months was used to calculate the forecast, this is the period from April 2020 to November 2020.

The optimal α and β have been used from the optimization phase of section 7.3. For the SBA and TSB method, the I_0, S_0 and C_0 are equal to the last value from the optimization phase with the optimal α and β. These values are used to calculate the forecast based on the first month of sales in the test phase. $F_{1,2}$ at exponential smoothing is in the test phase, equal to the sales in month 1. The performance of the methods has been tested with the MSE, Root Mean Squared Error (RMSE), bias and Mean Absolute Deviation (MAD). The formulas of these performance measures are shown below. The MSE and RMSE are both sensitive to outliers, but the outlier has a smaller share in the RMSE due to the root. The sum of all biases draws towards zero because the positive and negative values cancel each other out. That is why the absolute value of the bias is also calculated. The absolute value of the bias gives a better overview than the bias, which forecasting method deviates less from the actual demand.

$$MSE = \frac{1}{7}\sum_{t=1}^{7}\left(D_{t+1} - F_{t,t+1}\right)^2$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{7}\sum_{t=1}^{7}\left(D_{t+1} - F_{t,t+1}\right)^2}$$

$$Bias = \frac{1}{7}\sum_{t=1}^{7} D_{t+1} - F_{t,t+1}$$

$$MAD = \frac{1}{7}\sum_{t=1}^{7}\left|D_{t+1} - F_{t,t+1}\right|$$

Table 7.1 shows the performance of the forecasting methods used in this research. The values in this table are the sum of the performance measure of all products. The FR&NO/SM&ER product group has been split into FR/SM, FR/ER, NO/SM and NO/ER, so that it is possible to analyse which forecast method works best per type of demand pattern. In addition, other studies are looking for a suitable forecast method for each type of demand pattern. Splitting FR&NO/SM&ER product group facilitates comparison with other studies. The RMSE is used as the main performance measure. Based on the MSE, RMSE and |Bias|, the TSB method performs best for both products groups together, but the difference with the SBA method is small. This difference is small because the SBA method performs better with the IR/LU products and the TSB method performs better with the FR&NO/SM&ER products. The FR&NO/SM&ER products have higher values for the performance measures compared to the IR/LU products because the sum of the total demand of the FR&NO/SM&ER products is many times higher than for the IR/LU products. Therefore, the FR&NO/SM&ER products have a lot of influence on the total performance scores. A disadvantage of the SBA method is the greatest bias of all methods for both product groups. The |Bias| of the SBA method is also higher than the |Bias| of the TSB method, this means that the TSB method has a smaller deviation from the actual demand. Because the difference between the SBA and TSB method is small based on the RMSE, the good results of the TSB method on the performance measures MSE, bias and |Bias| indicate that the TSB method performs best for both product groups.

The TSB method forecasts best for products with a high average demand. The products for which the TSB method outperforms the SBA method have a higher average demand. The products for which the SBA method performs better are mainly products with a large standard deviation in demand. For example, the performance difference for NO/ER between the SBA and TSB method is smaller than for FR/SM, FR/ER and NO/SM. The standard deviation for the NO/ER products is greater than for the FR/SM, FR/ER and NO/SM products, which means that the SBA method performs better. The SBA method also performs well with the IR/LU products, which have a large deviation in demand and months with zero demand. The TSB method performs better for the IR/LU products than the SBA method if there were at least 13 of the 16 months with zero demand in the optimization phase. Only 6% of IR/LU products have zero demand for at least 13 months. If there were more months of demand in the optimization phase, the SBA method appears to work better than the TSB method for the IR / LU products

According to the K-S test from section 4.5, almost all FR&NO/SM&ER products and 78% of the inventory-driven IR/LU products follow the normal distribution. Because the FR&NO/SM&ER products can best be forecasted by the TSB method and the IR/LU products by the SBA method, the demand distribution does not appear to determine the performance of the forecasting method. The performance of the forecasting method mainly depends on the average and standard deviation of the demand.

Another finding is that EXP 0.2 outperforms EXP. This is remarkable because at EXP the optimal alphas of all products have been used. The difference between the performance of EXP and EXP 0.2 is mainly due to products that have a significantly different demand pattern in the test phase than those products had in the optimization phase. These products show two different demand patterns in the test phase. The first demand pattern has an alternating demand pattern with zero demand periods and periods with demand of more than 1000 units. These products often have a high α (0.75 to 1), which means that more value is attached to the last positive demand. A high α reacts strongly to changing demand and therefore has large deviations when there are periods with high demand and after that a period with zero demand. EXP 0.2 forecasting method performs better with these products because a lower α responds better to large fluctuations in the demand than a high α. The other demand pattern is that a product has high sales in the first 1 to 3 months in the test phase and after that there are months with zero demand. Most of these products have been assigned an $\alpha = 0.05$ from the optimization phase, which means that it reacts slowly to the current demand. The EXP 0.2 forecasting method responds more quickly to the decreasing demand compared to $\alpha = 0.05$, which makes that EXP 0.2 performs better than EXP.

Other studies (Babai, Dallery, Boubaker, & Kalai, 2019; Romeijnders et al., 2012; Teunter et al., 2011) showed that the TSB method performed better than the SBA method for products with lumpy demand patterns and periods with zero demand. Based on the bias and |Bias| the results in this study are consistent with the other studies. However, in this research, the SBA method perform better in forecasting IR/LU products based on the MSE, RMSE and MAD. As indicated earlier, the TSB method for the IR/LU method only performs better than the SBA method, if there are many months with zero demand. Because only 6% of the IR/LU products have few months of sale, the SBA method performs better with the IR/LU products in this study. Including the demand interval as an extra smoothing estimate in the SBA and TSB method ensures that the SBA and TSB method performs better than the exponential smoothing. Only the bias from the two exponential smoothing methods are lower for both product groups than the SBA and TSB method.

This research partly supports the results of the research of Mor, Nagar and Bhardwaj (2019). The most suitable forecasting method is determined for each demand categorization group of Syntetos (2001).

According to them, the SBA method outperforms exponential smoothing in forecasting intermittent and lumpy products. They recommended using exponential smoothing for forecasting erratic products and both methods are suitable for forecasting smooth products. Table 7.1 shows that the SBA method outperforms exponential smoothing for both products groups, but only the MSE for EXP 0.2 for IR/LU is better than de SBA method. Based on the other performance measures, this research supports the finding that SBA is suitable for intermittent and lumpy products, but it does not support the finding that exponential smoothing is more suitable for erratic products. The TSB method for products with a smooth or erratic demand pattern perform even better than the SBA method. Mor et al. (2019) did not include the TSB method in their research.

	IR/LU ($\sum \mathbf{Demand} = \mathbf{29,035\ pcs}$) *Number of items: 2680*				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	20,414,282	69,492	8,271	26,866	49,860
TSB	22,880,019	74,638	268	24,925	54,990
EXP	23,902,898	77,721	2,526	26,334	56,512
EXP 0.2	19,287,214	72,925	3,249	28,454	53,581
	FR/SM ($\sum \mathbf{Demand} = \mathbf{509,278\ pcs}$) *Number of items: 445*				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	229,658,441	178,478	35,708	68,145	148,455
TSB	225,902,313	175,196	12,174	61,849	145,568
EXP	261,717,815	193,751	8,384	93,997	162,892
EXP 0.2	247,542,605	186,471	8,761	79,361	155,281
	FR/ER ($\sum \mathbf{Demand} = \mathbf{8,332\ pcs}$) *Number of items: 30*				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	2,234,270	6,392	2,150	2,971	4,831
TSB	1,891,612	5,978	1,140	2,147	4,556
EXP	2,338,528	6,480	2,709	2,950	5,188
EXP 0.2	2,211,279	6,351	2,582	2,988	5,054
	NO/SM ($\sum \mathbf{Demand} = \mathbf{371,425\ pcs}$) *Number of items: 2132*				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	200,546,203	214,857	43,586	82,858	176,888
TSB	186,981,898	209,161	7,020	64,357	173,270
EXP	213,715,504	233,553	2,723	106,404	194,085
EXP 0.2	191,375,125	221,359	5,767	92,338	181,418
	NO/ER ($\sum \mathbf{Demand} = \mathbf{195,918\ pcs}$) *Number of items: 2678*				

	MSE	RMSE	Bias	|Bias|	MAD
SBA	120,310,014	201,362	47,125	80,289	153,721
TSB	117,143,411	201,216	14,780	64,950	157,568
EXP	173,193,669	221,917	4,987	94,457	175,696
EXP 0.2	146,477,447	213,268	3,205	90,205	168,060
	Total				
	MSE	RMSE	Bias	|Bias|	MAD
SBA	573,163,210	670,582	136,841	261,129	533,755
TSB	554,799,252	666,188	35,382	218,229	535,952
EXP	674,868,413	733,421	21,328	324,143	594,373
EXP 0.2	606,893,670	700,374	23,564	293,346	563,393

Table 7.1: Performance of the forecast methods

The optimal α and β for the TSB method have been calculated for each product. The FR&NO/SM&ER and IR/LU products together, 46% of the products have an α of 0.05. 11% of the products have an α of 1. The rest of the products are evenly distributed over the alphas between 0.05 and 1. The β is similarly distributed as the α, only more products have a β of 0.05. 64% of the products have a β of 0.05 and 13% of the products have a β of 1. A low α and β means that the focus is less on the recent positive demand and the last interval between two positive demand moments.

7.5. Conclusion sub-question 3

This section gives the answer to sub-question 3:

Sub-question 3: What is the best demand forecasting method considering the item classification?

The TSB method performs best for both product groups together, but the difference with the SBA method is small. This is because the TSB method performs better with FR&NO/SM&ER products and the SBA method performs better with IR/LU products. A disadvantage of the SBA method is the large bias, which means that the SBA method has the greatest deviation from the actual demand. The TSB method outperforms the SBA method in all product group categories with a high average demand. As the standard deviation increases, the difference between the TSB method and the SBA method becomes smaller, as with the NO/ER products. The IR/LU products have a large standard deviation and the SBA method forecasts this product group best. Only when the demand history of an IR/LU products has at least 13 months with zero demand in the optimization phase, the TSB method performs better. Both the FR&NO/SM&ER and IR/LU products largely follow the normal distribution. Because a different forecasting method is most suitable for the product groups, the normal distribution of demand does not seem to influence the choice of the forecasting method. It is mainly about the size and standard deviation of the demand.

8. Inventory control model

The inventory management model used in this study is explained in this section. The goal of this model is to find the optimal reorder level s at minimal inventory cost. Service level differentiation is applied, which means that each SKU is assigned a service level and no longer that a group of SKUs is assigned a service level. The theoretical inventory management model with service level differentiation from Donselaar et al. (2021) has been used. The model is explained in section 8.1. Subsequently, section 8.2 explains how this theoretical inventory control model is implemented in the DoBr tool. Finally, the performance of the inventory management model with service level differentiation is compared with the current situation and this is discussed in section 8.3.

8.1. Theoretical model

Donselaar et al. (2021) minimizes the total inventory cost for a group of items with a restriction that the aggregated weighted fill rate is greater than or equal to the target fill rate P_2^*. The weight for SKU i in the restriction is based on the average demand per period for SKU i. Inventory is managed according to the (R, s, nQ)-inventory control model. This means that the inventory is periodically reviewed. If the IP is less than or equal to the reorder level s, the largest multiple of Q items is ordered so that $IP \geq s$. In addition, the demand per period is continuous with probability density function $f(x)$. Before the model is presented, the main variables used in this research are explained. The variables are based on Donselaar et al. (2021). After the explanation of the variables, the objective function and the restriction are described by formula (9) as a function of the fill rate and the inventory on hand at a certain point in time. The formulas used in this research are based on Donselaar et al. (2021) and Donselaar and Broekmeulen (2015). The difference with Donselaar et al. (2021)'s research is that they have assumed that the demand is gamma distributed. However, in this study the demand is normally distributed. In addition, Donselaar et al. (2021) analyzed products with different demand patterns as one group. This research distinguishes between demand patterns and analyzes how the weights should be expressed in service level differentiation so that inventory reduction can be achieved with an equal or improved aggregated service.

I:	Set of all items
$f_i(x)$:	Probability density function of the demand per period for SKU i
μ_i:	Average demand per period for SKU i
σ_i:	Standard deviation of the demand per period for SKU i
L_i:	Lead time for SKU i
R_i:	Review period for SKU i
τ:	Review moment
Q_i:	Lot-size for SKU i
s_i:	Reorder level for SKU i
$P_{2,i}$:	Fill rate for SKU i
w_i:	Weight factor for the fill rate of SKU i
X_i^+:	Inventory on hand at an arbitrary moment for SKU i
X_i^-:	Outstanding backorders at an arbitrary moment for SKU i
IP_i:	Inventory position at an arbitrary moment for SKU i
$D_{i,t}$:	Demand of SKU I during time period t
h_i:	Holding costs per unit period for SKU I
λ:	Lagrange multiplier

$$Min \sum_{i \in I} h_i E[X_i^+] \quad (9)$$
$$s.t. \sum_{i \in I} w_i \, P_{2,i} \geq P_2^*$$
$$\sum_{i \in I} w_i = 1$$

Donselaar et al. (2021) have derived four heuristics for different scenarios that help to solve the problem of formula (9). The heuristic with the least approximations and the most accurate approximations performs best in all scenarios outlined by Donselaar et al. (2021). This heuristic is based on exact expressions for a single product period review system with lot-sizing. The expected inventory is the only approximation in this heuristic. This heuristic is used for this study because it is suitable for an (R, s, nQ)-inventory control model. In addition, the heuristics performs very well, and the results almost correspond to the optimal reality. The objective function of formula (9) is rewritten so that an approximation can be found for solving the objective function. The objective function with this heuristic is described with a Lagrange multiplier as:

$$Min \sum_{i \in I} h_i E[X_i^+] + \lambda \left\{ P_2^* - \sum_{i \in I} w_i P_{2,i} \right\} \quad (10)$$

The system is first analysed at review moment τ. If an order is placed at that moment, this order will arrive at time $\tau + L$, where L is the lead time. During the next review moment at $\tau + R$, it is checked whether an order is needed again. This order then arrives at time $\tau + L + R$. If the lot-size Q is greater than the average demand during the review period, a new order is not required every period. Therefore, the time interval $[\tau + L, \tau + L + R)$ is called the 'potential' delivery cycle.

The expected inventory on hand is described in a periodic review system as the average inventory on hand at the beginning and at the end of a potential delivery cycle. This is the inventory on hand just after a potential delivery $(\tau + L)$ plus the inventory on hand just before a potential delivery $(\tau + L + R)$, and this must be divided by two. In mathematical terms the expected inventory on hand is described with formula (11). The expected inventory on hand at a certain moment $\tau + t$ with $t \in [L_i, L_i + R_i)$ is the expected inventory position at time τ minus the expected demand during t periods plus the expected outstanding backorders at time $\tau + t$ (Donselaar & Broekmeulen, 2015). In mathematical terms, the expected inventory on hand at an arbitrary point in time is described by formula (12).

$$E[X_i^+] \approx \frac{(E[X_i^+(\tau_i + L_i)] + E[X_i^+(\tau_i + L_i + R_i)])}{2} \quad (11)$$

$$E[X_i^+(\tau_i + t)] = E[IP_i(\tau_i)] - E\left[D_{i,t}\right] + E[X_i^-(\tau_i + t)] \quad (12)$$

Hadley and Whitin (1963) proved that the inventory position at time τ (IP(τ)) follows a uniform distribution after the interval $[s_i, s_i + Q_i)$ when the demand is continuous. This means that the expected inventory position at time τ is:

$$E[IP_i(\tau_i)] = s_i + \frac{Q_i}{2} \tag{13}$$

The fill rate $P_{2,i}$ in formula (10) is equal to the part of the demand that can be supplied directly from stock. That means that $1 - P_{2,i}$ is equal to the part of the demand which has been backordered. These are the expected additional backorders in the time interval $(\tau + L, \tau + L + R)$ divided by the average demand during this interval:

$$P_{2,i} = \frac{(E[X_i^-(\tau_i + L_i + R_i)] - E[X_i^-(\tau_i + L_i)])}{\mu_i R_i} \tag{14}$$

Formula (12) of the expected inventory on hand, formula (13) of the inventory position and the fill rate $\mathrm{P}_{2,\mathrm{i}}$ of formula (14) can be written in the objective function of formula (10). This results in the objective function of formula (15). The derivation of this formula is given in Donselaar et al. (2021).

$$\begin{aligned} Min \sum_{i \in I} h_i \left(s_i + \frac{Q_i}{2} - \frac{L_i + R_i}{2} \mu_i \right) + \lambda P_2^* - \lambda \sum_{i \in I} w_i \\ + \sum_{i \in I} E[X_i^-(\tau_i + L_i + R_i)] \left(\frac{h_i}{2} + \frac{\lambda w_i}{\mu_i R_i} \right) \\ + \sum_{i \in I} E[X_i^-(\tau_i + L_i)] \left(\frac{h_i}{2} + \frac{\lambda w_i}{\mu_i R_i} \right) \end{aligned} \tag{15}$$

To determine the optimal reorder level s_i, the derivative of the objective function of formula (15) is taken to s_i and this derivative is set equal to zero. Donselaar et al. (2021) describe in detail in the appendix that the derivative of $E[X_i^-(\tau_i + t)]$ with $t \in [L_i, L_i + R_i)$ is equal to $P(X_i^+(\tau_i + t) > 0) - 1$. This results in formula (16), with this formula the target ready can be determined. First it must be assumed that $P(X_i^+(\tau_i + L_i) > 0)$ is equal to 1. This means that the inventory on hand at the start of a potential delivery cycle is positive. Since the probability that the inventory on hand is higher at the beginning than at the end of a potential delivery cycle, $P(X_i^+(\tau_i + L_i) > 0)$ can be set to 1. If the target ready rate $P(X_i^+(\tau_i + L_i + R_i) > 0)$ for each item is calculated, the optimal reorder level can be determined that meets this target ready rate.

$$\frac{P(X_i^+(\tau_i + L_i + R_i) > 0)}{P\left(X_i^+(\tau_i + L_i) > 0\right)} = \frac{\lambda w_i - \frac{h_i \mu_i R_i}{2}}{\lambda w_i + \frac{h_i \mu_i R_i}{2}} \tag{16}$$

Formula (16) is used to find the reorder level for the situation with generic weights. In this study, volume-based and turnover-based weights are used. Volume-based weights depend only on the average demand, which means that $w_i = \frac{\mu_i}{\sum_{j \in I} \mu_j}$. The optimal reorder level with volume-based weights can be found with formula (17). If the reorder level is found with turnover-based weights, the weight is calculated by multiplying the purchase price with the average demand. This means that the turnover-based weights are $w_i = \frac{\mu_i v_i}{\sum_{j \in I} \mu_j v_j}$. The optimal reorder level with turnover-based weights can be found with formula (18).

For volume-based weights: (17)

$$\frac{P(X_i^+(\tau_i + L_i + R_i) > 0)}{P\left(X_i^+(\tau_i + L_i) > 0\right)} = \frac{\lambda - \frac{h_i R_i}{2}}{\lambda + \frac{h_i R_i}{2}}$$

For turnover-based weights: (18)

$$\frac{P(X_i^+(\tau_i + L_i + R_i) > 0)}{P\left(X_i^+(\tau_i + L_i) > 0\right)} = \frac{\lambda - \frac{R_i}{2}}{\lambda + \frac{R_i}{2}}$$

8.2. Inventory control model in DoBr tool

The optimal reorder level is calculated with the goal to minimise the expected inventory on hand and the target aggregated fill rate P_2^* is achieved. The aggregated fill rate is calculated as the sum of the weighted fill rate per product, with volume-based weights and turnover-based weights. The optimal reorder level is found by adjusting the Lagrange multiplier λ. By adjusting the Lagrange multiplier, the reorder level changes, which results in changes in the expected inventory on hand and the weighted fill rate.
The products follow an (R, s, nQ)-inventory control policy. The calculations for determining the reorder level, fill rate and expected inventory on hand take place in the DoBr tool. The demand follows a normal distribution. To implement the normal distribution of the demand, some formulas of section 8.1 have to be rewritten into the terms of the normal distribution. The generic expressions for the backorders and the non-stockout probability can be rewritten as formulas (19) and (20). The and ϕ are de standard normal cumulative distribution function en de standard normal probability density function.

$$\begin{aligned} E[X_i^-(\tau_i + t)] = {} & \frac{\sigma_t}{2Q}(s + Q - \mu_t)\varphi\left(\frac{s + Q - \mu_t}{\sigma_t}\right) \\ & - \frac{\sigma_t}{2Q}(s - \mu_t)\varphi\left(\frac{s - \mu_t}{\sigma_t}\right) \\ & + \frac{\sigma_t^2 + (s + Q - \mu_t)^2}{2Q}\phi\left(\frac{s + Q - \mu_t}{\sigma_t}\right) \\ & - \frac{\sigma_t^2 + (s - \mu_t)^2}{2Q}\phi\left(\frac{s - \mu_t}{\sigma_t}\right) - \left(s + \frac{Q}{2} - \mu_t\right) \end{aligned} \qquad (19)$$

$$P(X^+(\tau + t) > 0) = \frac{s+Q-\mu_t}{Q}\,\phi\left(\frac{s+Q-\mu_t}{\sigma_t}\right) - \frac{s-\mu_t}{Q}\,\phi\left(\frac{s-\mu_t}{\sigma_t}\right) + \frac{\sigma_t}{Q}\left[\varphi\left(\frac{s+Q-\mu_t}{\sigma_t}\right) - \varphi\phi\left(\frac{s-\mu_t}{\sigma_t}\right)\right] \qquad (20)$$

The steps that have been made for the calculations are explained in detail below.

Step 1: Volume-based and turnover-based ready rate

The first step is to calculate the ready rate with volume-based weights and turnover-based weights from formulas (17) and (18), because these ready rates are used to calculate the reorder level. To simplify the calculations, $P(X_i^+(\tau_i + L_i) > 0)$ is set equal to 1. This yields a solution close to the optimal solution of the heuristic used in this study. This means that the ready rate $P(X_i^+(\tau_i + L_i + R_i) > 0)$ is calculated.

The Lagrange multiplier λ is variable and can be adjusted. The holding costs are 25% of the purchase price of the product and the review period for each product is one week, which is equal to 0.23 months. As a result, the turnover-based ready rate is the same for each product. If the purchase price is very high when calculating the volume-based ready rate, then $\lambda - \frac{h_i R_i}{2}$ is negative. Since the ready rate has a range between 0 and 1, it is assumed that if the calculated ready rate is negative, it is set to 0.

Step 2: Reorder level

Input in DoBr tool: forecasted demand per month, standard deviation of the demand, case pack size, review period, lead time, target ready rate of step 1 and the demand distribution (Normal).

The ready rate from step 1 is used to determine the reorder level. Products can have a negative reorder level. This means that, for example, if the reorder level is equal to -6, an order will only be placed at the supplier if there are at least 6 backorders.

Step 3: Expected inventory on hand ($E[I^{OH}]$)

Input in DoBr tool: forecasted demand per month, standard deviation of the demand, case pack size, review period, lead time, reorder level of step 2 and the demand distribution (Normal).

The $E[I^{OH}]$ is calculated by taking the average of the inventory on hand at the start and end of a potential delivery cycle. The calculation of $E[I^{OH}]$ is explained with formulas (11) and (12). The goal is to minimize the value of $E[I^{OH}]$. The $E[I^{OH}]$ is rounded and multiplied by the purchase price, which yields the value of $E[I^{OH}]$.

Step 4: Fill rate

Input in DoBr tool: forecasted demand per month, standard deviation of the demand, case pack size, review period, lead time, reorder level of step 2 and the demand distribution (Normal).

The fill rate is calculated per product with formula (14). The reorder level calculated in step 2 is used for this calculation. This means that the fill rate per product meets the weighted ready rate from step 1.

Step 5: Aggregated weighted fill rate (P_2^*)

First, the weighted fill rate per product must be calculated. A distinction is made between volume-based and turnover-based weights. If the ready rate is based on the volume, the weighted fill rate is calculated with the average demand. The turnover-based weighted fill rate is calculated with the turnover: demand times purchase price. The weighted fill rate per product are calculated with the formulas below.

Volume-based fill rate = $\frac{Forecasted\ demand\ per\ month\ for\ item\ i}{Sum\ of\ all\ forecasted\ demand\ per\ month} * Fill\ rate\ of\ item\ i$

Turnover-based fill rate = $\frac{Forecasted\ demand\ per\ month\ for\ item\ i * purchase\ price}{Turnover\ of\ all\ items} * Fill\ rate\ of\ item\ i$

Then the aggregate weighted fill rate P_2^* is calculated as the sum of the weighted fill rate of all products.

8.3. Results inventory management model

The current inventory management model is compared with the situation in which service level differentiation is applied. The products included in this comparison have an (R, s, nQ)-inventory management policy and the products are inventory-driven products. In the current situation, order-driven products do not have a reorder level. This means that 2414 IR/LU and 3397 FR&NO/SM&ER products are included. In the current situation, the products have a service level based on their ABC/XYZ classification and this is used for calculating the reorder level in Slim4. This reorder level calculated by Slim4 is used in the comparison in this section for calculating the weighted fill rate and $E[I^{OH}]$ for the current situation. Steps three, four and five from section 8.2 have been applied, with the reorder level of Slim4 as input instead of the reorder level calculated in step 2 with the ready rate. The current situation and service level differentiation are shown in Table 8.1. The current aggregated weighted fill rates P_2^* of the IR/LU products are very low, 0.84 for volume-based weights and 0.87 for turnover-based weights. Of the IR/LU products, 1426 of the 2414 products belong to the CZ products in Slim4. This group has a fill rate of 0.5 in Slim4 and therefore have a low reorder level. As a result, the current value of $E[I^{OH}]$ is also low, because of this service level of 0.5. Therefore, the IR/LU products were also tested for an aggregated volume-based fill rate of 0.84 and an aggregated turnover-based fill rate of 0.87. Volume-based weights as well as turnover-based weights lead to an inventory decrease for both product groups, but the decrease is much bigger for volume-based weights. The service can even be improved and that still requires less inventory compared to the current situation.

	Volume-based weights				**Turnover-based weights**			
Current situation	**FR&NO/SM&ER**		**IR/LU**		**FR&NO/SM&ER**		**IR/LU**	
Number of items	3397		2414		3397		2414	
Aggr. Fill Rate	0.95		0.84		0.95		0.87	
Value $E[I^{OH}]$	€ 314,527		€ 129,738		€ 314,527		€ 129,738	
Service level differentiation	**Lagrange**	**Value $E[I^{OH}]$**	**Lagrange**	**Value $E[I^{OH}]$**	**Lagrange**	**Value $E[I^{OH}]$**	**Lagrange**	**Value $E[I^{OH}]$**
Aggregated Fill Rate 0.84	-	-	2.1	€ 45,335	-	-	-	-
0.87	-	-	-	-	-	-	4.05	€ 89,840
0.90	0.6	€ 130,366	3.8	€ 57,866	1.8	€ 243,818	5.15	€ 95,105
0.95	1.2	€ 174,919	8.15	€ 75,352	3.3	€ 286,552	9.7	€ 107,973
0.97	1.9	€ 204,845	13.3	€ 86,286	4.95	€ 311,339	14.7	€ 115,970
0.98	2.65	€ 226,268	18.95	€ 93,984	6.65	€ 327,984	20.2	€ 121,628
0.99	4.4	€ 258,694	31.9	€ 104,541	10.5	€ 352,070	32.8	€ 129,724

Table 8.1: Aggregated fill rate with service level differentiation and in the current situation

Service level differentiation is profitable compared to the current situation, especially if the weights are volume-based. These results are in line with previous studies (Donselaar et al., 2021; Teunter et al., 2017). Turnover-based weights require a higher expected inventory value than the volume-based weights. This is because the ready rate with turnover-based weights is the same for all products, because the review period of each product is one week. On the other hand, the ready rate with volume-based weights includes the holding costs in the formula, with the result that more expensive products have a lower ready rate and therefore a lower reorder level compared to the turnover-based weights situation. The more expensive products also have a lower average demand. These results are consistent with the study by Donselaar et al. (2021).

Volume-based weights

The service level differentiation causes a reduction in the value of E[I^{OH}] compared to the current situation with the FR&NO/SM&ER products at a volume-based $P_2^* = 0.95$. The FR&NO/SM&ER products can even improve their P_2^* compared to the current situation and then there is still a reduction in the value of E[I^{OH}]. The volume-based P_2^* of IR/LU products in the current situation is 0.84. Table 8.1 shows that even service level differentiation with a volume-based P_2^* of 0.99 causes a decrease in value of E[I^{OH}] of IR/LU products compared to the current situation with $P_2^* = 0.84$. If the FR&NO/SM&ER and IR/LU products aim for $P_2^* = 0.99$, the value of E[I^{OH}] of all products in both products groups is decreasing.

Turnover-based weights

As mentioned earlier, turnover-based weights cause higher inventory costs than volume-based weights. Turnover-based weights only cause a decrease in E[I^{OH}] for FR&NO/SM&ER products with $P_2^* = 0.9$, $P_2^* = 0.95$ and $P_2^* = 0.97$. The IR/LU products even have an inventory reduction at $P_2^* = 0.99$. This means that both product groups have a decrease in inventory value with service level differentiation compared to the current situation, but that FR&NO/SM&ER products can increase aggregated service level from 0.95 to 0.97 and the IR/LU products from 0.87 to 0.99. A further increase in P_2^* leads to an increase in E[I^{OH}].

Table 8.2 shows how many products have a fill rate higher than or equal to 0.9 or 0.8, or a fill rate less than 0.5 for a $P_2^* = 0.95$. The minimum service level in Slim4 are 0.5, therefore it is checked whether items have a fill rate less than 0.5. The results in this study support the findings of Donselaar et al. (2021). This means that volume-based weights lead to a lower fill rate than turnover-based weights and the fill rate for turnover-based weights have less variation. The 50% most expensive products, based on the purchase price, are also shown in Table 8.2. Especially the expensive products have a low fill rate for volume-based weights. In addition, it is also supported that the volume-based weights cause a skewed distribution of the service levels, the expensive products have a large share in the products with a fill rate less than 0.5. If many expensive products have a fill rate of less than 0.5, this means that the reorder levels and E[I^{OH}] of expensive products are low. A disadvantage of a low fill rate is that these products will have many backorders.

	All products	**50% most expensive products**	**All products**	**50% most expensive products**	**All products**	**50% most expensive products**
Type (number of items)	**FR≥0.9**		**FR>≥0.8**		**FR<0.5**	
FRNO Volume (3397)	1646	122	2263	579	434	432
IRLU Volume (2414)	1448	310	1838	649	212	210
FRNO Turnover (3397)	2827	1373	3340	1667	7	4
IRLU Turnover (2414)	1968	999	2289	1153	21	12

Table 8.2: Number of items per fill rate (FR) with an P_2^*= 0.95.

8.4. Conclusion sub-question 4

This section gives the answer to sub-question 4:

Sub-question 4: Which inventory control model should be used?

The use of service level differentiation results in a decrease in the value of $E[I^{OH}]$ compared to the current situation for IR/LU and FR&NO/SM&ER products with an (R, s, nQ)-inventory control model, at the same P_2^*. The largest reduction in inventory is realized with volume-based weights, which uses the average demand of a product. This is mainly because the ready rates for turnover-based weights are the same for all products and for volume-based weights the ready rates vary due to the difference in the purchase price (needed for the calculation of the holding costs). For example, the more expensive products generally have a lower ready rate with volume-based weights, which results in a lower reorder level, fill rate and value of $E[I^{OH}]$ with volume-based weights than with turnover-based weights. However, this does result in more backorders. Table 8.2 shows that a large number of these expensive items products have a fill rate of less than 0.5 for a volume-based $P_2^* = 0.95$.

Service level differentiation with volume-based weights is therefore recommended in situations such as at Van Walraven. The aim can be a P_2^* that is equal to the current situation, or a $P_2^* = 0.99$ for both product groups. This results in a total reduction of the inventory value and an improvement of the aggregated service level. However, the service can also be improved with turnover-based weights, which also reduces inventory. With a $P_2^* = 0.97$ for both product groups is the $E[I^{OH}]$ lower than the current situation and the service is improved. The IR/LU products can even aim for a turnover-based weight $P_2^* = 0.99$, which also results in a small inventory decrease. It is important to indicate that a company should consider whether the target aggregate fill rate is well defined so that the objective function of the company can be achieved (Donselaar et al., 2021). The purchase price of a product has a major impact on the fill rate for volume-based weights. The company has to choose between low inventory costs due to low fill rates for expensive products and more backorders (volume-based weights), or on the other hand, a higher fill rate for expensive products, fewer backorders and higher inventory costs (turnover-based weights).

9. Other improvements for reducing the inventory

Several products have a surplus buffer. This is a manually added buffer on top of the calculated safety stock. This surplus buffer is added for various reasons, for example, extra safety buffer for lumpy demand or because a new product is an order-driven product without a reorder level, and it is expected that this product will have sales. 1583 products from the data selection have a surplus buffer with a value of 75,358 euros. These products mainly have a surplus buffer because of a large customer who do not want to miss out these products for his projects. The customer needs the products constantly and not specifically for one project; therefore, no call-off order has been entered. The surplus buffer of the products in the data selection provides 3.3% of the current inventory value. However, if one looks at all products in the Van Walraven range, those products have a surplus buffer of almost 129,270 euros, which is 4.4% of the total current stock value. The products that have been kept out of the scope, which are mainly products that have had a low sales in the past two years, therefore provide almost 54,940 euros in surplus buffer. These products are usually order-driven products without a reorder level. With this surplus buffer an order-driven product is still in stock. Adding a surplus buffer to these products increases the service to the customer, but these products have had low sales in the past two years, making it difficult to sell this surplus buffer at all. The advice is to re-examine the products with a surplus buffer that have had low sales in the past two years whether a surplus buffer is necessary and otherwise remove them immediately. It must also be ensured that products with low sales are not allocated a surplus buffer.

This section has answered sub-question 5. Furthermore, the improvements investigated in this study are explained in the recommendations in section 10.2.

Sub-question 5: What improvements can be recommended based on the gained insights?

10. Conclusion

10.1. Conclusion to the research question

The conclusion of the main research question of this study is discussed in this section. The answers to the sub-questions can be taken together for a general conclusion to the main research question. The main research question of the study is:

How can an infrastructure and installation wholesaler minimize the inventory, while maintaining the service level?

The product classification of Slim4 and the demand categorization of Syntetos (2001) have made it clear that the frequent and normal products with a smooth and erratic demand pattern and also the irregular products with a lumpy demand pattern have the most inventory. Therefore, the focus of this research is on these FR&NO/SM&ER and IR/LU products.

First of all, quotations and call-off orders do not appear to be suitable as advance demand information for the inventory control model. Quotations and call-off orders are only requested and order by a small part of the customers. For perfect ADI, the use of ADI is only useful if all or none of the customers provide ADI. Quotations were requested for 20% of the turnover and only 1.5% of the turnover were call-off orders. In addition, only 12% of the quotations are converted into an order and 25% of the call-off orders are cancelled. The risk that imperfect ADI is cancelled or not converted into an order is high. If this was used as imperfect ADI and the order is cancelled or not converted, it could lead to excess stock. Nevertheless, the inventory can be reduced by placing call-off orders in stock at a later time. At the moment, call-off orders are immediately placed in stock when they are entered in the system. By placing the call-off orders in stock at a later moment, it can be prevented that cancelled call-off orders are already in stock. The average inventory value per day of the call-off orders also decreases if the call-off orders are placed in stock 7 days before the date of the first delivery, respectively a decrease of 90% of the average inventory value per day.

The IR/LU can be best forecasted with the SBA forecasting method and the TSB method performs better by forecasting the FR&NO/SM&ER products. The TSB method outperforms the SBA method in all product group categories with a high average demand. As the standard deviation increases, the difference between the TSB method and the SBA method becomes smaller, as with the NO/ER products. The IR/LU products have a large standard deviation and the SBA method forecasts this product group best. If one method has to be chosen for both products groups, the TSB method performs best. In any case, the SBA and TSB methods outperform exponential smoothing, which is currently used for forecasting demand.

The use of service level differentiation results in a decrease in the value of $E[I^{OH}]$ compared to the current situation for IR/LU and FR&NO/SM&ER products with an (R, s, nQ)-inventory control model, at the same P_2^*. The largest reduction in inventory is realized with volume-based weights, which uses the average demand of a product. This is mainly because the ready rates for turnover-based weights are the same for all products and for volume-based weights the ready rates vary due to the difference in the purchase price (needed for the calculation of the holding costs). The aim can be a P_2^* that is equal to the current situation, or a $P_2^* = 0.99$ for both product groups with volume-based weights. This results in a total reduction of the inventory value. The service can also be improved with turnover-based weights, which also reduces inventory. With a turnover-based $P_2^* = 0.97$ for both product groups is the $E[I^{OH}]$ lower than the current situation and the service is improved.

Finally, the inventory can be further reduced by removing the surplus buffer of products. The surplus buffer is manually added to the reorder level on top of the safety stock. Many order-driven and slow-moving products have a surplus buffer, because without the surplus buffer little or no inventory of these products is available. Due to the low sales of these products, it can be difficult to sell this inventory, resulting in excess stock. Removing and not adding a surplus buffer to products with very low sales can result in a reduction of the excess stock.

10.2. Recommendations

Based on the conclusion from section 10.1, the following recommendations can be given to Van Walraven to reduce the current inventory while maintaining the service level:

1. Place the call-off orders in stock at a later time, because 76% of the call-off orders are taken from stock one working days before the date of the first delivery. This reduces the current inventory value of the call-off orders if the call-off orders are placed in stock 7 days in advance and it reduces the chance that cancelled call-off orders are already in stock.
2. Reduce the products with a surplus buffer. The surplus buffers are mainly allocated to products with low sales. If the sales of these products remain that level, it can even become difficult to sell the products of this surplus buffer. A surplus buffer increases the change of excess stock.
3. Forecast the IR/LU products with the SBA forecasting method and the FR&NO/SM&ER products with the TSB method. Update the forecast monthly.
4. Implement service level differentiation for products with an (R, s, nQ)-inventory management model with an aggregate volume-based fill rate of 0.99. It is important to indicate that a company should consider whether this target aggregate fill rate is well defined so that the objective function of the company can be achieved (Donselaar et al., 2021). The purchase price of a product has a major impact on the fill rate for volume-based weights. The company has to choose between low inventory costs

due to low fill rates for expensive products and more backorders (volume-based weights), or on the other hand, a higher fill rate, fewer backorders and higher inventory costs (turnover-based weights).

10.3. Contribution to the literature

Several studies have been conducted into forecasting lumpy demand in the spare parts industry. This research shows that the TSB method does not necessarily perform better in forecasting lumpy demand than the SBA method. In other studies, the TSB method often outperforms the SBA method for products with irregular demand, because the TSB method make a forecast in periods with zero demand. This research shows that the SBA method performs better for products with a large standard deviation and that the TSB method performs better for products with a high average demand and a smaller standard deviation.

Donselaar et al. (2021) developed four new heuristics to reduce inventory by using an aggregate weighted fill rate constraint. The heuristic with the least approximations and the most accurate approximations performs best in all scenarios outlined by Donselaar et al. (2021), is used to determine the reorder level. This heuristic is based on exact expressions for a (R, s, nQ)-inventory control model. The difference with Donselaar et al. (2021)'s research is that they have assumed that the demand is gamma distributed. However, in this study the demand is normally distributed. This study supports the findings of the study of Donselaar et al. (2021) and adds that the heuristic is applicable to manage products with irregular, smooth and erratic demand.

Little literature is available on the use of ADI for products with a lumpy demand. Donselaar et al. (2001) focus explicitly on the use of ADI for products with an irregular demand in project environments. That study focused on a manufacturer. Inventory management at a manufacturer is linked to a production schedule. No research has yet been conducted into the use of ADI for irregular demand at a company, where there is no link with the production planning, but only with the inventory management. This research at the infrastructure and installation wholesaler looked whether there is available data that can be used for ADI. It appears that few customers of the infrastructure and installation wholesaler give ADI through quotation and call-off orders. So therefore, the uncertainty with IR/LU products is not removed by the use of quotations and call-off orders as ADI. This study examines how the duration of the call-off order in stock can be shortened to reduce the inventory. This improvement produces a lower inventory value per day for the call-off orders. This study starts looking at the use of ADI at wholesalers with high competition and project demand. More research can be done into the reasons for the low conversion rate of quotations and the cancellations of call-off orders.

10.4. Limitations and future research

During the optimization phase of demand forecasting, the smoothing constants with the lowest MSE are chosen for the SBA and TSB method and the alpha with the lowest MSE for exponential smoothing. There is a small probability that when forecasting demand with the SBA and TSB method, a product will have two optimal smoothing constant combinations with the same MSE. In this case, the combination with the lowest alpha is designated as the optimal combination. In addition, the lowest optimal alpha will also be chosen for exponential smoothing. In fact, both optimal combinations should be included in the test phase, but the method used in this study allows only one optimal combination.

Service level differentiation as an improvement of the current inventory control model has only been applied to products with an (R, s, nQ)-inventory control policy. This means that for products with an (R, s, S) and (R, s, S, nQ)-inventory control policy, no service level differentiation is applied. This research showed that the products with an (R, s, nQ)-inventory control policy accounted for a large share in the current inventory. In addition, the calculation of products with an (R, s, nQ)-policy require little computing time and computer power, because the MOQ and IOQ are equal, so the calculations are simplified. The research of Donselaar et al. (2020) was used for the service level differentiation and they have developed their heuristic for an (R, s, nQ)-policy. The optimal heuristic from their research was used in this research at Van Walraven could be adjusted in a future research so that service level differentiation can also be applied to products with an (R, s, S) and (R, s, S, nQ)-policy. Note that service level differentiation for those inventory control policies require more computer power and computation time.

This study used the sales data from December 2018 to November 2020. Since March 2020, the current corona crisis has been ongoing. This may have influenced the methods and studies investigated in this study, but it could also have influenced the purchasing policy of customers. Further research can be conducted into the effects of the corona crisis on management inventory control policies and demand forecasting, but also whether demand patterns will change over time due to the corona crisis. Mapping the effect of the corona crisis on sales data will help in the future to determine which data is suitable for further investigations, and which data has been influenced too much by the corona crisis and therefore cannot provide a good picture of the future.

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Appendices

A. Appendix A:

	ABC/XYZ-class	AX	AY	AZ	Total
Smooth	*Number of items*	1410	106	8	1524 (7%)
	Current inventory value	25.85%	1.15%	0.29%	27%
	Turnover	45.22%	1.71%	0.13%	47%
Erratic	*Number of items*	690	230	7	927 (4%)
	Current inventory value	11.59%	4.23%	0.34%	16%
	Turnover	14.10%	3.57%	0.21%	18%
Intermittent	*Number of items*	13	109	92	214 (1%)
	Current inventory value	0.40%	2.50%	2.30%	5%
	Turnover	0.14%	1.55%	1.41%	3%
Lumpy	*Number of items*	35	195	79	309 (2%)
	Current inventory value	0.60%	4.27%	1.82%	7%
	Turnover	0.39%	2.62%	1.06%	4%
		BX	**BY**	**BZ**	**Total**
Smooth	*Number of items*	755	227	23	1005 (5%)
	Current inventory value	2.08%	0.88%	0.10%	3%
	Turnover	3.08%	0.83%	0.08%	4%
Erratic	*Number of items*	868	633	35	1536 (7%)
	Current inventory value	3.37%	3.56%	0.22%	7%
	Turnover	3.89%	2.68%	0.13%	7%
Intermittent	*Number of items*	12	221	402	635 (3%)
	Current inventory value	0.02%	0.94%	2.62%	4%
	Turnover	0.03%	0.64%	1.18%	2%
Lumpy	*Number of items*	40	601	467	1108 (%5)
	Current inventory value	0.29%	3.97%	4.40%	9%
	Turnover	0.13%	2.34%	2.08%	5%
		CX	**CY**	**CZ**	**Total**
Smooth	*Number of items*	326	306	72	704 (3%)
	Current inventory value	0.27%	0.26%	0.14%	1%
	Turnover	0.35%	0.24%	0.05%	1%
Erratic	*Number of items*	590	1066	127	1783 (9%)
	Current inventory value	0.59%	1.40%	0.30%	2%
	Turnover	0.66%	1.14%	0.14%	2%
Intermittent	*Number of items*	9	425	3549	3983 (19%)
	Current inventory value	0.01%	0.48%	4.34%	5%
	Turnover	0.01%	0.27%	1.83%	2%
Lumpy	*Number of items*	24	1264	4194	5482 (26%)
	Current inventory value	0.02%	1.72%	9.34%	11%
	Turnover	0.02%	1.04%	3.30%	4%

Table A.1: Overview of the combination of the demand categorization of Syntetos (2001) and the ABC/XYZ-classification

B. Appendix B: SBA calculation example and smoothing constants optimization of the SBA method

Period t	D_t	x	I_t	S_t	$F_{t,t+1}$	MSE
-7	4					
-6	17					
-5	10					
-4	8					
-3	7					
-2	10					
-1	0					
0	1	0	1.14	8.14	6.41	345.50
1	25	1	1.11	8.99	7.26	52.67
2	0	1	1.11	8.99	7.26	52.67
3	0	2	1.11	8.99	7.26	52.67
4	0	3	1.11	8.99	7.26	10.61
5	4	4	1.69	8.74	4.65	21.61
6	0	1	1.69	8.74	4.65	87.45
7	14	2	1.75	9.00	4.62	21.35
8	0					
						Avg. MSE = 80.57

Table B.1: Calculation of the SBA forecast ($\alpha = 0.05$ and $\beta = 0.2$)

		α																			
		0.05	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**	**0.95**	**1**
β	**0.05**	82.62	89	95	102	109	117	125	134	143	152	162	173	184	195	207	220	234	249	264	281
	0.1	81.37	87	93	99	106	113	121	129	138	147	156	166	177	188	200	213	226	240	255	271
	0.15	80.78	86	91	97	104	111	118	126	134	143	152	161	172	183	194	206	219	232	247	262
	0.2	**80.57**	85	90	96	102	108	115	123	131	139	148	157	167	178	189	200	212	225	239	253
	0.25	80.59	85	90	95	101	107	113	121	128	136	144	153	163	173	183	195	206	219	232	246
	0.3	80.75	85	89	94	100	106	112	119	126	133	141	150	159	169	179	189	201	212	225	238
	0.35	81.00	85	89	94	99	104	110	117	124	131	139	147	155	164	174	184	195	206	218	230
	0.4	81.30	85	89	93	98	103	109	115	122	128	136	144	152	161	170	179	189	200	211	223
	0.45	81.65	85	89	93	98	102	108	114	120	126	133	141	148	157	165	175	184	194	205	216
	0.5	82.02	85	89	93	97	102	107	112	118	124	131	138	145	153	161	170	179	189	199	209
	0.55	82.41	85	89	92	96	101	106	111	116	122	128	135	142	149	157	165	174	183	193	203
	0.6	82.82	86	89	92	96	100	105	109	115	120	126	132	139	146	153	161	169	178	187	196
	0.65	83.24	86	89	92	96	99	104	108	113	118	124	130	136	142	149	157	164	172	181	190
	0.7	83.68	86	89	92	95	99	103	107	112	116	122	127	133	139	146	152	160	167	175	183
	0.75	84.13	86	89	92	95	98	102	106	110	115	120	125	130	136	142	148	155	162	169	177
	0.8	84.59	87	89	92	95	98	101	105	109	113	118	122	127	133	138	144	151	157	164	171
	0.85	85.08	87	89	92	94	97	100	104	107	111	116	120	125	130	135	141	146	152	159	166
	0.9	85.58	87	89	92	94	97	100	103	106	110	114	118	122	127	132	137	142	148	154	160
	0.95	86.10	88	90	92	94	96	99	102	105	108	112	116	120	124	128	133	138	143	149	155
	1	86.65	88	90	92	94	96	98	101	104	107	110	114	117	121	125	130	134	139	144	149

Table B.2: Overview of the MSE of the SBA forecast of a IR/LU product.

C. Appendix C: TSB calculation example and smoothing constants optimization of the TSB method

Period t	D_t	S_t	C_t	$F_{t,t+1}$	MSE
-7	4				
-6	17				
-5	10				
-4	8				
-3	7				
-2	10				
-1	0				
0	1	8.14	0.88	7.13	319.52
1	25	8.99	0.91	8.20	67.23
2	0	8.99	0.64	5.74	32.94
3	0	8.99	0.45	4.02	16.14
4	0	8.99	0.31	2.81	1.41
5	4	8.74	0.52	4.54	20.57
6	0	8.74	0.36	3.17	117.19
7	14	9.00	0.55	4.99	24.89
8	0				
					Avg. MSE = 74.99

Table C.1: Calculation of the TSB forecast ($\alpha = 0.05$ and $\beta = 0.3$)

		α																			
		0.05	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**	**0.95**	**1**
β	**0.05**	80.7	86	92	99	105	113	120	128	136	145	154	163	173	184	195	207	219	233	247	263
	0.1	78.0	83	88	93	99	105	112	119	126	134	142	150	159	168	178	189	200	212	225	238
	0.15	76.5	81	85	90	95	100	106	112	119	126	133	140	148	157	166	175	185	196	207	219
	0.2	75.6	79	83	88	92	97	102	108	113	120	126	133	140	148	156	164	173	183	193	204
	0.25	75.1	78	82	86	90	95	99	104	110	115	121	127	134	141	148	156	164	173	182	192
	0.3	**75.0**	78	81	85	89	93	97	102	107	112	117	123	129	135	142	149	157	165	173	182
	0.35	75.1	78	81	85	88	92	96	100	105	110	115	120	125	131	138	144	151	158	166	175
	0.4	75.4	78	81	85	88	92	96	100	104	108	113	118	123	128	134	140	147	154	161	169
	0.45	75.8	79	82	85	88	92	95	99	103	107	112	116	121	126	132	138	144	150	157	165
	0.5	76.5	79	82	86	89	92	96	99	103	107	111	116	120	125	130	136	142	148	154	162
	0.55	77.3	80	83	86	90	93	96	100	104	108	112	116	120	125	130	135	140	146	153	159
	0.6	78.4	81	84	88	91	94	98	101	105	108	112	116	120	125	129	134	140	145	152	158
	0.65	79.6	83	86	89	92	96	99	102	106	110	113	117	121	125	130	135	140	145	151	158
	0.7	81.1	84	88	91	94	98	101	104	108	111	115	119	122	127	131	135	140	146	151	158
	0.75	82.8	86	90	93	97	100	103	107	110	113	117	121	124	128	132	137	142	147	152	158
	0.8	84.8	88	92	96	99	103	106	109	113	116	120	123	127	130	134	139	143	148	154	160
	0.85	87.2	91	95	99	102	106	109	113	116	119	123	126	130	133	137	141	146	150	156	162
	0.9	89.8	94	98	102	106	109	113	116	120	123	126	130	133	136	140	144	148	153	158	164
	0.95	92.8	97	102	106	110	114	117	121	124	127	131	134	137	140	144	148	152	156	161	167
	1	96.2	101	106	110	114	118	122	126	129	132	136	139	142	145	149	152	156	161	165	171

Table C.2: Overview of the MSE of the TSB forecast of a IR/LU product.