MASTER THESIS

INVENTORY MANAGEMENT OPTIMIZATION THROUGH A DEMAND FORECASTING IMPROVEMENT

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PREFACE

Dear reader,

With pleasure I present to you my master thesis *Inventory Management optimization through a Demand Forecasting improvement*. This report is the result of a master thesis assignment conducted in order to complete the master's program of the study Industrial Engineering & Management at the University of Twente. Considering my study background, a bachelor's degree in both Textiles and Industrial Engineering & Management, I was delighted to get the chance to combine these fields of interest by means of conducting my master thesis assignment at Verosol. Therefore, I would like to thank Detmar Roessink for giving me this opportunity and for his guidance throughout the research period. In addition, I would like to thank Kilian Bennink for his valuable input and the time he made available for our weekly meeting. Furthermore, I would like to thank all other colleagues of Verosol for the enjoyable time I had during my graduation period.

Moreover, I would like to thank my supervisors Matthieu van der Heijden and Leo van der Wegen for their clear feedback and willingness to help me. As a result, I was able to timely redirect the research when necessary and to deliver the result within a reasonable time period.

A special thanks goes to my fellow students, without whom I would not have had such a pleasant and enjoyable time during my master studies. Although COVID19 emerged and covered the largest part of the master study, we stayed in contact and I am thankful for their support throughout the graduation period.

Last, but not least, I would like to thank my family and loved ones for their understanding and unconditional support throughout this graduation period in specific and my repetitive decisions to continue studying; although making fun of me when I, at some moments in time, was questioning myself why I made the decision to continue with another study again.

In the continuation of this report, the following information may be found in the corresponding chapters. A description of Verosol, the problem they currently face at Verosol and the research approach are provided in Chapter 1. In Chapter 2, the current situation is described and its performance is quantified. Chapter 3 further elaborates on the information available in literature, whereas Chapter 4 describes the application of this information to the situation of Verosol in specific. In Chapter 5, the solution to the problem is evaluated and Chapter 6 provides its corresponding implementation approach. Lastly, the conclusions, recommendations and suggestions for further research are provided in Chapter 7.

All that remains for me is to wish you an enjoyable read.

Juliet Rouwers

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SUMMARY

Verosol offers **metallized indoor blinds** to its customers worldwide. The production process of Verosol is split in two sub-processes; first the fabric is metallized at Verosol Fabrics (VFA) and afterwards the metallized fabric is processed into a blind at Verosol Nederland (VNL). The scope of this research is restricted to the process occurring at VFA.

When reviewing the delivery performance of the years 2017 to 2021, it appeared that VFA did not meet its **delivery performance target** of **96%**. The averaged delivery performance over these years equals 92%. As indicated by the Production Director, the inventory control policy should be optimized in order to enable an actual delivery performance of at least 96%. After analysing the problem, it appeared that the input of the inventory control policy, i.e. the demand forecast, should be optimized in advance. For this reason, the research objective is set to establishing a statistically based demand forecasting model in order to serve as input for the future inventory control policy of VFA. Throughout the continuation of this research an answer is provided to the following research question:

"*What statistical forecasting method(s) should be applied in order to forecast the demand of VFA and how do these forecasting results affect the current SS levels?*"

When evaluating the current situation of VFA, it is observed that a total of **128 SKUs** are included in the research scope and that VFA faces two types of demand for these SKUs, i.e. regular and project demand. **Regular demand** refers to orders of a smaller order size occurring more often and not known in advance, whereas **project demand** refers to non-frequently recurring orders of a relatively large size and often known well ahead in time. In addition, it is observed that **demand variability** in both order size and order frequency is inherent to the demand that VFA faces, partly caused by the presence of the project demand. For this reason, the initial idea was to establish a statistical demand forecasting model for the regular demand, while an analysis of the project demand characteristics serves as input for a separate project demand forecast.

During the research a need for a change in the research direction appeared; no distinction could be made between regular and project demand based on historic data. In order to distinguish between regular and project demand, an alternative approach is applied throughout the further continuation of the research; i.e. 3 **demand scenarios** have been established. Each demand scenario is assumed to include the regular demand up to a certain order size threshold (m), i.e. up to 100m, 350m and all order sizes for demand scenarios 1, 2 and 3, respectively. The orders that are excluded are assumed to be project orders, i.e. for these orders it is assumed that the period required to transform the raw material into a finished product is shorter than the time between the moment the order is placed and the requested date of delivery.

For each demand scenario, the following actions have been conducted in order to determine which statistical forecasting method(s) are most suitable: (1) a selection of SKUs is made, (2) the SKUs are grouped by means of classification methods and (3) different demand forecasting methods are applied of which the performance is expressed in the MAD (m), bias (m), bias (%) and sMAPE (%).

The **selection of SKUs** included in the demand forecasting model is based on the amount of historic sales data available from 2018 to 2021. From this analysis it is observed that approximately 20% of the SKUs offered by VFA did not face demand in these 4 years. In addition, 34 of 128 SKUs (≈ 27%) faced demand all 4 years. These 34 SKUs are included in the model for each demand scenario, considering the fact that more input data is beneficial for the forecasting performance and that 4 years is a minimal requirement for e.g. the forecasting methods that incorporate seasonality.

The ABC- and Demand Pattern (DP)-**classification methods** have been applied in order to group the SKUs. When applying the ABC-method it appeared that approximately 65% of the 34 SKUs (25% of the 128 SKUs) is classified as A-item, followed by approximately 29% (20% of the 128 SKUs) as B-item and the remaining 6% (55% of the 128 SKUs) as C-item. This distribution is more or less consistent over the demand scenarios. When reviewing the result of the DP-classification method, it appeared that a shift occurs when reviewing the demand scenarios in increasing order; i.e. the number of SKUs classified as either *smooth* or *intermittent* decreases, while the number of SKUs classified as either *erratic* or *lumpy* increases. This shift indicates a decrease of the forecast-ability when reviewing the demand scenarios in increasing order.

Next, the most suitable **demand forecasting method** is determined for each DP-class and each demand scenario. The methods considered within this research are Simple Exponential Smoothing (SES), Holt, Winters and Croston. Three variants of the Winters method are available, all differ in the seasonality that is taken into account; i.e. monthly, regular quarterly and shifted quarterly seasonality. For all the aforementioned forecasting methods, a static and adaptive variant is available and for the Winters method in specific, the seasonality could be SKU-individual or grouped over all SKUs. From a preliminary forecasting performance analysis, it appeared that the adaptive variant outperforms the static variant for all methods and the grouped seasonality outperforms the SKU individual seasonality.

Of the remaining forecasting methods, it can be observed that the most simplified methods considered, i.e. SES and Croston, are the best performing forecasting methods for each DP-class and demand scenario in general. For some single SKUs in a group of SKUs, a forecasting method other than the one most suitable for the group is determined as most suitable; e.g. the Holt method. When comparing the performances of the statistical forecasting methods of demand scenario 3 with the current method, a significant performance improvement is observed. The averaged improvement corresponds to -112% and -10% for the scale-independent performance measures, i.e. the bias (%) and sMAPE (%). In spite of the forecasting performance improvements, it could be observed that relatively high values of the performance measures still remain. Identifiable and potential causes are (1) the current inability to separate the demand types in the historic data, (2) the demand variability inherent to the demand VFA faces and (3) structural changes of the demand pattern that occurred throughout the test set, resulting in wrongly classified SKUs. Such structural changes could also be the cause for choosing an SKU-individual forecasting method, different than the forecasting method selected for the corresponding group of SKUs

The problem solution, i.e. the most suitable forecasting method(s), is evaluated by means of determining the minimal required **Safety Stock (SS) level** for each demand scenario, i.e. summed over all SKUs per demand scenario. Considering the alternative research approach, and as aforementioned, it is assumed that the regular demand is supplied from inventory, whereas the project demand is produced on order; i.e. the project demand is not considered when establishing the minimal required SS levels. Within the calculation of the SS levels, the customer service level (S_1) is used as a guideline and defined as the probability of stock out before a replenishment order arrives. The value of S_1 is set to 94%, 96% and 98% in order to evaluate the sensitivity of the SS levels. Table iv.1 provides the established SS levels as a proportion of the current SS levels for an S_1 of 96%, the current delivery performance target.

Table iv.1. The established SS levels as a proportion of the current SS levels.

Demand scenario	Minimal required SS level *S_1 of 96%*
1	51%
2	105%
3	201%
Current situation	100%

When evaluating the result of the SS level calculation, it could be observed that the current SS levels are too low, i.e. the current forecasting approach equals demand scenario 3. In addition, the minimal required SS level increases when reviewing the demand scenarios in increasing order. This increase could be partly assigned to the increase in the order size taken into account and to the increased demand variability when reviewing the demand scenarios in increasing order. When reviewing the SKU-individual SS levels, it could be observed that the increase in the aggregated SS level is mainly caused by a few SKUs with abnormal peaks in their time series, e.g. due to project demand. These observation for an S_1 of 96% also apply for the remaining values of S_1.

The **main conclusions** that flow from the findings of the research period correspond to (1) the statistical forecasting methods outperform the current forecasting method and (2) the sales data should first be registered and stored correctly in order to optimally benefit of a statistical forecasting method. The following points with regard to data handling should be adjusted: register the demand type of each incoming order, log the development of project orders and register the external factors that could potentially affect the demand pattern of an SKU, e.g. the RM unavailability. The advice related to the implementation of a statistical forecasting method equals the last conclusion, i.e. first the input data for the forecasting model should be collected correctly in advance of serving as input for the forecasting model.

Several **recommendations** follow on these conclusions. Concisely, these recommendations relate to (1) reviewing the product offer of VFA, (2) documenting the demand types, (3) documenting the development of project orders, (4) documenting the external factors that potentially affect the demand pattern of VFA, (5) varying with customer service level targets, (6) defining a clear demand forecasting purpose, (7) delivering judgemental input in addition to the statistical demand forecasting model and (8) the logging of the forecasting performance. Lastly, based on the insights obtained during the research period, the approach as with demand scenario 2 is recommended to use as a robust guideline when distinguishing between regular and project demand; i.e. deliver orders up to an order size of 350m from inventory. An optimal order size threshold should be determined, as further elaborated in the following paragraph.

Three topics for **further research** could be established as a follow up on this research. These topics relate to (1) an evaluation of the optimal order size threshold up to which to deliver from inventory for VFA in specific, (2) the evaluation of customer specific demand patterns in order to serve as potentially valuable input to the forecast of regular demand and (3) the establishment of a suitable inventory control policy.

ABBREVIATIONS

Throughout the report several abbreviations and terms are used. A concise overview of the frequently used abbreviations and terms throughout the report is provided below.

Abbreviation	Definition
a	*Level*
ABC	*Always, Better, Control*
ADI	*Average inter-Demand Interval*
ANOVA	*Analysis of Variances*
ARIMA	*Auto Regressive Integrated Moving Average*
ARMA	*Auto Regressive Moving Average*
b	*Trend*
CO	*Customer Order*
CV	*Coefficient of Variation*
CV^2	*Squared Coefficient of Variation*
DP	*Demand Pattern*
ERP	*Enterprise Resource Planning*
F	*Seasonal estimate*
FCFS	*First Come First Serve*
FNS	*Fast, Normal, slow*
IC	*Intercompany customer*
L	*Lead time*
LIC	*Licensee customer*
m	*Meters*
MA	*Moving Average*
MAD	*Mean Absolute Deviation*
MAPE	*Mean Absolute Percentage Error*
MPSM	*Management Problem Solving Method*
MSE	*Mean Squared Error*
MTS	*Made To Stock*
NLIC	*Non-licensee customer*
NPI	*New Product Introduction*
PVC	*Polyvinyl Chloride*
R	*Review Period*
RM	*Raw Material*
SES	*Simple Exponential Smoothing*
SKU	*Stock Keeping Unit*
sMAPE	*Symmetric Mean Absolute Percentage Error*
SS	*Safety Stock*
VFA	*Verosol Fabrics*
VNL	*Verosol Nederland*

TABLES & FIGURES

Multiple tables and figures are included throughout the continuation of this report. An overview of the tables and figures is provided below.

Tables

Figures

CONTENT

1 INTRODUCTION

The main purpose of this chapter is to provide information with regard to the company Verosol and to provide insight in the background of the problem that Verosol faces. Section 1.1 provides information about Verosol. Section 1.2 provides an evaluation of the observed problem. Lastly, Section 1.3 provides the research approach including the research objective, the research scope and the research questions.

1.1 Company description

Verosol is founded in 1963 by Cornelis Verolme in The Netherlands and nowadays has several office locations in the Netherlands, Australia and Spain, of which the main office is located in Eibergen in The Netherlands (Verosol, 2021). Verosol has a leading position in reflective textiles processed in indoor blinds, referred to as **metallized indoor blinds**, and is part of Kvadrat; a leading manufacturer of high-quality design textiles.

As aforementioned, Verosol is a market leader in metallized indoor blinds. In advance of assembling the indoor blind, a thin layer of aluminium is applied on one side of the fabric; resulting in a metallized indoor blind. Verosol offers several types of indoor blinds to its customers, among others pleated blinds, roller blinds and curtains (Verosol, 2021). All indoor blinds that Verosol offers are customizable in terms of colour, length and width. Due to the use of metallized fabric, the indoor blinds of Verosol outperform nonmetallized indoor blinds with regard to the regulation of light and warmth produced by the sun. Most of the light and warmth is reflected by the thin layer of aluminium before the warmth could be absorbed by the room or the window covering itself; the light is not transmitted through the fabric itself, only through the openings in the fabric structure (Verosol, 2021). A certain openness in the fabric structure is kept in order to enable see-through of the blind. The functioning of this process is visualized in Figure 1.1.

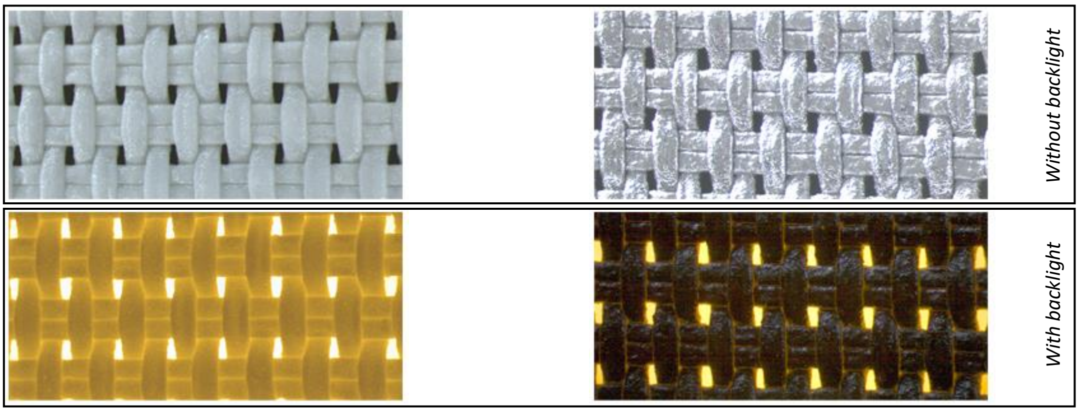

Figure 1.1. Light transmittance performance; Left: nonmetallized fabric; Right: metallized fabric.

The production process occurring at Verosol in Eibergen is divided in two organizational entities; (1) the metallization of fabric at **Verosol Fabrics** (VFA) and (2) the assembly of indoor blinds at **Verosol Nederland** (VNL). Since July 2022 these entity names are changed into **Kvadrat High Performance Textiles** and **Kvadrat Shade Assembly**, respectively. Throughout the continuation of this report the initial names Verosol, VFA and VNL will be used to refer to the company for which the research has been conducted. This research relates to the organizational unit VFA only. For this reason, the focus of the information provided shall be limited to information related to VFA. The final product of VFA is metallized fabric in different lengths, widths, colours and applications; either pleated or unpleated. Pleated fabrics are processed in pleated blinds and unpleated fabrics are processed in roller blinds or curtains; VFA is one of the suppliers of VNL in terms of fabric used for the assembly of metallized indoor blinds.

1.2 Problem identification

Within this Section, Sections 1.2.1 and 1.2.2 provide a description and visualisation with regard to the problems that VFA currently faces. In Section 1.2.3 the core problem to be solved is selected.

1.2.1 Problem background

Within VFA it is noted that demand is not always met on time over the past years and therefore the **delivery performance target** of **96%** is not met. Figure 1.2 provides an overview of the yearly delivery performance rate of the past years.

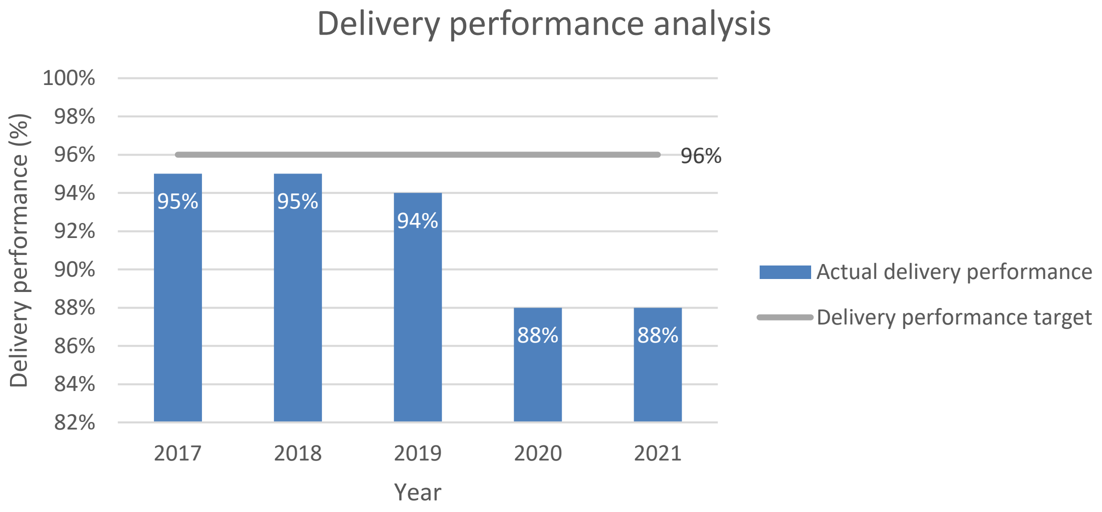

Figure 1.2 Delivery performance of VFA Verosol over the past years.

Within VFA the delivery performance rate is calculated by means of the formula provided in equation (1). Within this formula *on time delivery* is specified as the delivery of an order before or on the delivery date that is initially communicated to the customer.

$$Delivery\ performance\ rate\ (\%) = \frac{Number\ of\ on\ time\ delivered\ orders\ per\ year}{Total\ number\ of\ delivered\ orders\ per\ year} * 100 \qquad (1)$$

The delivery performance rates of the past years indicate a need for improvement of the inventory management policy in order to meet the target of 96%, confirmed by the Production Director of VFA. When reviewing the current inventory management policy it is observed that the base of this policy, a correct and continuous insight in future demand, is not sufficient within VFA.

Within the current forecasting procedure as executed by VFA, the demand forecast is reviewed monthly and incorporates a forecast horizon of 12 months; each month the expected demand for the coming year is manually set in alignment with 1-year historic sales data. The monthly expected demand is derived accordingly by means of proportions of the yearly expected demand. When establishing the monthly expected demand, no distinction is made among the different products that VFA offers to its customers; i.e. metallized fabrics with a different composition, width, colour and application. In addition, the monthly proportions are not revised each year. The manually reviewing and updating of the demand forecast indicates the absence of a statistical forecasting model, causing the demand forecast to be not as optimized and accurate as it could be. Also, the absence of a rolling horizon of the demand forecast is a consequence of manually establishing and updating the demand forecast. In case the expected demand is not adjusted for a certain product each month, the forecast horizon is not extended due to a lack of communication between systems; making the current forecast horizon not a rolling horizon and causing a lack of continuous insight in the expected demand.

In addition, employees of VFA indicate that VFA faces two different demand types, each having different characteristics with regard to the size of an order, the order frequency and the demand uncertainty. When reviewing the 1-year historic data serving as a base for the demand forecast, no distinction is made among the two demand types; causing a biased view of the future demand that will take place as orders with a higher demand uncertainty are assumed to happen with a demand uncertainty equal to the demand type with the lowest demand uncertainty.

Lastly, an absence of insight in the forecasting performance of VFA is observed; causing the inability to access the forecasting procedure. The inability to access the forecasting procedure makes it hard to adapt the procedure when necessary, enabling the continuation of an incorrect forecasting procedure (Silver, Pyke, & Thomas, 2017). As a result, the demand forecast may not be as accurate as possible.

1.2.2 Problem cluster

In order to illustrate the relations between the aforementioned observations, Figure 1.3 provides a visualisation in terms of a so-called *problem cluster*. The relations between the observations are defined by means of arrows.

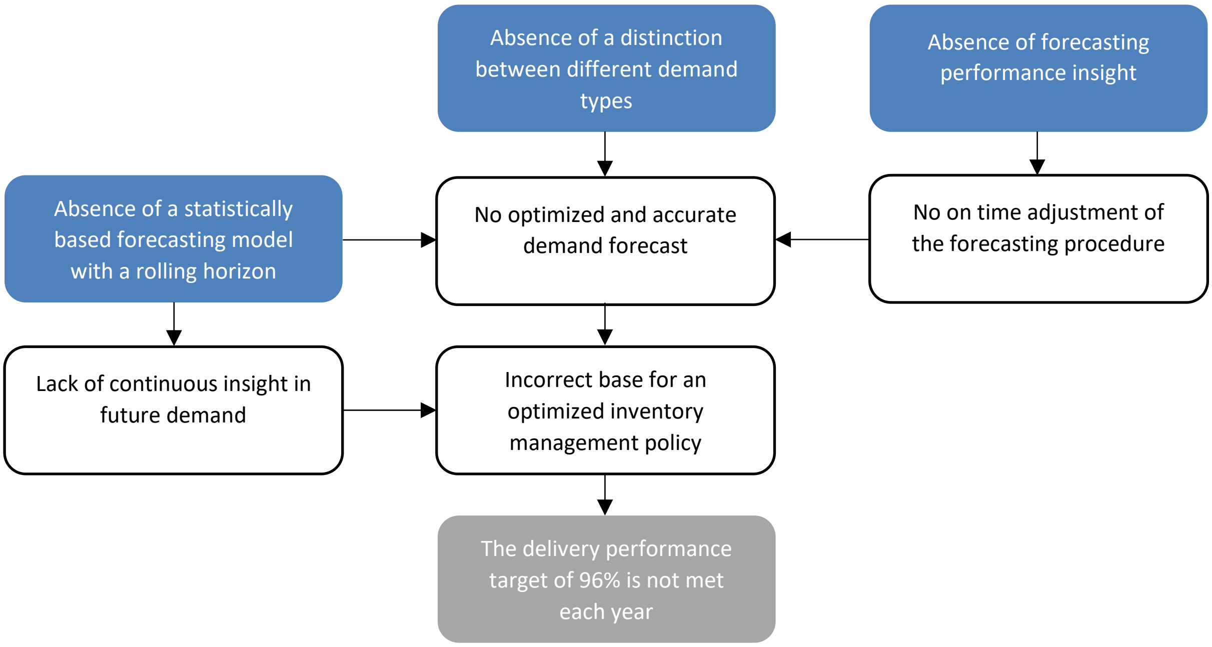

Figure 1.3 Problem cluster.

As aforementioned, VFA observes the problem given at the end of the causal chain as provided in Figure 1.3. According to Heerkens & Van Winden this observed problem is labelled as an action problem; a discrepancy between the norm and the reality, as perceived by the problem owner. The action problem is formulated as the following:

"The delivery performance target of 96% is not met over the past 4 years"

For this problem instance the norm is defined as a delivery performance of 96%, the reality is a delivery performance below 96% as visualized in Figure 1.2.

1.2.3 Core problem selection

In order to solve the observed action problem, the core problem to be solved is selected from the problem cluster by means of the Management Problem Solving Method (MSPM) as proposed by Heerkens & Van Winden. Given the causal chain within the problem cluster as provided in Figure 1.3, the core problem at the end of the causal chain that is selected as main core problem according to the MPSM of Heerkens & Van Winden is:

"The absence of a statistically based demand forecasting model with a rolling horizon"

The other core problems*, the absence of a distinction between the demand types* and *the absence of forecasting performance insight*, could be incorporated in the problem solving approach accordingly due to the correlation between the core problems. For this reason, a solution will be provided for these core problems simultaneously. The earnings of solving the selected core problem is a more accurate base for the inventory management policy of VFA.

1.3 Research approach

Within this section, Sections 1.3.1 and 1.3.2 elaborate further on the research objective and the main research question. Section 1.3.3 provides information on the research scope and Section 1.3.4 provides the problem solving approach by means of research questions and a description of the research setup.

1.3.1 Research objective

The main objective of this research is to improve the delivery performance of VFA by means of improving the current inventory management policy. In order to fulfil this objective, the base of the inventory management policy should be optimized in advance; i.e. the demand forecast. For this reason, the corresponding research objective is formulated as the following:

"Establish a statistical demand forecasting model with a rolling horizon in order to serve as a base for the inventory management policy of VFA"

The inventory management policy for which the demand forecast will be established relates to the inventory management of finished and semi-finished products as minimum stock levels are kept for these products within VFA. Finished products include the fabric composition, width, colour and application. Semi-finished products only include the fabric composition and width. Storing fabrics as semi-finished products is only applicable for raw material (RM) provided uncoloured, further elaborated on in Section 2.1.1.

In order to specify the forecasting model to be established, several forecasting attributes should be set in alignment with its purpose; i.e. creating a sufficient base for the inventory management policy. These forecasting attributes are the following; (1) the forecast horizon, (2) the forecasting time buckets and (3) the aggregation level.

The forecast horizon incorporates how far in the future the information is used and is split in time buckets, time units for which a single demand forecast is made. The forecast horizon is set to the delivery time (L) and review period (R) for each SKU; further elaborated on in Section 2.1.1. A month is set as a time bucket, given the fact that the delivery times of RMs are expressed in months within VFA. The aggregation level of the forecast model affects the forecasting performance; the higher the aggregation level, the higher the decrease of the forecasting uncertainty (Silvestrini & Veredas, 2008) (Rostami-Tabar, Zied Babai, Syntetos, & Ducq, 2013) (Chopra & Meindl, 2013) (Chatfield C. , 1995). Eventually resulting in lower safety stock (SS) levels and, therefore, lower minimum inventory levels (Axsäter, 2006) (Silver, Pyke, & Thomas, 2017).

For this reason, the design of the future inventory management policy is assumed to remain the same; i.e. the forecasting model will be partly on Stock Keeping Unit (SKU)-level for coloured RM and on a more aggregated level for uncoloured RM, taking into account the product type and fabric width only.

1.3.2 Research question

In order to achieve the research objective as described in Section 1.3.1, the following main research question is formulated:

"*What statistical forecasting method(s) should be applied in order to forecast the demand of VFA and how do these forecasting results affect the current SS levels?*"

1.3.3 Research scope

The scope of the research should be set accordingly in order to be able to provide a solution to the selected core problem within the available research period. As aforementioned in Section 1.1, the focus of this research is the process of VFA only within Verosol. The main purpose is set to improving the delivery performance of VFA by means of optimizing the inventory management policy. In order to enable this optimization, the base of the inventory management policy should be optimized on beforehand. For this reason, the scope of the research is set to establishing a demand forecasting model that serves as a base for an inventory management policy within VFA. Figure 1.4 depicts the research scope within the broader problem perspective of Verosol.

Figure 1.4 Visualisation research scope.

VFA categorizes its customers in four groups; Intercompany (IC), Licensee (LIC), Non-licensee (NLIC) and Contract Work. The customers assigned to the category *Contract Work* supply their own fabric to VFA, after which VFA metallizes the textile; the RM for the other customer groups is purchased by VFA itself and thus should be incorporated in the inventory management policy. For this reason, the scope of the research is limited to the customer groups IC, LIC and NLIC and the forecasting model will only incorporate the fabric types purchased by VFA itself; covering approximately 98% of the sales in 2021. In addition, the research scope contains three product groups; roller blinds, pleated blinds and curtains. This selection of both customer- and product groups covers approximately 96% of the sales in 2021.

1.3.4 Research questions

In order to fulfil the main research objective in a structured manner, several research questions have been formulated following the MPSM-structure as described by Heerkens & Van Winden. Table 1.1 provides an overview of the relation between the MPSM-phases and the application throughout this research and report. The paragraphs below Table 1.1 further elaborate on the result of the research questions and the purpose of each chapter within this report.

Table 1.1 Research and report structure.

MPSM		Research report		
Phase	*Description*	*Research question topic*	*Chapter*	*Chapter description*
1	Defining the problem	-	1	Introduction
2	Formulating the problem approach	-	1	Introduction
3	Analysing the problem	1	2	Current situation
4	Formulating (alternative) solutions	2	3	Literature
		3	4	Model design
5	Evaluating & choosing a solution	4	5	Solution evaluation
6	Implementing a solution	5	6	Solution implementation

As introduced in the sections before, **Chapter 1** relates to the introduction of the problem, the research objective and the scope of the research. Each of the following chapters relates to a single research question topic as provided in Table 1.1.

Chapter 2 focuses on the identification of the current situation by means of providing the demand and product characteristics relevant for the research. In addition, insight in the current forecasting process and its effect on the operations of VFA will be provided. The research questions that correspond to this chapter are:

1. "What is the current situation of VFA with respect to demand forecasting?"

Operational characteristics

1.1 What are the known product characteristics relevant for the research?
1.2 What are the known demand characteristics relevant for the research?

Demand forecasting process

1.3 What is the design of the current demand forecasting process?
1.4 What is the performance of the current demand forecasting process?
1.5 What impact does the current forecasting performance have on the operations of VFA?

Next, **Chapter 3** provides insight in demand forecasting methodologies available in literature and suitable for the situation VFA currently faces with regard to the product and demand characteristics. In addition, insight is provided in suitable forecast performance measures for VFA and the relation between demand forecasting and inventory control. The research questions that correspond to this chapter are:

2. "What information is available in literature with regard to demand forecasting?"

Item classification

2.1 What methods are available in literature in order to classify SKUs for demand forecasting purposes?

Demand forecasting

2.2 What methods are available in literature for establishing a forecasting model suitable for the demand and product characteristics VFA faces?
2.3 What forecasting performance measures are suitable for VFA?

Inventory control

2.4 How can a minimal required SS value be derived from the forecasted demand?

Chapter 4 provides insight in the performances of the forecasting methods that appeared most suitable for VFA and determines the best forecasting method in terms of the established performance measures. In addition, the performance of the best forecasting method is compared to the performance of the current forecasting method. The research questions that correspond to this chapter are:

3. "How is the current forecasting procedure improved when applying a statistical forecasting method?"	
3.1	Which forecasting method is most suitable in order to solve the forecasting problem of VFA?
3.2	What is the performance of the best forecasting method compared to the current forecasting method?

Chapter 5 provides insight in the impact of the best forecasting method on the operations of VFA in terms of establishing the minimal required SS levels. The research questions that correspond to this chapter are:

4. "To what extent is the current situation of VFA improved by means of introducing the new demand forecasting procedure?"	
4.1	How does the new demand forecasting method affect the minimal required SS levels within VFA?

The last research questions will be addressed in **Chapter 6**. These research questions provide insight in actions that should be undertaken within VFA in order to enable the implementation of the established forecasting model and to sustain its contributions to the operations of VFA. The research questions that correspond to this chapter are:

5. "How to implement the established forecasting method within VFA?"	
5.1	What actions should be taken by whom in order to enable the demand forecast model to be implemented?
5.2	What actions should be taken by whom in order to sustain the working of the implemented demand forecasting model?

The last chapter, **Chapter 7,** provides the conclusion, relevant recommendations and suggestions for further research. Lastly, an overview of the literature used throughout this report is provided in the **References**, followed by the **Appendices**.

2 CURRENT SITUATION

The main purpose of this chapter is to provide insight in the current situation of VFA by means of evaluating relevant product and demand characteristics in Section 2.1. In addition, the current demand forecasting process is evaluated in Section 2.2.

2.1 Operational characteristics

The product that VFA offers to its customers is metallized fabric of which the RM is either purchased by VFA itself or supplied by the customer. Within the scope of this research the RM is purchased by VFA itself. Section 2.1.1 provides the corresponding product characteristics of VFA and Section 2.1.2 provides the characteristics of the demand VFA faces.

2.1.1 Product characteristics

The product offer of VFA could be reviewed on different aggregation levels; either on product family, product type- or on SKU-level. Fabrics with approximately the same characteristics and outlook are classified in the same **product family**. Each product family is further specified in **product types**, numbers indicating a specific fabric with its corresponding characteristics; such as the composition, weaving structure and the process it undergoes within VFA. These product types are further specified on **SKU-level**, indicating the specific width, colour and application of the fabric. The application of the fabric can either be a roller curtain (unpleated), a pleated curtain (pleated) or a regular curtain (unpleated). An example of the application of the aggregation levels within the product offer of VFA is provided in Table 2.1.

Table 2.1. Example of the aggregation levels of the product offer of VFA.

Product family	Product type	Stock Keeping Unit (SKU)		
		Width	*Colour*	*Application*
General name of a class that contains several product types; i.e. Silverscreen or Enviroscreen.	Number that indicates a specific fabric type; i.e. 202 or 802.	The fabric type is further specified in width, colour and application; i.e. 240 cm in colour EB01 and unpleated.		

The scope of the research is further specified based on an evaluation of the added value of each product type in combination with an evaluation of the standard collection VFA provides to its customers in terms of widths and colours for each product type. The added value is determined by means of (1) evaluating the contribution to the sales (€) and the volume sold in meters (m) over the years 2018 to 2021 and (2) using input from both the Purchasing and Sales department. Table I.1 in Appendix I provides an overview of the product offer on SKU-level within the scope of this research, including **1,130 SKUs.** Table I.2 provides the corresponding level of aggregation for each product type kept as a guideline for both the current and future inventory control policy.

The scope is set in agreement with the Production Director of VFA and covers approximately 91% of the sales in 2021. Figure 2.1 provides a visualisation of the contribution of each product type to the sales in 2021. The research scope contains 19 product types in total, all provided in Figure 2.1.

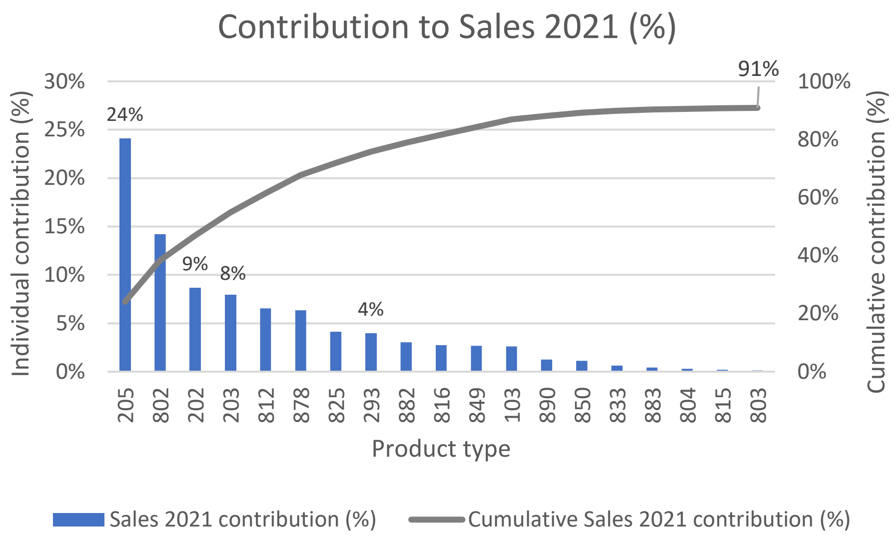

Figure 2.1. Contribution to the 2021 sales for each product type part of the research scope.

Within the established research scope, several distinctions could be made based on (1) the composition of the fabric, (2) the supply state of the RM and (3) the state of storage. For each product type information with regard to these distinctions is provided in Table I.3 in Appendix I. Figure 2.2 depicts these distinctions within the research scope, expressed in the number of SKUs.

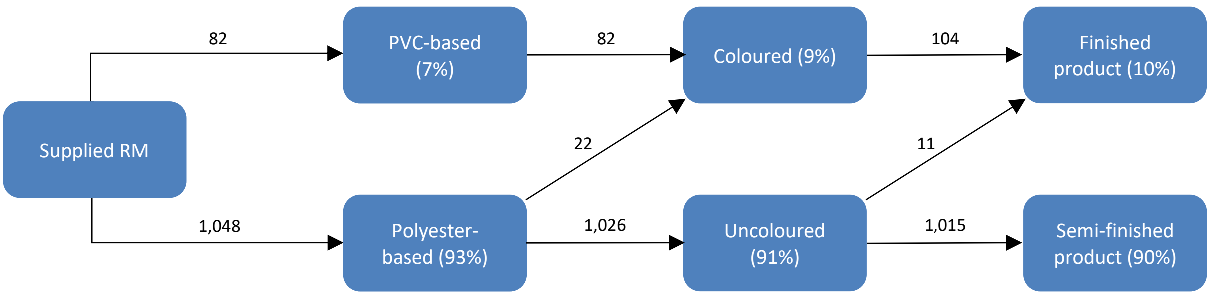

Figure 2.2. VFA Product offer classification (evaluation expressed in the number of SKUs).

The fabric that VFA offers to its customer is either Polyvinyl Chloride (PVC)- or polyester-based. Of the 1,130 SKUs, 82 SKUs are PVC-based (7%) and the others are polyester-based (93%). The distinction can be further specified based on the supply state of the RM, either coloured (9%) or uncoloured (91%). In case the RM is PVC-based, the RM is always supplied in colour. As depicted in Figure 2.2 some of the polyester-based SKUs are supplied in colour (2%), whereas the main part is supplied uncoloured (91%). Another distinction could be made among the state in which the products are currently stored within VFA; either as semi-finished or finished product. For semi-finished products the colour and application are undecided yet, whereas these are decided for the finished products. In case the RM is supplied in colour, the processed RM will always be stored as finished product. In case the RM is supplied uncoloured, a minimum inventory level is established for only a small part of the SKUs (1%). In total, for 10% of the SKUs a minimum inventory level is established.

When relating Figure 2.1 to Figure 2.2 proportional differences could be observed. For example, the PVC-based product types (202, 203, 205, 293) together represent 46% of the 2021 sales, whereas these products only represent 7% of the total number of SKUs within the scope of the research.

Lastly, Table I.3 in Appendix I also provides information with regard to the delivery times of the RM for each product type included in the research scope. The delivery times vary between 2 to 5 months, with an average of 4 months. For 50% of the product types, the maximum delivery time is indicated at 5 months. Within the given delivery times it is assumed that the supplier of VFA has the needed RMs in house. For this reason, exceptions with long delivery times due to the absence of RMs at the suppliers' side are not taken into account. The provided delivery times include the transportation time and production processing time of VFA, therefore indicating the total time from the moment of ordering the RM till storing the semi-finished or finished product. The influence of COVID-19 is assumed to be an exceptional case and, therefore, its influence on the current delivery times is neglected.

2.1.2 Demand characteristics

The demand VFA faces is expressed either in meters (m) or squared meters (m^2) per SKU per customer order and is observed to be variable in terms of both order size and order frequency, depending on the product type. As indicated by the Production Director and the Purchasing- and Sales department of VFA a distinction can be made among the demand VFA faces; either regular or project demand. **Regular demand** refers to orders of a smaller order size occurring more often, whereas **project demand** refers to non-frequently recurring orders of a relatively large size and often known well ahead in time.

In order to visualize this partition in demand, an analysis of the typical demand pattern VFA faces yearly is depicted in Figure 2.3; the demand patterns of the years 2018 to 2021 are observed to be comparable. In Figure 2.3 the frequency of the order sizes occurring in 2021 are categorized in bins of 50m. The middle part of the histogram is removed in order to ensure the readability of the figure, a complete histogram is provided in Figure II.2 in Appendix II. From Figure 2.3 it can be observed that a relatively large part of the orders are of a relatively small order size. The order size threshold (m) for 80% and 95% of the orders in 2021 is provided in Table 2.2. In addition, insight is provided in the contribution to the sales and volume sold in 2021 for both order proportions.

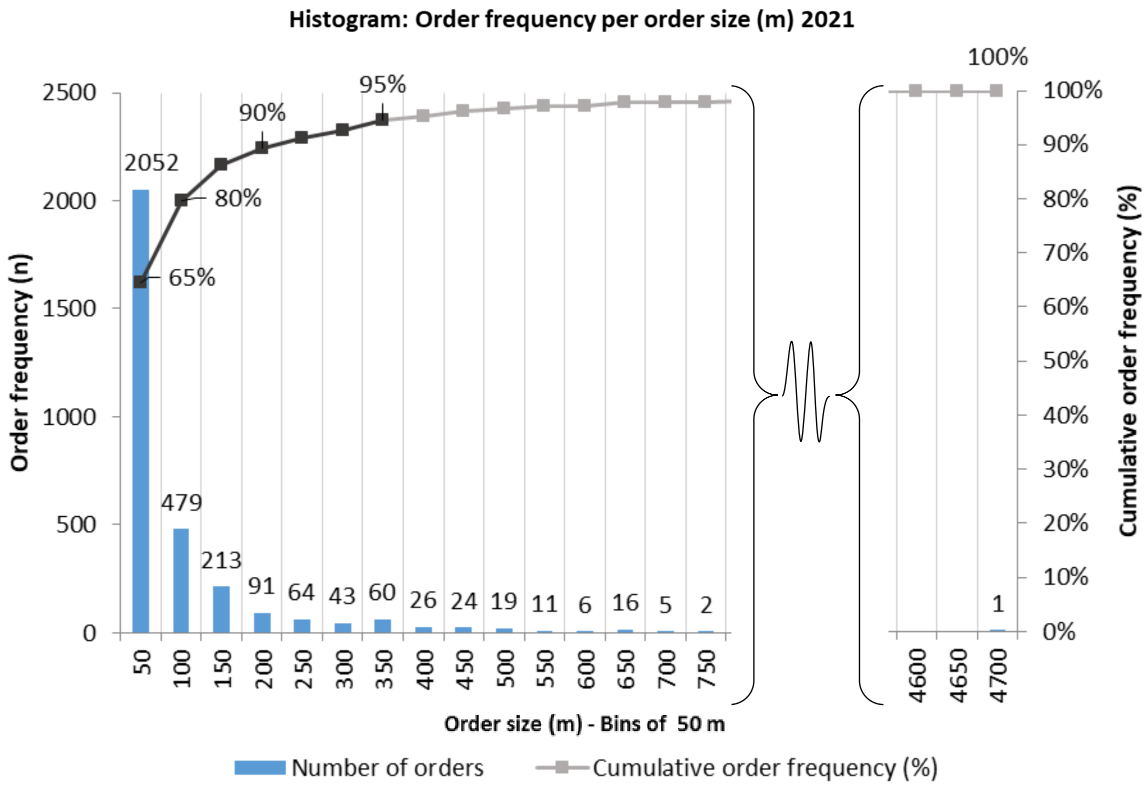

Figure 2.3. Histogram of the order size (m) occurrences in 2021.

Table 2.2. Order size evaluation for 80% and 95% of the orders in 2021.

	Proportion of orders per year	
	80%	**95%**
Order size threshold (m)	100	350
Contribution to sales (%)	33%	63%
Contribution to volume sold (%)	31%	60%

From Table 2.2 it could be observed that 95% of the orders have an order size less or equal to 350 m, counting for 63% of the yearly sales in 2021. This observation emphasizes the importance of project demand; 5% of the orders are of a larger order size and account for 37% of the yearly sales.

An assumption that is confirmed by the employees of VFA is the fact that the project orders come with a larger uncertainty than the regular orders. The project orders are known for a longer period ahead on a more general level, without any specified details such as the required amount of fabric or the specific fabric type, colour and width. Over a period of time these details are further specified and the uncertainty of the order decreases. On the contrary, in a few cases the larger orders arrive without any signal in advance. In case an order is completely known a period of time ahead longer than the delivery time of the RM and production time, then this order does not have to be delivered from inventory and thus does not have to be included in the data serving as a base for the forecasting model. For this reason, such orders should be excluded from the historic order data.

Historic order data is reviewed accordingly in order to exclude the orders known far ahead in time, i.e. project orders, and in order to examine the development of the uncertainty of these orders; as this development could provide relevant input for the forecasting model. Among the historic order data in the ERP-system no indication is provided whether an order is related to a project; and thus known in advance. For this reason, other sources have been consulted in order to distinguish between regular and project demand. These sources are the Customer Order (CO) lead time, the current sales quotation, the forecast lists provided by customers of VFA and backed-up information from a program currently out of use. An analysis of the results is provided in Appendix II. From this analysis it is also observed that it is not possible to categorize the historic demand as either regular or project demand with the historic data currently available.

Aside from the inability to categorize demand as either regular or project demand, no useful and reliable data has been found in order to determine and asses the uncertainty of the historic project demand. Important information is missing such as the development of the probabilities through time and the date the project became first known to VFA.

2.2 Demand forecasting process

In order to establish a demand forecast suitable for VFA, information is provided with regard to the current demand forecasting procedure in Section 2.2.1. In Section 2.2.2 the performance of this forecasting procedure is quantified and assessed. Lastly, Section 2.2.3 elaborates on the consequences of the forecasting performance on the operations within VFA.

2.2.1 Process description

Within VFA, demand is forecasted by both the Purchasing and Sales department. Both departments forecast demand with different objectives, further elaborated on in the following paragraphs.

Sales department

The Sales department is responsible for the forecast of the so-called project orders larger than 500 m^2 on the mid- to long term; i.e. approximately 3-12 months. Indications of these orders are known at the Sales department and the process of realizing an order starts in cooperation with the customer.

An indication could for example be an information request of the customer. These orders are also known as *work in the pipeline* and are not forecasted without any indication of an order. Decisions with regard to the minimum inventory levels are not based on this demand forecast and this forecast does therefore not influence the inventory management policy.

Purchasing department

The Purchasing department is responsible for the demand forecasting on which the minimum inventory levels are based and therefore relates directly to the delivery performance of VFA. This demand forecasting process is based on 1 year historic order data of all order sizes; i.e. both regular and project demand. The forecast includes a horizon of 1 year and therefore provides a yearly estimate. Each month this yearly estimate is reviewed and adjusted if necessary. As this yearly estimate serves as a base for decisions related to the inventory management policy and therefore relates to the topic of the research, this paragraph further elaborates on this demand forecast in specific.

Currently, demand is forecasted on SKU-level in case of RM supplied in colour and on a more aggregated level in case of RM supplied uncoloured; no distinction is made between colour and the yearly estimate is provided for each available width per product type. For example for product type 205, of which the RM is supplied in colour, a yearly estimate will be established for, among others, width 240 and colour EB01. While for product type 878, of which the RM is supplied uncoloured, a yearly estimate will be established for width 240, independent of the colour of the finished product. Aside from the distinction in the RM supply state, a distinction could be made with regard to the application of the fabric. Currently, a yearly estimate is generated for each possible application of the product type; i.e. a separate yearly estimate for product type 878 as pleated curtain and a separate yearly estimate for product type 878 as roller curtain.

Figure 2.4 provides a robust overview of the demand forecasting procedure as carried out by the Purchasing department of VFA. The base of the forecasting procedure is an Excel-file with the aforementioned yearly estimates. Each month this yearly estimate is evaluated for each product type with its certain widths, applications and, if applicable, colours. Input for this demand forecast evaluation is 1-year historic order data provided in time buckets of a month. For each product type, specific width, application and colour (if applicable) the historic order data is logged and the data of the last 12 months is displayed in a graph. Within the Excel-file a selection of the product to review can be made accordingly. In case the historic data indicates an adjustment of the current yearly estimate, the Purchasing- and Sales department together decide whether to adjust this number or not. If so, this number will be manually adjusted in the Excel-file. After finalizing the demand forecast in Excel for each product type, the adjusted yearly estimates are manually imported in the ERP-system. For each product type the cumulative yearly estimates for each width are

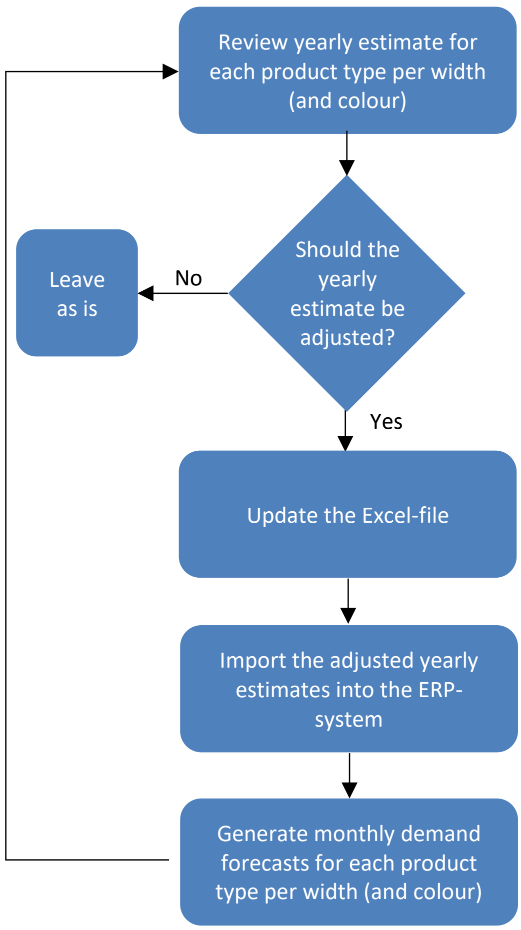

Figure 2.4. Demand forecasting procedure VFA.

Imported. In case the yearly estimates are also established per application and colour, these estimates are summed in order to obtain a total yearly estimate for each possible width per product type.

When importing to the ERP-system, the yearly estimate is translated into a monthly estimate by means of fixed proportions for the next 12 months. These proportions are determined by means of evaluating the monthly proportions of the expected sales per month in the yearly budget, yearly established by the Sales department. These monthly proportions are the same for each forecasted item. These proportions are not assigned to a specific month, but to the first month after updating the yearly estimate and so on; the current proportions are provided in Table 2.3.

Table 2.3. Monthly demand proportions.

Month after updating	Demand proportion (%)
1	8.5
2	6.5
3	9.2
4	8.3
5	9.7
6	10.5
7	9.9
8	6.7
9	9.4
10	9.7
11	6.2
12	6.1

This way of working indicates different monthly demand proportions in case the yearly estimate is updated and imported to the ERP-system in different months for two different product types for example. A fictive example is provided in Table 2.4. A reason for sustaining this way of working is related to limitations of the ERP-system in case of assigning the monthly proportions to a fixed month.

Table 2.4. Fictive example monthly demand distribution within the forecasting procedure of VFA.

	Monthly demand proportion				
Product type	*January*	*February*	*March*	*April*	*May*
Product type X	Adjust yearly estimate	8.5%	6.5%	9.2%	8.3%
Product type Y	-	-	Adjust yearly estimate	8.5 %	6.5%

From observations of the Excel-file and interviews with the Purchasing department some facts may be mentioned with regard to the current forecasting procedure. From observations of the Excel-file it became clear that (1) no distinction is made between the different pleating heights for pleated fabric, (2) some product types are not forecasted on colour while a minimum inventory level of finished products is kept, (3) no distinction is made between the metallized and non-metallized product types in case of the same fabric composition and weaving structure, e.g. product types 815 and 816, and (4) the performance of the forecasting procedure is not measured and logged.

From interviews with the Purchasing department it became clear that (1) no distinction is made between the two different demand types, (2) the forecasting procedure is the same for each forecasted item and are not backed by statistical forecasting procedures provided in literature and (3) the monthly demand proportions are not consistently reviewed each year.

2.2.2 Process performance

Insight in the current demand forecasting performance should be obtained in order to evaluate the impact of a newly proposed demand forecasting model and usable insights may be provided for the future demand forecasting model. As aforementioned, the forecasting performance is currently not logged within VFA, the current demand is forecasted on SKU-level in case RM is supplied in colour and on a more aggregated level in case RM is supplied uncoloured. This approach results in a total of 52 forecasted items in January 2020 and 64 forecasted items in January 2021. This increase in forecasted items is caused by New Product Introductions (NPIs) throughout 2020. In the further continuation of this section, the demand is expressed in m² as the current forecast unity is m².

In order to quantitatively assess the performance of the current demand forecasting procedure, the performance is expressed in the forecast accuracy; a measure indicating how far away our forecast is from the actual value (Silver, Pyke, & Thomas, 2017). Within this research the performance of the current forecasting procedure is evaluated by means of a combination of the Mean Absolute Deviation (MAD), the bias and the symmetric Mean Absolute Percentage Error (sMAPE) as performance measures. Reasoning for the combination of these performance measures and the corresponding formulas are provided in Section 3.2.3. The results of the analyses with the different performance measures applied to each forecasted item are provided in Table III.4 in Appendix III and discussed in the following paragraphs, while reviewing each performance measure individually. Table 2.5 summarizes the results as provided in Appendix III.

Table 2.5. Summarizing overview of the results per year for each performance measure (MAD, Bias, sMAPE).

	2020			*2021*		
Performance measure	**Min.**	**Max.**	**Average**	**Min.**	**Max.**	**Average**
MAD (m²)	25	3,759	993	6	3,847	870
Bias (m²)	-2,428	1,985	102	-1,402	3,638	466
Bias (%)	-238%	305%	26%	-100%	1.054%	132%
sMAPE (%)	27%	192%	104%	33%	191%	109%

MAD

The MAD provides an indication of the size of the average forecast error. The lower this value, the better the forecasting performance. The result of the MAD as performance measure is provided in the form of a histogram in Figure III.4 in Appendix III. From this figure it may be observed that the largest part of the forecasted items has an absolute forecast error up to 800 or 1200 m^2 in 2020 and 2021.

Bias

The bias provides insight in the fact whether the forecast is consistently too high or too low. If the bias is consistently larger or smaller than 0, the forecast is said to be biased. Within this research the bias is evaluated in both squared meters (m²) and as a proportion (%) in order to obtain insight in the size of the bias. An initial view of the forecasting performance with regard to the bias is depicted in Figure 2.5; the cumulative value of both the forecasted and actual demand of all forecasted items for each month in 2020 and 2021 is provided. From this figure it could be observed that the forecasted demand value exceeds the actual demand value. For 2020 the forecasted demand is higher than the actual demand in 7 of the 12 months. For 2021, the forecast is higher than the actual demand in each month, indicating that the forecast is consistently too high.

The initial observation of a consistently too high forecast is confirmed by the result of the analysis with the bias as performance measure, depicted in Figure III.5 in Appendix III. This figure provides a more extensive overview by means of depicting the bias (%) for each forecasted item over the years 2020 and 2021. Most values are larger than 0%, i.e. 65% and 80% of the values for 2020 and 2021, respectively.

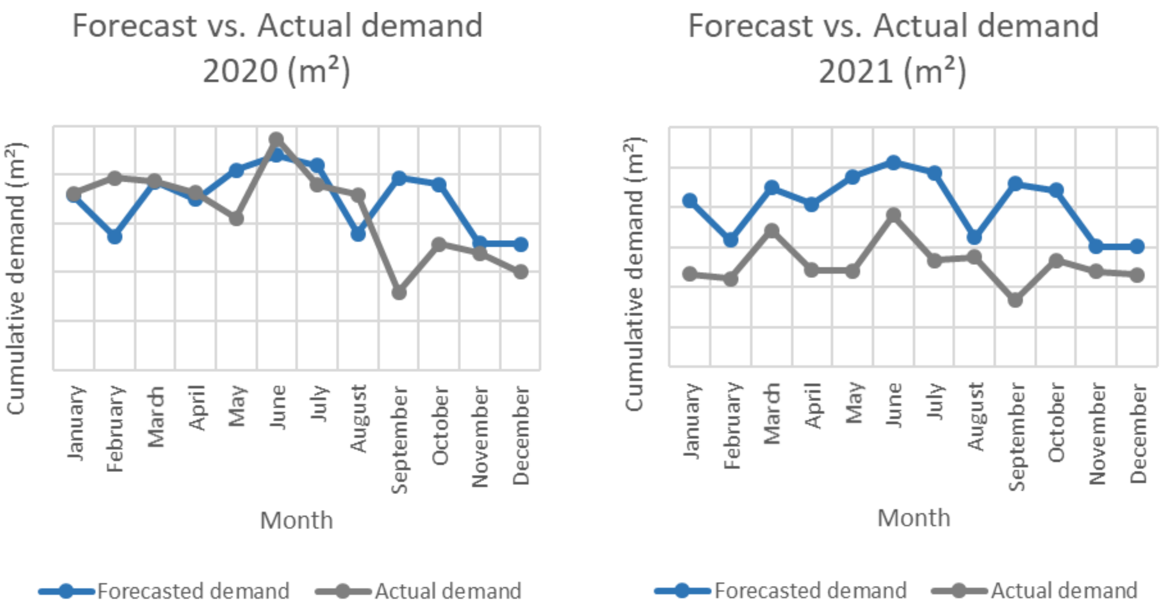

Figure 2.5. Cumulative forecasted vs. actual demand (m²) 2020 and 2021.

sMAPE

Insight in the size of the forecast error relative to the actual value is provided by means of analysing the forecast with sMAPE as performance measure. A lower value of sMAPE indicates a better forecasting performance with a lower bound of 0%. Contrary to the bias, the negative and positive errors can not cancel each other out, as the absolute forecast error is incorporated in the formula. The result of this analysis is depicted in Figure III.6 in Appendix III in the form of a histogram. From Figure III.6 it may be observed that the largest part of the forecasted items has a relative absolute forecast error between 80% to 160% for 2020 and 2021.

Overall performance

When comparing the peaks amongh the SKU-individual performance measures in 2021, it appeared that the peaks are distributed among the SKUs for the several performance measures; no peaks in each performance measure are assigned to an SKU simultaneously. In addition, it appeared that most of the sMAPE values are relatively high, considering the upper limit of 200%; i.e. 40 out of 64 items. When reviewing the bias (%), there are 6 peaks in the performance measure value that stand out compared to the other values. The values of the MAD and bias (m²) have also been reviewed, but a comparison of these results would not be adequate due to the scale-dependency of these performance measures; i.e. if the demand of an SKU increases, the performance measure value increases simultaneously.

When reviewing the individual values of each performance measure and the averaged values for both 2020 and 2021, as provided in Table 2.5, it can be observed that these values are relatively high. An explanation for these relatively high values could be the fact that no distinction is made between regular and project demand in the data serving as a base for the current demand forecast, resulting in an increased demand variability. The increased demand variability together with the relatively long forecasting horizon, i.e. 12 months, affects the predictability of the demand in a negative way. In addition, these performance measures are based on a specific moment in time, i.e. the forecasts established at the beginning of 2020 and at the beginning of 2021 for both full years. As described in Section 2.2.1, these forecasts may be adjusted throughout the continuation of the year. In case a larger project order is expected towards the end of the year and this was not known at the beginning of the year, then the forecast will be adjusted. Considering the fact that these changes could not be traced back with the corresponding seasonal estimate used, the forecasts established at the beginning of 2020 and 2021 are used when evaluating the performance. As a consequence, the forecast adjustments as explained above are not incorporated and could, therefore, negatively affect the forecasting performance; resulting in relatively high forecasting performance measure values.

In order to evaluate the impact of the demand variability on the heigth of the performance measures, in this case the sMAPE value, the correlation between the Coefficient of Variation (CV) and the sMAPE values is determined by means of a correlation plot and a correlation coefficient. The CV relates to the variation in order size of each forecasted item in order to express the demand variability, calculated by means of Equation (2).

$$CV = \frac{\sigma}{\mu} \tag{2}$$

The expectation would incorporate an increase in the sMAPE value in case of an increased value of the CV. An evaluation of the CV and sMAPE value for each forecasted item in 2020 results in a correlation coefficient of approximately -0.43; indicating a moderate negative relation among the two variables; an observation against the expectation. The corresponding correlation plot is provided in Figure 2.6. From both the correlation coefficient and the correlation plot a positively correlated relation between the demand variability and the sMAPE value cannot be adopted.

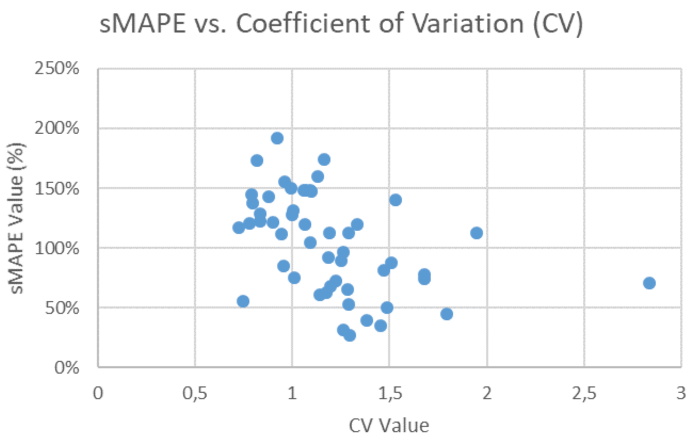

Figure 2.6. Correlation plot of the sMAPE (%) against the CV.

When relating the results of the performance measures MAD, bias and sMAPE to the types of forecasted items, i.e. product types, several observations could be made with regard to the current forecasting procedure. When reviewing the sMAPE values it could be observed that the value is lower in case the forecasted items are aggregated on colour, i.e. the RM is supplied uncoloured for these product types. This observation is depicted in Figure III.7 in Appendix III, the average sMAPE value per product type is provided over the years 2020 and 2021. In addition, the sMAPE values are averaged based on the fact whether the RM is supplied in colour or uncoloured. A similar pattern is observed for the bias (%), depicted in Figure III.8 in Appendix III. The averaged values of these performance measures decrease with approximately 50% and 70%, respectively, in case the RM is supplied uncoloured. For the MAD and bias (m^2) no particular pattern, with regard to the product types or RM, could be observed.

2.2.3 Impact on operations

As stated by Axsäter (2006), Silver, Pyke & Thomas (2017) and Gardner (1990), a demand forecast representing reality as good as possible is the foundation for a well performing inventory management policy. The field of inventory control aims to find a balance between the capital that is fixed in inventory and the customer service level that is set as a target; i.e. meet the customer service level target with the minimum needed amount of capital fixed in inventory. As indicated, the demand forecasting performance affects the operational activities of the company in a broader way; eventually affecting the achieved delivery performance of a company. Within this section insight is provided on how the operations of VFA are affected by the current forecasting performance. Information is obtained from interviews with the Purchasing, Sales and Planning department of VFA.

As aforementioned, the demand forecast of VFA is used in order to establish the minimum inventory levels in the warehouse. The current demand forecast of VFA is based on all demand that occurred over the last year; no distinction is made between regular and project demand. As a consequence, a biased view of the future demand is created, logically resulting in a too high established future demand; the larger project orders do not reoccur with the same certainty as the smaller regular orders. Currently, the minimum inventory levels within VFA are based on the result of this demand forecast, resulting in too high minimum inventory levels according to the Planning department of VFA.

As a consequence of these too high inventory levels, too much inventory is kept in the warehouse according to the Purchasing and Planning department of VFA; resulting in too little warehousing space. In addition, it is indicated that the current excess inventory keeps inventory places occupied, which could be potentially assigned to inventory of other SKUs which could not be delivered from inventory currently. For this reason, the minimum inventory levels are only considered as an indication by the Planning department of VFA and not as a minimum level required to fulfil the delivery performance target.

As aforementioned, insight in the different demand types is lacking within VFA; no distinction is made between regular and project demand. Due to this lack of insight, this characteristic is not considered when fulfilling demand with inventory from stock. The current policy with regard to fulfilling demand with inventory from stock is the First Come First Serve (FCFS)-policy. For example, a larger project order arrives as first order in the system and this order can be fulfilled by the inventory from stock; while this is not a necessity considering the longer completion time. Then the available stock is assigned to this order. If, for example, the next 3 orders are smaller regular orders, these orders cannot be fulfilled from stock and a delay occurs. Within VFA there is no clear policy strictly followed with regard to up to which order size to deliver from stock.

As a consequence, the delivery performance of VFA is influenced by the overview of actions and related impacts as provided above.

2.3 Chapter conclusion

In order to provide a base for the further continuation of the research, a summary of the most important conclusions drawn with regard to the current situation is provided below.

The aggregation level of the current forecasting procedure is wrongly determined as a consequence of forecasting with two purposes, i.e. (1) in the light of purchasing and (2) in the light of inventory control.

> Both purposes require different input information provided by the demand forecast. As shown in Section 2.1.1 a total of 1,130 SKUs is incorporated in the research scope, representing approximately 91% of the sales (€) in 2021. Of these 1,130 SKUs, 104 SKUs should be forecasted on SKU-level as the required RMs are supplied in colour; i.e. specifying product type, fabric width, fabric colour and application. The forecast of the remaining 1,026 SKUs is on a more aggregated level with regard to colour and application, resulting in a total of 24 different SKUs. In total, 104 + 24 = 128 SKUs should be included in a future forecast in the light of inventory control. The difference between this number, 128, and the current number of forecasted items, 64 in 2021, is caused by the fact that the level of aggregation is wrongly determined and some new items were not included in the forecast yet.

No distinction can be made between the two demand types, i.e. regular and project demand, which VFA faces

In Section 2.1.2 it becomes clear that the demand VFA faces is observed to be variable in terms of both order size and order frequency. In addition, the demand flow can be divided into regular and project demand, the regular demand representing the more frequently occurring, smaller orders and the project demand the more infrequently occurring, larger orders often known well ahead of time. From Section 2.1.2 it can be concluded that the data currently available is not extensive and reliable enough to enable a distinction between both demand types. In addition, no insight could be obtained in the development of a project order in terms of the order uncertainty. For this reason, the research direction should be adjusted; the distinction between regular and project demand will be imitated by means of demand scenarios. Each demand scenario contains demand data up to a certain order size threshold (m). A suitable forecasting method will be established for each demand scenario and the impact of forecasting up to a certain order size thresholds (m) on the inventory control will be evaluated. Section 4.1.2 further elaborates on the establishment of the different demand scenarios.

The current forecasting procedure offers opportunities for improvements

In Section 2.2 the demand forecasting performance is assessed, of which the focus is solely on the demand forecast generated by the Purchasing department. The following conclusions can be seen as most important;

- No distinction is made between the two demand types present in the data on which the demand forecast is based.
- The forecasting methodology is equal for each SKU and not based on a statistical forecasting method provided in literature.
- Each month a demand estimate is established for the next year. This yearly estimate is distributed in monthly estimates by means of monthly proportions. These monthly proportions are not strictly assigned to a specific month, causing wrongly assigned monthly demand proportions.
- In case a product type is offered both metallized and nonmetallized, no distinction is made between the product variants when forecasting demand; demand is aggregated.
- The current demand forecasting performance is not logged. When evaluating the current demand forecasting performance in Section 2.2.2 it can be concluded that the demand forecast is consistently too high, that the performance measure values are relatively high and that the forecast for the coloured RM is less accurate than the forecast for the uncoloured RM, when expressing the performance in sMAPE and the bias (%).

The current demand forecast causes too high minimum inventory levels

Recalling the relation between the demand forecast and the minimum inventory levels, based on Section 2.2.3 it can be concluded that the current demand forecast causes too high minimum inventory levels according to VFA; considering the fact that the project orders are also included in the data evaluated for the demand forecast. Also, there is no strict guideline currently kept with regard to up on to which orders size to deliver from inventory; negatively affecting the delivery performance of VFA.

The literature as provided in Chapter 3 will further elaborate on the following topics; (1) item classification methods, (2) suitable demand forecasting methods for the product offer of VFA and (3) the relation between demand forecasting and inventory control.

3 LITERATURE REVIEW

Within this chapter literature is provided related to the main research aim. Within this research, this relates to an improvement of the delivery performance by means of creating a solid foundation on which a future inventory management policy could be established. Inventory control, by means of an inventory management policy, relates to creating an optimal balance between improvement of the customer service level(s) and a decrease of the capital fixed in inventory (Axsäter, 2006) (Gardner, 1990). Demand forecasting contributes to creating a solid foundation for a future inventory management policy; an accurate description of future demand is required for effective decision making in inventory management (Axsäter, 2006) (Silver, Pyke, & Thomas, 2017) (Chopra & Meindl, 2013).

In connection to inventory control in particular, the uncertainty of the demand forecast needs to be evaluated in order to determine the SS levels required to obtain a certain level of customer service. The more uncertain the forecast, the larger the potential forecast errors will be. The SS levels required are based on these forecast errors and will increase accordingly when the forecast error increases (Axsäter, 2006) (Silver, Pyke, & Thomas, 2017) (Gardner E. , 1990).

In the following sections literature is provided related to demand forecasting and inventory control. The literature review is structured in the following order; at first several item classification techniques are provided in Section 3.1, followed by several demand forecasting methods and corresponding performance measures in Section 3.2. Lastly, Section 3.3 provides literature about establishing a suitable SS level within a certain inventory control policy and Section 3.4 summarizes the relevant literature.

3.1 Item classification

Nowadays the product offer of companies is often extensive, creating an increase in the management complexity of the complete product offer. Each single item within the product offer of a company is referred to as an SKU. Within this research the term SKU is defined in alignment with the definition of Silver, Pyke & Thomas (2017); “Items of stock that are completely specific as to function, style, size, colour and, often, location”. Often, these individual SKUs are grouped by means of item classification methods.

3.1.1 Purpose of item classification

The classification of the SKUs reduces the complexity of managing the often extensive offer of SKUs and covers the distinction of a number of classes based on the similarities of these SKUs. Item classification enables decision making for single SKU classes rather than for individual SKUs; reducing the costs of decision making (Silver, Pyke, & Thomas, 2017) (van Kampen, Akkerman, & Van Donk, 2012) (Boylan, Syntetos, & Karakostas, 2008).

From literature it can be observed that the classification of SKUs contributes to a reduction in the costs of decision making in two ways; by means of (1) distributing the available managerial attention correctly and by means of (2) simplifying the application of forecasting and inventory control policies as the grouped SKUs are associated with the same methods for forecasting and inventory control (Boylan, Syntetos, & Karakostas, 2008) (Heinecke, Syntetos, & Wang, 2013) (Axsäter, 2006).

The classification of SKUs is often not considered as an aim itself according to Van Kampen, Akkerman & vVan Donk (2012) and Syntetos, Boylan & Croston (2005), but as an intermediate procedure while obtaining the main objective; establishing a demand forecast or inventory control policy. For this reason, little literature focuses on the classification of SKUs as main research topic and literature elaborates in less detail on the classification of SKUs (van Kampen, Akkerman, & Van Donk, 2012)

(Boylan, Syntetos, & Karakostas, 2008). Van Kampen, Akkerman & Van Donk (2012) provide a review of the literature dedicated solely to the classification of SKUs within the field of Production and Operations Management. From this literature review Van Kampen, Akkerman & Van Donk (2012) state that 3 main applications of item classification were found in the literature thus far in the field of Production and Operations Management; i.e. inventory management, demand forecasting and production strategy, respectively. Among the literature reviewed, the largest part focussed on inventory management, a smaller part on demand forecasting and only a few on production strategy (van Kampen, Akkerman, & Van Donk, 2012).

3.1.2 Classification techniques

In general, a distinction between item classification techniques can be made based on the type of data source that is used; either judgemental or statistical (Cavalieri, Garetti, Macchi, & Pinto, 2008) (van Kampen, Akkerman, & Van Donk, 2012) (Chopra & Meindl, 2013). In addition, a distinction can be made between the perspectives from which the items are classified. Van Kampen, Akkerman & Van Donk (2012) observed various perspectives and categorized these in four SKU characteristics that are important within item classification in the field of Production and Operations Management; *volume*, *product*, *customer* and *timing*, respectively. The SKU characteristics *product* and *volume* were widely used in the classification methods reviewed, while *customer* was only used in a few occasions; indicating that this characteristic is not essential in this field of application. The SKU characteristic *timing* is in general only used in item classification for demand forecasting.

Considering the objective of this research the classification, techniques discussed in the following sections will be related to inventory control and demand forecasting. The classification techniques are all based on statistical data, while attempts are made to minimize the influence of subjectivity within this research.

Within the field of inventory control and demand forecasting, the most frequently observed item classification techniques are the Always-Better-Control (ABC)-analysis and the XYZ-analysis. Another also commonly known approach, but less often applied in practice, is the Fast-, Normal- and Slow-moving (FNS)-analysis. Another classification method, provided in specific in the light of demand forecasting, focusses on the demand pattern of individual SKUs; the so-called Demand Pattern (DP)-analysis.

The **ABC-classification** method continues on the Pareto-principle and evaluates the, often annual, usage of an SKU; indicating that the SKU characteristic *volume* is important within this analysis (Silver, Pyke, & Thomas, 2017) (van Kampen, Akkerman, & Van Donk, 2012). Based on the usage an SKU is classified as either an A, B or C-item in order to distribute the managerial attention among the individual SKUs. This ABC-classification method is also mentioned by Balaji & Senthil Kumar (2014) and Axsäter (2006). The boundaries between the classes provided in literature differ from each other. In general the argument relates back to the Pareto-rule; in the reviewed literature class A, i.e. 20% of the items, accounts for approximately 80% of the annual sales. The boundaries as provided by Silver, Pyke & Thomas (2017), Balaji & Senthil Kumar (2014), Zenkova & Kabanova (2018) and Scholz-Reiter, Heger & Meinecke (2012) are depicted in Table 3.1. Overall, the boundaries are expressed in the cumulative contribution of item i to the annual sales (S_i). Only Axsäter (2006) expresses the boundaries as a percentage of the total number of items.

Table 3.1. ABC-Classification boundaries provided in literature.

	Literature source				
Class	*Axsäter (2006)*	*(Silver, Pyke, & Thomas, 2017)*	*Balaji & Senthil Kumar (2014)*	*Zenkova & Kabanova (2018)*	*Scholz-Reiter, Heger & Meinecke (2012)*
A	10%	$S_i \leq 0.8$	$S_i \leq 0.8$	$S_i \leq 0.8$	$S_i \leq 0.8$
B	30%	$0.8 \leq S_i \leq 0.95$	$0.8 \leq S_i \leq 0.95$	$0.8 \leq S_i \leq 0.95$	$0.8 \leq S_i \leq 0.95$
C	60%	$S_i > 0.95$	$S_i > 0.95$	$S_i > 0.95$	$S_i > 0.95$

Besides the ABC-analysis, the **XYZ-classification** method is also proposed as an overall well known item classification method. This method classifies SKUs based on their variability in demand over a certain time period and therefore *volume* and *timing* are the important SKU characteristics (van Kampen, Akkerman, & Van Donk, 2012). The variability in demand is expressed in the Coefficient of Variation (CV). Class *X* includes the most stable, almost constantly demanded products, class *Y* is less stable and class *Z* contains products with exceptional demand patterns (van Kampen, Akkerman, & Van Donk, 2012) (Scholz-Reiter, Heger, & Meinecke, 2012) (Zenkova & Kabanova, 2018).

In addition to the ABC- and XYZ-analysis, the FNS-analysis is applied within the field of inventory control and demand forecasting. The **FNS-classification** method is based on the demand rate of an SKU within a certain time period while excluding the time periods with zero demand (Cavalieri, Garetti, Macchi, & Pinto, 2008) (Gelders & van Looy, 1978) (van Kampen, Akkerman, & Van Donk, 2012). Within this classification method, the boundaries between the classes depend on the data that has been evaluated and no universally applicable guideline is provided in literature to set these boundaries.

Often, also indicated above, similar classification methods are used for different purposes such as demand forecasting and inventory control. This is reasonable due to the present dependency between both the purposes; inventory control is most often the subsequent process after demand forecasting. Nevertheless, Van Kampen, Akkerman & Van Donk (2012) specify a difference in the item classification methods for both inventory control and demand forecasting. This difference relates to the SKU characteristic used for the item classification; *timing* is an important SKU characteristic when classifying SKUs in the light of demand forecasting.

The importance of *timing* as SKU characteristic in item classification for demand forecasting probably relates to the fact that a suitable forecasting procedure depends on the variability in the demand pattern (van Kampen, Akkerman, & Van Donk, 2012). Variability in demand may relate to either (1) the demand volume or (2) the timing of demand. This analysis of demand variability results in the **DP-classification** method.

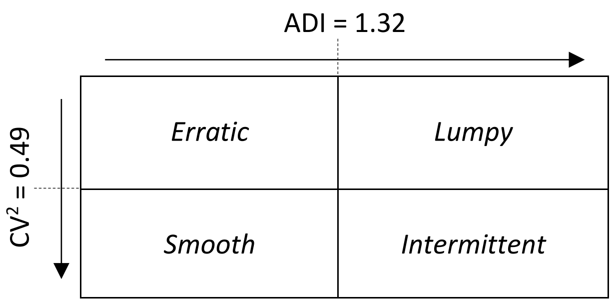

Figure 3.1. DP-Classification framework.

Within forecasting, a review of the demand pattern over time is important when classifying SKUs; a smooth, sporadic or lumpy demand pattern influences the performance of the applied forecasting procedures and, thus, indirectly the performance of the inventory control policy. Syntetos, Boylan & Croston (2005) and Boylan, Syntetos & Karakostas (2008) indicate that academic literature provided elaborating on the classification of demand patterns is limited. From the available literature it is observed that the Average inter-Demand Interval (ADI) and the squared Coefficient of Variation (CV^2), if demand occurs, are important factors when classifying demand patterns (van Kampen, Akkerman, & Van Donk, 2012) (Williams, 1984) (Syntetos, Boylan, & Croston, 2005). Syntetos, Boylan & Croston (2005) established a classification framework as provided in Figure 3.1, based on these two factors, in order to classify a demand pattern either as smooth, erratic, intermittent or lumpy. The usability of this framework is emphasized by Boylan, Syntetos & Karakostas (2008) and the description and directives for each class are the following;

- **Smooth**: low variability in order size and low variability in order placement with $CV^2 < 0.49$ and ADI < 1.32.
- **Erratic**: high variability in order size and low variability in order placement with $CV^2 \geq 0.49$ and ADI < 1.32.
- **Intermittent**: low variability in order size and high variability in order placement with $CV^2 > 0.49$ and ADI ≥ 1.32.
- **Lumpy**: high variability in order size and high variability in order placement with $CV^2 \geq 0.49$ and ADI ≥ 1.32.

The subsequent formulas are operationalized when determining the values of the ADI and CV^2;

- **ADI**: the average interval between 2 consecutive demand periods for item i, where Np_i represents the number of periods with non-zero demand (Costantino, Di Gravio, Patriarca, & Petrella, 2017).

$$ADI_i = \frac{\sum_{n=1}^{Np_i} t_i^n}{Np_i}$$

- **CV²**: the standard deviation of the demand of item i, divided by the average demand (d_i), where $d_i = \frac{\sum_{n=1}^{Np_i} d_i^n}{Np_i}$ (Costantino, Di Gravio, Patriarca, & Petrella, 2017).

$$CV_i = \frac{\sqrt{\frac{\sum_{n=1}^{Np_i}(d_i^n - d_i)^2}{Np_i}}}{d_i}$$

For every classification method, re-categorization of SKUs is a necessity and occurs at fixed time intervals, e.g. quarterly or annually; depending on the preference of the company. When re-categorizing items, outliers in the newly known demand data should be evaluated and excluded in order to minimize the possible item movements from one category to another because of only a few extreme observations (Syntetos, Boylan, & Croston, 2005).

3.2 Demand forecasting

Within this research a forecast is defined according to Silver, Pyke & Thomas (2017); “A description of future demand scenarios used to support a resource allocation decision”. A demand forecast may consist of a combination of (1) forecasting based on an extrapolation of historic data, i.e. a quantitative method, and (2) forecasting based on judgments about future events, i.e. a judgemental method. Of these two, the first is most commonly used in practice and is an important approach to obtain short-term demand forecasts of high quality (Silver, Pyke, & Thomas, 2017)(Axsäter, 2006) (Chopra & Meindl, 2013).

Different types of demand forecasts serve for different purposes. Forecasts may differ e.g. in the level of product detail or in the length of the forecast horizon; how far in the future demand is predicted. In connection to inventory control forecasts are on a high product detail level, i.e. on SKU-level, and concern a relatively short forecast horizon; very rarely more than a year (Silver, Pyke, & Thomas, 2017) (Axsäter, 2006). For this reason, the following literature elaborates further on **short-term forecasting** on **SKU-level**, based on **quantitative forecasting methodology**.

3.2.1 Demand forecasting process

Several approaches for demand forecasting are provided in literature. Hyndman & Athanasopoulos (2018) provide the following approach, distinguishing the basic steps of demand forecasting;

1. **Problem definition**: define a general understanding of the function of the forecast; i.e. the way the forecast will be used, who requires the forecast and how the forecasting function fits within the organisation.
2. **Gathering information**: obtain the information relevant for the establishment of the forecast; i.e. historic demand data and expert opinion of those who collect the data and use the forecasts.
3. **Preliminary (exploratory) analysis**: evaluate the historic data in order to determine whether a consistent pattern, trend and/or seasonality is present. In addition, the data is reviewed on outliers that could be justified or modified by means of expert opinion.
4. **Choosing and fitting models**: fit and compare several forecasting methods; fitting of the models implies the parameter estimation based on the historic data.
5. **Using and evaluating a forecasting model**: assess the forecasting performance of each forecasting method and select the best method to implement within the organisation.

Silver, Pyke & Thomas (2017) provide a more detailed framework for step 4 and 5 in particular, provided in Figure 3.2. In advance of selecting a suitable forecasting method, the historic data should be divided in a train- and test set in order to enable model validation (Boylan, Syntetos, & Karakostas, 2008) (Silver, Pyke, & Thomas, 2017) (Montgomery, Jennings, & Kulahci, 2015). A typical data partition

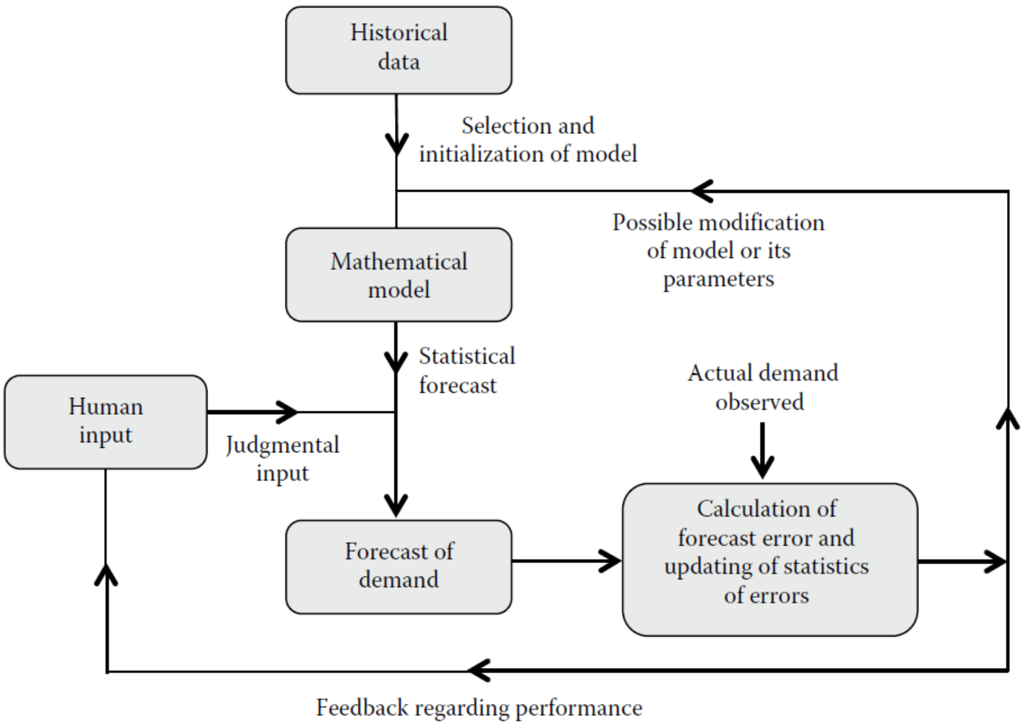

Figure 3.2. Demand forecasting framework (Silver, Pyke, & Thomas, 2017).

rule to validate models is provided by Bishop (1995) and proposes a 80-20% split among the historic data.

3.2.2 Demand estimators

The most suitable forecasting method depends on the underlying demand pattern within the time series; i.e. the observed demand indexed as a function of time. The general structure of the observed demand is the following:

$$Observed\ demand\ at\ time\ t\ (x_t) = Systematic\ component\ (a, b, F, C) + Random\ component\ (\varepsilon)$$

The observed demand includes a systematic component and a random component. Each possible element of both components represents the following:

- **Level** (a): indicates the constant scale of a time series;
- **Trend** (b): provides an indication of either a growth or decline present within the time series;
- **Seasonality** (F): indicates a constantly recurring fluctuation in the time series due to natural forces or human decisions;
- **Cyclical movements** (C): represent variations in a time series due to business cycles;
- **Irregular random fluctuations** (ε): represent the occurrence of unpredictable events and is the residue that remains after the effect of the other 4 components is filtered out;

When considering short-term forecasting the cyclical movements are not considered in general as the forecast horizon is too short for an identification of these movements. Also, the irregular random fluctuations are always present. A preliminary data analysis, by means of plotting the data and/or statistical procedures, should suggest the presence of a, b and F (Silver, Pyke, & Thomas, 2017) (Chopra & Meindl, 2013) (Nwogu, Iwueze, & Nlebedim, 2016). Silver, Pyke & Thomas (2017) and Axsäter (2006) state that more extensive demand models are available as a base for demand forecasting, requiring detailed statistical analysis of the demand structures. In practice, this is superfluous in connection to inventory control (Axsäter, 2006).

As aforementioned, the focus is on quantitative forecasting methods; i.e. the model summarizes specific patterns in the data and makes use of a statistical relationship between historic and current values of the time series (Montgomery, Jennings, & Kulahci, 2015). Montgomery, Jennings & Kulahci (2015) categorize the most widely used methods as either (1) **regression models**, (2) **smoothing models** or (3) **time series models**. This categorization is based on the characteristics of a forecasting method. Regression models assume a relationship between the variable of interest and the predictor variable(s), whereas the difference between smoothing and time series models is the dependency among the stochastic variations. The stochastic variations are assumed to be independent within the smoothing models; a simplification of reality according to Axsäter (2006). Within the time series models these stochastic variations are assumed to be dependent. Table 3.2 presents the performance of each forecasting method category for different forecasting horizons, expressed in the Mean Absolute Prediction Error.

Table 3.2. Mean Absolute Prediction Error per forecasting method category and forecast horizon (Montgomery, Jennings, & Kulahci, 2015).

	Forecasting horizon		
Forecasting method category	*1-period ahead*	*6-periods ahead*	*12-periods ahead*
Regression	12-18%	17-20%	20-25%
Smoothing	10-15%	17-25%	18-45%
Time series	10%	17%	25%

Forecasting methods part of smoothing models are, among others, the Moving Average (MA) and exponential smoothing methods such as Simple Exponential Smoothing (SES). Forecasting methods part of time series models are, among others, Auto Regressive Moving Average (ARMA) or Auto Regressive Integrated Moving Average (ARIMA) method. Among these 3 forecasting categories, the ARIMA method and exponential smoothing methods are the most widely used approaches to forecast time series; of which the ARIMA method is more sophisticated compared to the exponential smoothing methods. Montgomery, Jennings & Kulahci (2015) indicate that the more sophisticated techniques are often harder to use and that they do not result in a substantial decrease of the forecasting error as shown in Table 3.2. In addition, Box & Jenkins (1970) indicate the exploration of ARIMA methods as potential forecasting methods in case more than 50 observations are available for the model initialisation. Also, Makridakis, et al. (1993) and Makridakis & Hibon (2000) concluded that the relatively simple forecasting procedures performed much better for individual item forecasting than the statistically sophisticated procedures; for short-term forecasting SES, the Holt and Brown trend procedures and Winter's forecasting model performed well.

In general, the more elements are included in the forecasting procedure, the more extensive and thus the more expensive the forecasting procedure. Such an extensive and costly procedure should be avoided if possible (Silver, Pyke, & Thomas, 2017) (Axsäter, 2006). Considering the findings of Makridakis et al. (1993), Makridakis & Hibon (2000) and the amount of historic data available within this research setting, the focus continues on the exponential smoothing methods.

As aforementioned in Section 2.1.2, VFA faces variability in demand in both order size and order frequency; i.e. facing time series with periods of no demand. When reviewing time series with periods of no demand, SES, MA or Croston's method are indicated as the standard forecasting method for items classified as slow-moving or less important while having a demand pattern with periods of no demand (Sani & Kingsman, 1997) (Willemain, Smart, Shockor, & DeSautels, 1994) (Syntetos, Boylan, & Croston, 2005). In case the ADI > 1.25 the SES model performs inefficient and the use of Croston's method should be considered instead (Johnston & Boylan, 1996). Whereas Johnston & Boylan (1996) suggest Croston's method as replacement for SES under a certain condition, Croston's method is considered to be biased by Syntetos, Boylan & Croston (2005). Teunter, Syntetos & Zied Babai (2011) indicate that Croston's method is (1) unsuitable for dealing with the obsolescence of demand issues and (2) positively biased. As a consequence, alternative forecasting methods have been established in literature, all variants of the original Croston's method. Alternative methods that are multiple times proposed in literature are the Syntetos & Boylan Approximation (SBA), the Levén & Segerstedt method, the Wallström method, the TSB method and the Vihn method (Syntetos, Boylan, & Croston, 2005) (Levén & Segerstedt, 2004) (Wallström & Segerstedt, 2010) (Teunter, Syntetos, & Zied Babai, 2011) (Vihn, 2005). Several studies indicate a superior performance of an alternative method over Croston's original method, but the directives of which method performs best differ among the available literature over time.

From the available literature, no alternative method shows consequent outstanding results. Causes for this diversity may be the different data set characteristics or performance evaluation techniques among the studies. Some literature indicate the preference of Croston's original method over the alternative methods. Segerstedt & Levén (2014) indicate that the original Croston's method is preferred over the suggested alternative methods; some methods overestimate and others underestimate demand in certain circumstances. In addition, Boylan & Syntetos (2007) state that Croston's original method is preferred over the Levén & Segerstedt method. Also Zied Babai, Syntetos & Teunter (2014) indicate that Croston's method seems to outperform the alternative methods when focussing on inventory control and intermittent or lumpy demand patterns in specific. Xu, Wang & Shi

(2012) reviewed the available literature with regard to Croston's method and its alternatives for intermittent demand forecasting and suggest that further research should be conducted on the performance of Croston's method against the alternative methods; indicating no alternative method is outperforming Croston's original method. For this reason, the focus remains on Croston's original forecasting method.

Xu, Wang & Shi (2012) state that the link between forecasting and inventory control deserves more attention for intermittent demand forecasting. Zied Babai, Syntetos & Teunter (2014) indicate that most of the comparative forecasting studies for intermittent demand focus solely on forecast accuracy rather than inventory control implications. This observation is emphasized by Xu, Wang & Shi (2012).

In general, SES or MA is a suitable forecasting method for most items (Axsäter, 2006) (Johnston & Boylan, 1996) (Boylan, Syntetos, & Karakostas, 2008). Of these, SES is preferred over MA as more weight is assigned to the most recent observations, whereas the weights for the historic and most recent observations are equal when applying MA (Axsäter, 2006) (Silver, Pyke, & Thomas, 2017). For the more important SKUs or classes of SKUs Axsäter (2006), Silver, Pyke & Thomas (2017) and Chopra & Meindl (2013) state that other methods, considering the presence of a trend and/or seasonality, could be useful in terms of obtaining more accurate forecasts. The improvement of the accuracy outweighs the increase in method complexity for these cases. The methods considered in connection to inventory control are Holt, also known as a trend-corrected Exponential Smoothing or Double Exponential Smoothing (Swamidass, 2000), and Winters method. Of the SES, Holt and Winters method 2 variants are presented in literature, a static and adaptive variant. In case the estimated parameter values, such as *a* and *b*, are not updated when new demand is observed, the static variant is applied. If the parameter values are updated in case new demand is observed, the adaptive variant is applied. The adaptive variant is most often applied, as the most recently observed demand may provide valuable insight in the development of the demand with regard to a structural change in the initiated level or trend (Chopra & Meindl, 2013). Appendix IV elaborates on the specific initialization and updating procedures of each forecasting method applied throughout the continuation of this research.

From the available literature it can be observed that incorporating seasonality in the forecasting model is only recommended for items with very obvious seasonal variations and in case enough historic data is available, i.e. 4 complete seasonal cycles is preferred (Axsäter, 2006) (Silver, Pyke, & Thomas, 2017). In case of incorporating seasonality, different types of seasonality could be established. First of all, an additive or multiplicative seasonal model could be incorporated. Within an multiplicative seasonal model, the seasonal estimate (*F*) is multiplied with the level (*a*) and trend (*b*) and therefore the seasonal impact (de)increases simultaneously when *a* and/or *b* (de)increases, this is not the case for the additive model. Within literature, the multiplicative variant is most often addressed and applied. In addition, the seasonal period could differ, e.g. either weekly or monthly seasonality, and the initialisation and updating of the seasonality could be SKU-individual or based on a group of SKUs. An erratic demand pattern for single SKUs could serve as a reason for applying grouped-based seasonality (Dekker, Van Donselaar, & Ouwehand, 2004). A group of SKUs may be composed by shared product characteristics or by a statistical analysis such as K-means (Boylan, Chen, Mohammadipour, & Syntetos, 2014). Product, or time series, aggregation for both initialization and updating of parameters is preferred as indicated by Dekker, Van Donselaar & Ouwehand (2004). In addition, it is preferable to update the seasonality every period when new demand is observed.

3.2.3 Forecasting performance measures

As aforementioned in Section 2.2.2, the forecasting performance is expressed in the forecast accuracy. The Mean Squared Error (**MSE**), the Mean Absolute Deviation (**MAD**) and the Mean Absolute Percentage Error (**MAPE**) are the most commonly known and applied forecasting accuracy measures provided by Silver, Pyke & Thomas (2017), Shcherbakov et al. (2013) and Chopra & Meindl (2013). In addition to the forecasting accuracy, the **bias** of a forecasting method is analysed in order to obtain insight in the fact whether the forecast is consistently too high or consistently too low.

A disadvantage of the application of the MSE and MAD is the effect of the magnitude of the demand values on the value of the performance measures; the larger the demand values, the larger the values of the performance measures. Therefore, this scale dependency could provide a biased view in case the average demand values among the forecasted SKUs differ significantly (Silver, Pyke, & Thomas, 2017) (Shcherbakov, et al., 2013). The MAPE is an absolute percentage error. A disadvantage of MAPE is the biased view generated in case the actual and forecasted demand values are very low; a forecast of 1 unit against an actual demand of 2 units, results in an error of 50% according to MAPE (Silver, Pyke, & Thomas, 2017). In addition, Shcherbakov et al. (2013) mention not to use this performance measure when the actual demand value equals 0 as a division by 0 is not possible. An alternative provided by Shcherbakov et al. (2013) is the symmetric MAPE (**sMAPE**), for which a division by 0 only occurs in case both the actual and forecasted demand are 0.

Silver, Pyke, & Thomas (2017) and Shcherbakov et al. (2013) emphasize that no single performance measure is universally best and an evaluation based on a single performance measure can result in an inaccurate analysis. For this reason, a combination of forecast performance measures is suggested when analysing the forecasting performance. A combination of a scale-dependent performance measure, MAD, a percentage error measure, sMAPE, and the bias is set as the combination of performance measures within this research. Both the MAD and the bias are expressed in meters (m), whereas the sMAPE is expressed as a proportion (%). The corresponding formulas are provided in Equations (3), (4) and (5). Within these formulas n represents the number of periods, t represents a specific time period, x_t represents the actual demand for period t and $\hat{x}_{t-1,t}$ represents the forecasted value for period t. The result of Equation (5) is translated into a percentage in order to improve the interpretability and in order to create an additional scale-independent performance measure, the corresponding formula is provided in Equation (6).

$$MAD\ (m) = \frac{1}{n}\sum_{t=1}^{n}\left|\hat{x}_{t-1,t} - x_t\right| \tag{3}$$

$$sMAPE\ (\%) = \frac{1}{n}\sum_{t=1}^{n} 200 * \left|\frac{\left|e_{t-1,t}\right|}{(x_t + \hat{x}_{t-1,t})}\right| with\ e_{t-1,t} = \hat{x}_{t-1,t} - x_t \tag{4}$$

$$Bias\ (m) = \sum_{t=1}^{n}\frac{e_{t-1,t}}{n}\ with\ e_{t-1,t} = \hat{x}_{t-1,t} - x_t \tag{5}$$

$$Bias\ (\%) = \frac{\sum_{t=1}^{n}\frac{e_{t-1,t}}{n}}{\sum_{t=1}^{n}\frac{x_t}{n}}\ with\ e_{t-1,t} = \hat{x}_{t-1,t} - x_t \tag{6}$$

3.3 Forecasting related to inventory control

As aforementioned, a forecast of the demand is the bases and input of an inventory management policy. Once a suitable forecasting method is selected and the uncertainty of the forecast is established, an inventory control policy can be selected. Segerstedt & Levén (2014) indicate that the underestimation of demand has more consequences than the overestimation of demand in case the forecast is established with the purpose of inventory control; an underestimation of demand will lead to product shortages and eventually to lost sales.

The connection between the demand forecast and the inventory control policy emerges when establishing the height of the **SS**; i.e. the more uncertain the forecast, the higher the required SS (Axsäter, 2006). Silver, Pyke & Thomas (2017) define the SS as the amount of inventory kept on hand, on the average, to allow for the uncertainty of demand and the uncertainty of supply on the short run. The short run represents e.g. the time between the placement of a purchase order and the delivery of the order. The height of the SS is manageable in the sense that this value is directly related to the aimed level of customer service (Silver, Pyke, & Thomas, 2017).

Several, most common ways for establishing the SS are provided by Axsäter (2006) and Silver, Pyke & Thomas (2017). Establishing the SS may have several purposes, each with different ways to establish the SS. The SS may be based on simple-minded approaches, cost minimization or customer service. Of the simple-minded approaches, the Equal Safety Factors approach is applicable for a broad range of items for which the value of k is the same. This approach is used in many practical applications and is directly related to the customer service level S_1, i.e. the probability that a replenishment order arrives before the stock on hand is finished (Axsäter, 2006).

$$SS = k\sigma_{R+L} \tag{7}$$

A drawback of this manner of SS calculation, is the fact that batch sizes are not taken into account and order size variability is not considered (Silver, Pyke, & Thomas, 2017) (Axsäter, 2006); i.e. few inventory may still be on stock, while this is not enough to fulfil a specific order. Nevertheless, this equation is commonly used in practice and a relatively simple manner to obtain an initial indication of the minimal required SS. Within Equation (7) k represents the safety factor and σ_{R+L} represents the standard deviation of the forecast error during the review period (R) and lead time (L). The value of k should be sufficiently large in order to obtain a certain value for S_1, assuming a normally distributed lead time demand, and is determined by means of the cumulative normal probability distribution. Ideally, the value of σ_{R+L} could be estimated based on several independent forecasted values, i.e. the period of R+L may not overlap each other. Often, this is not possible due to the limited length of the test set. An alternative way to estimate the value of σ_{R+L} is provided in Equation (8). When applying Equation (8) it is assumed that the forecast errors are independent and identically distributed (i.i.d.). If not the case, this calculation of σ_{R+L} may underestimate the value of σ_{R+L}.

$$\sigma_{R+L} = \sigma_1\sqrt{R+L} \tag{8}$$

Silver, Pyke & Thomas (2017) indicate that the assumptions taken into consideration when assuming Equation (8) are violated to some extent. Nevertheless, the application of this formula is often quite reasonable (Silver, Pyke, & Thomas, 2017) (Axsäter, 2006).

3.4 Chapter conclusion

From the previous sections the relation between demand forecasting and inventory control became clear, i.e. inventory control always builds upon the demand forecasting procedure. At first, the SKUs will be grouped by means of item classification method(s). Next, a suitable forecasting method will be applied to each group of SKUs and the forecasting performance will be evaluated in order to determine the minimum level of the required inventory for each SKU. In order to provide a base for the establishment of the forecasting model, a summary of the most important conclusions drawn with regard to the sourced literature is provided below.

Continue with the ABC- and DP-classification methods in order to group the SKUs

The DP-classification method will be considered as a base throughout the continuation of this research. In addition, classification techniques applied for both demand forecasting and inventory control will be considered. Within this research the ABC-classification method will be considered solely from the 3 inventory control classification techniques discussed. Considering the nature of the demand VFA faces, both the XYZ- and FNS-classification techniques are not of added value as classification techniques.

Continue with the exponential smoothing methods in order to forecast the demand of VFA

Considering the findings that (1) the more sophisticated forecasting methods do not outperform the simpler methods, (2) the more sophisticated methods are superfluous to short-term demand forecasting on SKU-level and (3) the amount of historic data available within this research setting, i.e. not enough for the more sophisticated methods, the focus continues on the exponential smoothing methods. The forecasting methods considered are SES, Holt, Winters and Croston. According to the literature, SES, Holt and Winters are most applicable for demand classified as smooth, whereas Croston is most applicable for the remaining demand patterns, i.e. erratic, intermittent and lumpy. In the literature related to the DP-classification as depicted in Figure 3.1, Croston could also serve as a forecasting method suitable for smooth demand patterns. Variants on Croston will not be considered, as none of the variants performs consequently outstanding. For the Winters forecasting method both the individual and grouped seasonality are applied, considering the variability in both order size and order frequency that VFA faces. Table 3.3 provides an indication of when to apply which forecasting method, based on the underlying demand characteristics and the scope of the literature as provided above. Appendix IV provides the specific initialization and updating formulas of each forecasting method.

Table 3.3. Demand characteristics per forecasting method.

Forecasting model	Demand characteristics
SES	No trend, no seasonality
Holt	Trend present, no seasonality
Winters	Trend present, seasonality present
Croston	Periods with no demand

The MAD (m), bias (m), bias (%) and sMAPE (%) will be used as forecasting performance measures

As aforementioned, the performance of the forecast should be measured by means of forecasting performance measures. The scale-dependent performance measures considered are the MAD (m) and the bias (m). The scale-independent measures considered are the bias (%) and the sMAPE (%). The corresponding formulas are provided in Section 3.2.3.

Of the demand forecasting procedure as provided by Chopra & Meindl (2013), steps 1 and 2 are addressed in Chapter 2. Steps 3, 4 and 5 will be addressed in Chapter 4 accordingly. Subsequent to establishing a suitable forecasting method for the grouped SKUs, the level of the SS should be determined. In order to determine the value of the required SS, the formula as provided in Equations (7) and (8) will be applied throughout the further continuation of this research.

4 MODEL DESIGN

Within this chapter the best forecasting method is selected for the demand that VFA faces. The method selection is enabled by means of a forecasting model, established with Visual Basics in Excel. Several preparatory data evaluation actions are discussed in Section 4.1, whereas the model characteristics are provided in Section 4.2. Section 4.3 evaluates and compares the forecasting performances of the current forecasting method and the alternative forecasting method, whereas Section 4.4 briefly summarizes the conclusions of this chapter. Throughout the further continuation of this research, the demand will be forecasted in meters instead of m² as is the case within the current forecasting procedure.

4.1 Preparatory data evaluation

In order to establish a suitable forecasting model, some preparatory actions should be considered at first. As aforementioned in Section 3.2.1, the data should be evaluated and cleaned if necessary. Some additional actions have been conducted in specific need of this research, i.e. the establishment of demand scenarios. The following paragraphs further elaborate on the preliminary data analysis, the establishment of demand scenarios, the selection of SKUs, the evaluation of the corresponding time series and the establishment of a train- and test set among the historic data.

4.1.1 Preliminary data analysis

In advance of using the historic data, the data should be evaluated and adjusted in favour of the data usability when forecasting demand. In the light of this research the evaluation of data resulted in actions related to credit data and NPIs. In advance of these evaluations, general adjustments have been applied to the data set.

General adjustments

When observing the data it became clear that variants of similar fabric types are present, while the same fabric type is meant with the variants. These variants have been reduced to one fabric type for each fabric type. In addition, the initial product width of the products is assumed to be the product width for which the demand occurred. In some cases the final product width of the product is adjusted, e.g. due to circumstances occurring during the production process; these so-called under-configurations are omitted in agreement with the Production Director and the Purchasing department. Next, it is observed that different variants are used of some colour codes, while all variants refer to the same colour. These variants have been reduced to one colour code for each colour. Lastly, the smaller orders of less than 15 meters (≈4.5% for 2018 & 2019 and ≈1.5% for 2020 & 2021) have been excluded from the demand data used for the forecast, as these orders are assumed to be no standard orders; the minimum batch quantity for sales is 15 meters or more, depending on the fabric type. Lastly, some exceptional order occurrences have been identified, all with a relatively small order size compared to the corresponding financial impact. In agreement with the Purchasing department these orders have been excluded from the data.

Credit data removal

Each year, there is a relatively small proportion of orders (≈5%) that is categorized as a credit order. Within the ERP-system a credit order often relates back to an order that occurred 1 or 2 months in advance of the credit order, causing a biased view of the monthly demand when including the credit orders. In agreement with the Production Director and the Purchasing- and Sales department, the credit orders are excluded from the historic data used for the forecasting model.

Due to limitations of the ERP-system a specific event occurs when omitting all credit orders, causing a biased view of the actual demand. This event relates to the cases when new pricing agreements have taken place, after the order is labelled as completed in the ERP-system. The order is inserted in the ERP-system with the "old" price. A new order is inserted in the ERP-system with the "new" price accordingly and a credit order is created in order to remove the first order with the "old" price from the ERP-system. When simply removing these specific credit orders, the demand of these orders is doubled for every case. In order to prevent the creation of a biased view of these orders with impact, especially in case of large orders, the credit orders with an order size of more than 100 meters have been reviewed. In case a similar demand order as the credit order appeared twice in the data, one of the demand values as well as the credit order were removed from the data set. These adjustments count for a relatively small part of the total orders (≈0.5%).

New Product Introduction (NPI) evaluation

When evaluating the historic data of each SKU, it became clear that VFA introduced new products or new variants of yet existing SKUs throughout the years 2018 to 2021; e.g. another fabric width or a complete new product. Appendix V provides an overview of the historic data available for each SKU. 4 Years of historic data is available for 48 of the 128 SKUs within the research scope. For 61 of the 80 remaining SKUs an NPI occurred during 2019 and 2020, shortening the available historic data with approximately 1.5 year on the average. For the remaining 19 SKUs an NPI occurred at a later moment in time, precisely indicated in Table V.6 in Appendix V.

The more historic data is available of an SKU, the more information can be obtained for a demand forecast, eventually positively affecting the forecasting performance. In order to increase the amount of available historic data of an SKU, data of alternative historic widths and similar colours has been reviewed. In alignment with the Purchasing department it is determined whether a historic colour or width could serve as substitute historic data for an SKU part of the current product offer of VFA. This substitution in historic data appeared to be applicable for 10 SKUs in total.

Graphical analysis

A graphical analysis is conducted on the available time series in order to evaluate the presence of the different time series elements. From this graphical analysis it is observed that many time series contain a trend and have periods with no demand; an example is depicted in Figure 4.1. In addition, it is observed that there are no products with significant seasonality, such as Christmas decorations (Silver, Pyke, & Thomas, 2017). However, a moderate seasonality is observed for some SKUs; e.g. in Figure 4.2 a little seasonality is visible, but not consistently recurring in the same periods each year. When evaluating the seasonality in case of aggregated demand, depicted in Figure 4.3, it could be observed that little seasonality is visible, but also not consistently recurring in the same periods each year.

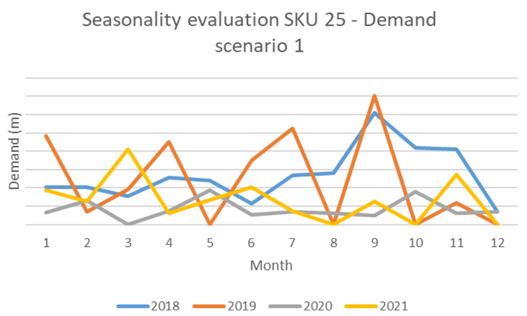

Figure 4.1. Seasonality graph of SKU 25 for demand scenario 1.

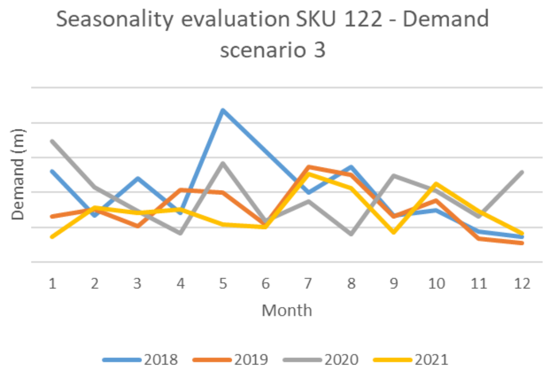

Figure 4.2. Seasonality graph of SKU 122 for demand scenario 3.

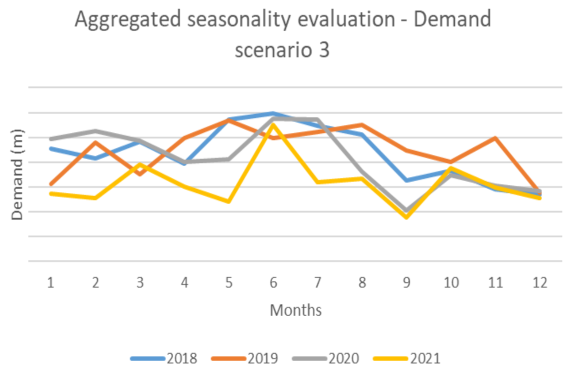

Figure 4.3. Seasonality graph of the aggregated demand for the SKUs with 4 years of historic data in demand scenario 3.

4.1.2 Demand scenarios

The conclusion flowing from Chapter 2, as stated in Section 2.3, relates to the fact that no distinction can be made between the two different demand types that VFA faces, i.e. regular and project demand, solely based on historic data. It is assumed that project demand is often known well ahead in time and therefore does not have to be considered when controlling the inventory and thus, does not have to be included in the forecast established in the light of this research. In order to imitate the effect of the inclusion of the project demand on the minimum inventory levels, different demand scenarios have been established with each a different order size threshold in meters (m).

This threshold represents the boundary between regular and project demand for a specific demand scenario and therefore specifies the maximum order size that is included in the historic data evaluated for the demand forecast. The demand scenarios are determined by means of evaluating the financial contribution and corresponding order size (m) for a certain proportion of the yearly orders for each year from 2018 to 2021.

For the years 2018 to 2021 the orders are sorted in ascending order based on the order size (m) per order. Table 4.1 provides the threshold (m) per year in case of including a certain proportion of the total orders, i.e. 50%, 80%, 95% and 100%. In Table 4.2 the corresponding financial contribution of these proportions is provided.

Table 4.1. Order size threshold (m) per year per proportion of orders.

Demand scenario	Proportion of orders	Order size threshold per year (m)			
		2018	*2019*	*2020*	*2021*
1	*50%*	35	35	35	34
2	*80%*	100	105	127	100
3	*95%*	309	334	427	353
4	*100%*	2.754	3.613	2.317	4.666

Table 4.2. Financial contribution (%) per year per proportion of orders.

Demand scenario	Proportion of orders	Financial contribution per year (€)			
		2018	*2019*	*2020*	*2021*
1	*50%*	17%	14%	13%	15%
2	*80%*	39%	36%	35%	33%
3	*95%*	69%	67%	68%	63%
4	*100%*	100%	100%	100%	100%

From both Table 4.1 and Table 4.2 it could be observed that the thresholds, both in order size (m) and financial contribution, are more or less stable over the years for each evaluated proportion of orders. When reviewing the financial contribution of 50% of the orders, it could be observed that this is relatively low (≈15%). For this reason, the demand scenario representing 50% of the orders is, in agreement with the Purchasing department, excluded as demand scenario. In addition, a relatively large difference in the financial contribution of demand scenarios 3 and 4 is observed, given the fact that the difference in the proportion of orders included is only 5%. This observation emphasizes the importance of the project demand in the demand that VFA faces.

The demand scenarios as provided in Table 4.3 are established in agreement with the Purchasing department. These scenarios will be used throughout the further continuation of this research.

Table 4.3. Order size threshold (m) per demand scenario.

Demand scenario	Order size threshold (m)
1	*100*
2	*350*
3	*∞*

4.1.3 SKU selection

A selection of SKUs to focus on has been made among the 128 SKUs part of the research scope. This selection is based on the historic data available; the more historic data available, the more precise the forecasting parameters could be established and the more accurate the forecast will be. Table 4.4 provides a summarizing overview of the selection process for each demand scenario. For all 3 demand scenarios SKUs with no demand during 2018 to 2021 have been excluded. Next, the newly introduced items throughout 2018 to 2021 have been excluded, resulting in a selection of SKUs with 4 years of historic data. Lastly, items with a consecutive 12-monthly period of no demand during 2018 to 2021 have also been excluded. For each demand scenario a total of 34 identical SKUs remain after the selection. The characteristics for each of the 34 selected SKUs is provided in Table VI.7 in Appendix VI.

Table 4.4. Selection process per demand scenario.

	Demand scenario		
	1	*2*	*3*
Total number of SKUs	128	128	128
No demand 2018-2021	31	25	24
No demand period of 12 months	63	69	70
Number of SKUs left	**34**	**34**	**34**

4.1.4 Time series evaluation

The time series of the selected SKUs have been evaluated in order to exclude potential anomalies. These anomalies occur with high exception and could negatively affect the forecasting performance. For several time series high peaks or a high fluctuation in monthly demand have been observed, for which no specific cause could be assigned from the historic data or from interviews with the Purchasing department; a high fluctuation in demand appeared to be inherent to the demand structure VFA faces. One specific cause that may affect all product types, as mentioned by the Sales department, is the fact that larger project orders are split into smaller orders sometimes. These smaller orders could be delivered sequentially to the customer in 1 month, causing an abnormal peak in the demand pattern for e.g. demand scenario 1, while the complete order is actually not part of the demand included in demand scenario 1. As the type of demand, either regular or project demand, is not logged these peaks cannot be filtered out.

For specific product types, the Purchasing department mentions the RM availability as a potential cause for some of the peaks in the demand. For some fabric types difficulties have been observed with the availability of the RM, causing sequential periods of low or no demand. The Sales department contacts its customers when the material becomes available again, followed by a peak in next month's demand. This reasoning applies to the product types 202, 205 and 890 in specific; representing 23 of the 34 selected SKUs. Of product type 205 this reasoning does not apply for all colours as is the case for product type 890.

The unavailability of RM occurs some periods, for some product types. Nevertheless, the historic availability of the RM is not logged. In addition, the Purchasing department emphasizes that the fluctuation in demand is inherent to the demand structure VFA faces. For these reasons, it is not clear what demand to mark as an anomaly or not and a cause for the potential anomalies could not be found. As a consequence, no adjustments to the time series have been made in advance of demand forecasting. Table VI.8 in Appendix VI provides an overview of the causes, if applicable, that could potentially have affected the time series of specific product types.

4.1.5 Data splitting

Within the complete historic data set a distinction should be made between a train- and test set, further elaborated on in Section 3.2.1. The maximum length of the historic data available is 4 years. Figure 4.3 and Figure 4.4 provide the data split in case of the application of both the static and adaptive forecasting variant. The train set for both variants include 87% of the historic data. For both forecasting variants, the forecasting performance is measured over the forecasts generated for the test set, i.e. from July 2021 to December 2021.

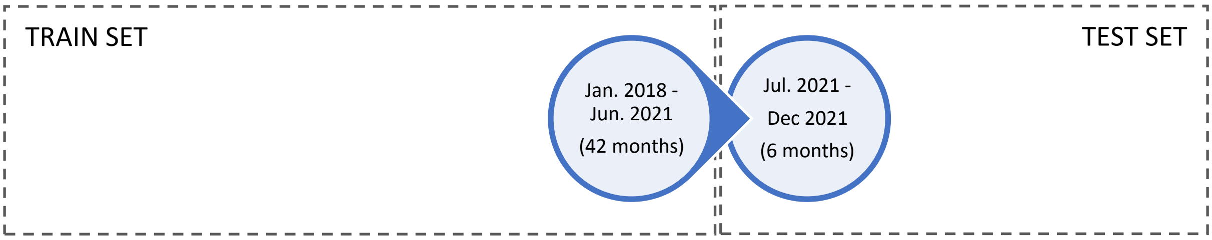

Figure 4.4. Data partition in case of the static forecasting variant.

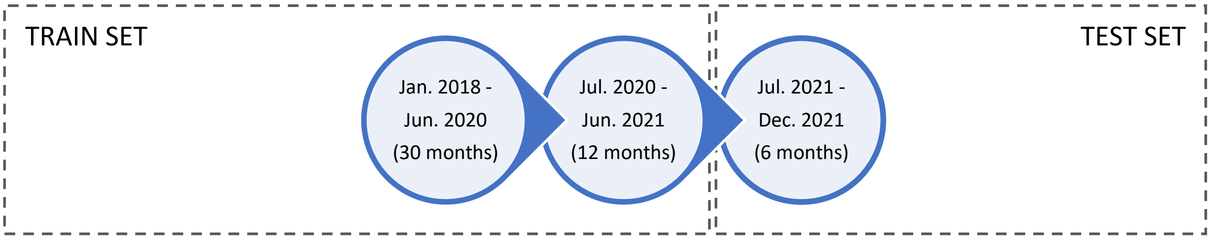

Figure 4.5. Data partition in case of the adaptive forecasting variant.

4.2 Model characteristics

After a preparatory data evaluation, the available data serves as a base for a demand forecasting model. In advance of establishing a demand forecasting model, the items should be classified. Section 4.2.1 provides information related to classification of the 34 SKUs, whereas Section 4.2.2 continues with selecting a suitable forecasting method for each class of items.

4.2.1 Item classification

As aforementioned in Section 3.4, the items are classified using the ABC- and DP-classification techniques. The ABC-classification is grouped-based, whereas the DP-classification is SKU-individual. For this reason, the ABC-classification includes all 128 items and the DP-classification includes a total of 34 of the 128 items. Both classification techniques are applied on the past 12 months of the train data. The corresponding results of both the individually applied classification methods as well as a combination of the classification methods are provided below.

ABC-classification

The result of this classification for the 128 SKUs is provided in Table VII.9 in Appendix VII, whereas the sub-selection of the 34 SKUs is provided in Table 4.5. The following directives are used when classifying the items:

- **Class A**: cumulative financial contribution of $\leq$ 80%
- **Class B**: cumulative financial contribution of $>$ 80% and $\leq$ 95%
- **Class C**: cumulative financial contribution of $>$ 95% and $\leq$ 100%

Table 4.5. Number of SKUs per class per demand scenario (selection of 34 SKUs).

Class	**Demand scenario**		
	1	*2*	*3*
A	18 (53%)	22 (65%)	22 (65%)
B	13 (38%)	11 (32%)	10 (29%)
C	3 (9%)	1 (3%)	2 (6%)
Total	34	34	34

When classifying the 128 SKUs, it could be observed that the largest part of the 128 items is classified as a C-item (≈ 55%) for all demand scenarios, followed by the A-items and B-items; approximately following the standard distribution among the A-, B- and C-classes. It could also be noted that the number of C-items is slightly decreasing, whereas the number of A-items is slightly increasing when reviewing the demand scenarios in increasing order. When reviewing the sub-selection of the 34 SKUs as provided in Table 4.5, it could be observed that the largest part of the selected SKUs is classified as an A-item, followed by the B- and C-items. In addition, it could be observed that the number of A-items is slightly increasing, while the number of B-items is slightly decreasing when reviewing the demand scenarios in increasing order. The number of C-items stays more or less the same.

DP-classification

As aforementioned, this classification method is limited to the SKUs selected in Section 4.1.3. The result of this classification is provided in Table 4.6, while using the following directives when classifying the items:

- **Smooth**: low variability in order size and low variability in order placement with $CV^2 < 0.49$ and ADI < 1.32.
- **Erratic**: high variability in order size and low variability in order placement with $CV^2 \geq 0.49$ and ADI < 1.32.

- **Intermittent**: low variability in order size and high variability in order placement with CV^2 > 0.49 and ADI ≥ 1.32.
- **Lumpy**: high variability in order size and high variability in order placement with CV^2 ≥ 0.49 and ADI ≥ 1.32.

Table 4.6. Number of items per class per demand scenario.

Class	**Demand scenario**		
	1	*2*	*3*
Smooth	14 (41%)	11 (32%)	9 (26%)
Erratic	3 (9%)	7 (21%)	10 (29%)
Intermittent	9 (26%)	7 (21%)	5 (16%)
Lumpy	8 (24%)	9 (26%)	10 (29%)
Total	**34**	**34**	**34**

From Table 4.6 it could be observed that the number of items classified as smooth and intermittent is decreasing when reviewing the demand scenarios in increasing order, whereas the number of items classified as erratic and lumpy is increasing simultaneously.

For each DP-class potential SKU characteristics have been reviewed in order to determine whether some characteristics could be assigned to the classes. The SKU characteristics reviewed are (1) the supply state of the RM, either coloured or uncoloured, (2) the fabric width of an item and (3) the fabric type of an item. For none of the classes an obvious pattern appeared when evaluating the SKU characteristics, only a few movements between classes appeared. The increase in the order size taken into account for each demand scenario could be indicated as the cause of these movements.

Combination of ABC- and DP-classification

For each demand scenario the ABC- and DP-classification are combined for the 34 selected SKUs, in order to relate the demand pattern characteristics to the item importance. The combined classification matrix for each demand scenario is provided in Table 4.7. In addition, both the ABC- and DP-class per SKU are provided in Table VII.10 in Appendix VII. Table VII.11 in Appendix VII provides the specific SKUs per ABC- and DP-class. When reviewing the combined classification matrices for all demand scenarios, the following is observed:

- For each demand scenario it could be observed that most of the A-items are classified as either smooth or erratic; indicating a good forecast-ability for the most important items.
- When reviewing the less important items, B- or C-items, most items are classified as either intermittent or lumpy; indicating a decrease in the forecast-ability of the demand patterns.

Table 4.7. Combined classification matrices per demand scenario.

Demand scenario 1

	ABC-Class			
DP-Class	*A*	*B*	*C*	*Total*
Smooth	12	2	0	14 (41%)
Erratic	3	0	0	3 (9%)
Intermittent	2	6	1	9 (26%)
Lumpy	1	5	2	8 (24%)
Total	18 (53%)	13 (38%)	3 (9%)	**34**

Demand scenario 2

	ABC-Class			
DP-Class	*A*	*B*	*C*	*Total*
Smooth	10	1	0	11 (32%)
Erratic	5	2	0	7 (21%)
Intermittent	2	4	1	7 (21%)
Lumpy	5	4	0	9 (26%)
Total	22 (65%)	11 (32%)	1 (3%)	**34**

Demand scenario 3

	ABC-Class			
DP-Class	*A*	*B*	*C*	*Total*
Smooth	7	2	0	9 (26%)
Erratic	8	2	0	10 (29%)
Intermittent	2	3	0	5 (16%)
Lumpy	5	3	2	10 (29%)
Total	22 (65%)	10 (29%)	2 (6%)	**34**

4.2.2 Item forecasting

As concluded in Section 3.4, the following forecasting methods will be applied when determining the best forecasting method: SES, Holt, Winters with SKU individual seasonality, Winters with grouped seasonality, i.e. aggregating the time series of all 34 SKUs, and Croston. For each variant of Winters 3 types of seasonality have been considered; (1) monthly seasonality, (2) regular quarterly seasonality based on the yearly quarters and (3) shifted quarterly seasonality based on the seasonal quarters, respectively. The difference between seasonality types 2 and 3 are the months that are incorporated per quarter; within type 2 quarter 1 contains January till March and within type 3 quarter 1 contains December till February. Appendix IV further elaborates on the different types of seasonality, whereas Table 4.8 provides an overview of the applied forecasting methods.

Table 4.8. Applied forecasting methods.

Forecasting method	Description
SES	Simple Exponential Smoothing
H	Holt's Exponential Smoothing
W-Indv$_{M}$	Winters' Exponential Smoothing (individual, monthly seasonality)
W-Indv$_{RS}$	Winters' Exponential Smoothing (individual, regular quarterly seasonality)
W-Indv$_{SS}$	Winters' Exponential Smoothing (individual, shifted quarterly seasonality)
W-Grp$_{M}$	Winters' Exponential Smoothing (grouped, monthly seasonality)
W-Grp$_{RS}$	Winters' Exponential Smoothing (grouped, regular quarterly seasonality)
W-Grp$_{SS}$	Winters' Exponential Smoothing (grouped, shifted quarterly seasonality)
CR	Croston's

As introduced in Section 3.2.2, two variants of forecasting methods are available; a static and adaptive variant accordingly. In order to maintain a clear focus on the most beneficial forecasting methods, first a decision is made whether to continue with the static or adaptive variant of the forecasting methods. Next, the best forecasting method is selected for each DP-class and demand scenario. A correct working of the applied forecasting methods is validated by means of applying the forecasting methods to examples provided in literature. In order to keep the explanation of the forecasting methods as brief and transparent as possible, Appendix IV provides the forecasting and corresponding updating formulas for each forecasting method considered. In addition, the initialization method is briefly described for each forecasting method in Appendix IV.

The performance measures used in the continuation of this research are provided in Equation (3), (4), (5) and (6) in Section 3.2.3. In addition, a corresponding description for each performance measure is provided. Both evaluations, (1) which forecasting variant to use and (2) which forecasting method to apply, are applied to the selected 34 SKUs and described in the following paragraphs.

Forecasting variants

In order to determine with which forecasting variant to continue, the performance measures of both forecasting variants for each forecasting method are compared with each other. In order to enable a comparison, the applied circumferences and the smoothing parameters are kept the same for both the forecasting methods and the forecasting variants. The circumferences and the values of the smoothing parameters are set as described below:

- The division between the **train-** and **test-set** occurred according to the static and adaptive forecasting variant; further elaborated on in Section 4.1.5.
- For both forecasting variants the length of the **forecasting horizon (τ)** is set to 1 for each SKU as a forecast with a shorter horizon outperforms a forecast with a longer horizon in any case (Axsäter, 2006).
- For both forecasting variants the values of **α**, **β** and **γ** are set to 0.19, 0.053 and 0.1 accordingly, as this is the most suitable combination of smoothing parameters values as mentioned by Silver, Pyke & Thomas (2017) for the SES, Holt and Winters method. This observation is emphasized by Axsäter (2006), when considering a forecasting procedure in which the parameters are updated monthly; applicable for this research setting. An α-value of 0.19 is assumed to be suitable for Croston's method as well (Croston, 1978) (Zied Babai, Syntetos, & Teunter, 2014).

Figure 4.6 depicts the averaged values of the static and adaptive forecasting variants when evaluating the bias (%) per SKU for demand scenario 1. Graphs of the remaining, averaged performance measures for each demand scenario are provided in Appendix VIII. An exceptional averaged value for SKU 126 is observed in Figure 4.6, reason for this is the infrequent demand pattern in combination with the length of the period taken in order to initialize the forecasting parameters such as the level and the trend for each forecasting variant. When reviewing Table VII.10 it could be observed that SKU 126 is an A-item classified as smooth in demand scenarios 1 and 2 and classified as erratic in demand scenario 3. Figure 4.7 depicts the actual demand of SKU 126 in 2018 to 2021. As described in Section 4.1.4 and in Table VI.8 in Appendix VI, the RM availability is the cause for this specific demand pattern. When reviewing Figure 4.6 and the figures provided in Appendix VIII, it could be observed that the adaptive forecasting variant appears to outperform the static forecasting variant for most of the averaged performance measures.

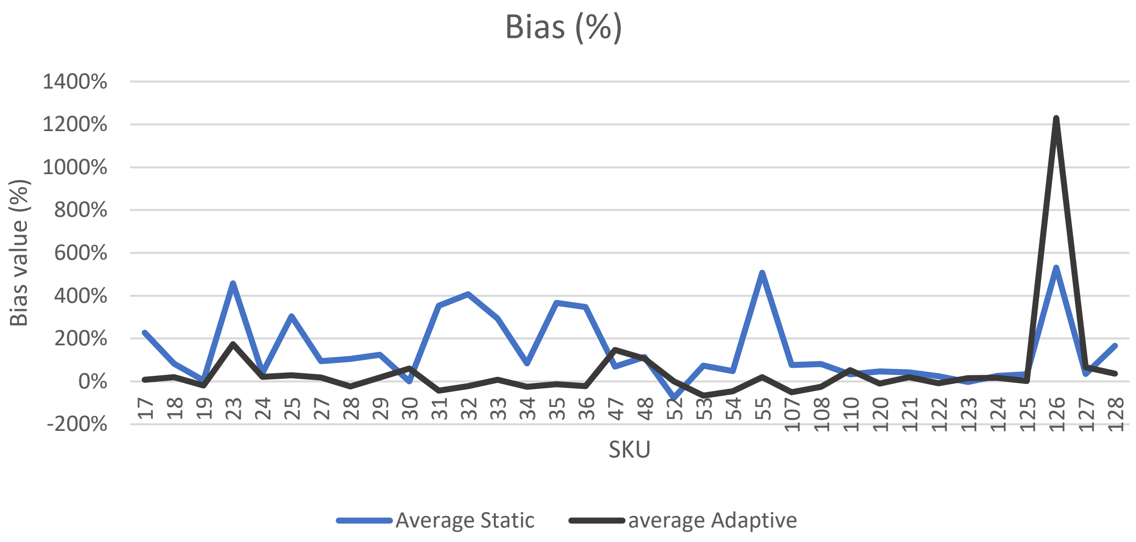

Figure 4.6. Averaged bias (%) of the static and adaptive forecasting variant in demand scenario 1.

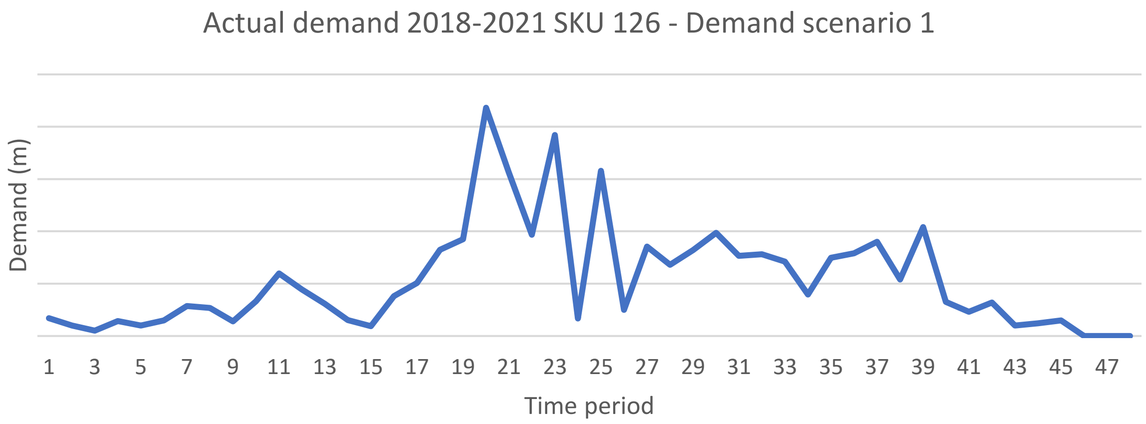

Figure 4.7. Actual demand SKU 126 demand scenario 1.

In order to confirm whether the adaptive forecasting variant significantly outperforms the static variant a paired-sample, 2-tailed T-test is applied for each forecasting method with H_0 equal to *there is no significant difference between the performances of the static and adaptive variant of each performance measure*. A significance level of 0.05 is assumed within these tests. Table VIII.13 in Appendix VIII provides the results of the T-tests. Table 4.9 provides a summarizing overview of the results as provided in Table VIII.13 by means of indicating the number of significant differences per performance measure for each demand scenario; for each combination a total of at most 9 significant differences is possible.

Table 4.9. Number of significant differences within the Forecasting variant performance evaluation: p-value of a paired-sample, 2-tailed T-test (level of significance = 0.05).

	Performance measure				
Demand scenario	*MAD (m)*	*Bias (m)*	*Bias (%)*	*sMAPE (%)*	*Total significant differences*
1	8 out of 9	9 out of 9	6 out of 9	2 out of 9	25 out of 36
2	7 out of 9	8 out of 9	7 out of 9	0 out of 9	22 out of 36
3	1 out of 9	2 out of 9	6 out of 9	3 out of 9	12 out of 36

From these results it could be observed that there are relatively many significant differences when reviewing the MAD (m), bias (m) and the bias (%) for demand scenarios 1 and 2. For all demand scenarios, there are relatively few significant differences when reviewing the sMAPE (%) as performance measure.

From the results as provided in Table VIII.13, it could be observed that the number of significant differences decreases relatively much for the Winters forecasting method variants when evaluating the 3 demand scenarios. For both SES and CR the number of significant differences decreases, but only slightly compared to Winters method variants. In addition, it could be noted that the number of significant differences decreases when reviewing the demand scenarios in increasing order. This observation aligns with the expectation, as the demand variability and uncertainty also increases when reviewing the demand scenarios in increasing order; as indicated in Section 4.2.1 a shift occurred towards erratic and lumpy demand patterns. An increased demand uncertainty negatively affects the forecast-ability of any forecasting method. For this reason, the decrease in significant differences could be explained. Therefore, when deciding on which forecasting variant to apply, the importance of each demand scenario decreases when the demand scenario increases. For both demand scenarios 1 and 2 the total number of significant differences is above the total number of non-significant differences; approximately 24 against 12. Together with the graphical observation that the adaptive forecasting variant appears to outperform the static forecasting variant for most of the performance measures, the focus in the continuation of this research will be on the **adaptive forecasting variant**.

Forecasting methods

Within this paragraph, the best forecasting method is selected for each DP-class per demand scenario. In advance of selecting the best forecasting method, (1) the corresponding smoothing parameters (α, β, γ) are optimized and (2) some forecasting methods are excluded from a further continuation of the performance analysis in order to maintain focus on the most beneficial forecasting methods. Both topics are separately discussed in the following paragraphs. For each of the forecasting methods, the following applies:

- The division between the **train-** and **test-set** occurred according to the adaptive forecasting variant; further elaborated on in Section 4.1.5.
- The length of the **forecasting horizon (τ)** is set equal to the delivery time (L), SKU dependent, and the review period (R), equal to $\frac{14}{30}$ month for every SKU, in order to represent reality and in order to enable a comparison with the current forecasting method. Table I.3 in Appendix I provides information on the value of L for each SKU considered.
- In order to optimize the performance of each forecasting method, the **smoothing parameters** have been **optimized** for each forecasting method per DP-class per demand scenario. Within this optimization, τ is set equal to the review period (R) and the delivery time (L) for each SKU. Multiple experiments have been conducted with the smoothing parameters values, ranging between 0.05 and 0.3 with steps of 0.05, in order to determine the optimal values of the smoothing parameters. Appendix IX further elaborates on the experimentation and the establishment of the optimal smoothing parameter values; the corresponding optimal values, when minimizing the MAD, are provided in Table IX.14 in Appendix IX.

After the smoothing parameter optimization and in advance of determining the most suitable forecasting method for each DP-class and demand scenario, both the Winters methods have been compared and evaluated in order to determine whether one outperforms the other. When evaluating the initialized seasonal estimate values, it appeared that these were given very irregular values for some SKUs when applying Winters method with individual seasonality. These irregular values are caused by the strong fluctuation in demand, inherent to the demand that VFA faces. The effect of the demand fluctuation of a single SKU on the seasonal estimate value is reduced when grouping the time series of SKUs; resulting in less irregular seasonal estimate values. From a graphical analysis of the performance measures it appeared that all Winters methods with individual seasonality performed worse than the Winters methods with grouped seasonality for most of the performance measures, DP-classes and demand scenarios. This observation is emphasized by means of a statistical analysis in the form of a paired sample, 2-tailed T-test for each DP-class, demand scenario and performance measure with H_0 equal to *there is no significant difference between the performance measure of the individual and grouped seasonality variant of Winters method* with a significance level of 0.05. An overview of the corresponding p-values is provided in Table X.15 in Appendix X. Among the 144 potential differences, only 15 significant differences were found between the Winters method with individual and grouped seasonality. Considering the above observations, i.e. the irregular seasonal values and both the graphical and statistical analysis, the preference is given to Winters method with the grouped seasonality. Therefore, Winters method with individual seasonality is excluded from a further continuation of the performance analysis. The remaining forecasting methods to be evaluated are **SES**, **H**, **W-Grp$_{M}$**, **W-Grp$_{RS}$**, **W-Grp$_{SS}$** and **CR**.

In order to determine the best forecasting method among these remaining methods for each DP-class and demand scenario, both a graphical and statistical analysis has been performed; considering the optimized smoothing parameter values for each DP-class and each demand scenario as provided in Table IX.14 in Appendix IX.

The **graphical analysis** is conducted on (1) the forecasted values compared to the actual values and (2) on the forecasting performance measure. At first, the forecasted values as a result of each forecasting method are evaluated for each SKU in a specific DP-class and demand scenario; an example is depicted in Figure 4.8. From this analysis it could be observed that no forecasting method shows an outstanding performance. In addition, from the graphical analysis it could be observed that the forecasts generated by the Holt and Winters method will eventually drop below 0 for several SKUs when reviewing the demand scenarios in increasing order. A cause for this could be the relatively high variability in order size and order frequency as these negative forecasting values are mostly observed with SKUs classified as erratic, intermittent or lumpy. When evaluating the SKUs classified as smooth, the negative values do not appear in demand scenarios 1 and 2 and solely appear in demand scenario 3. This observations is in alignment with the expectation, as the demand variability increases in case the demand scenario increases. Also, the SES and Croston method appear to perform comparable when evaluating smooth and erratic demand. The forecasted difference between these methods increases slightly when reviewing the demand scenarios in increasing order. Lastly, it could be observed that the SES and Croston method perform comparable for several SKUs in the lumpy DP-class, independent of the demand scenario.

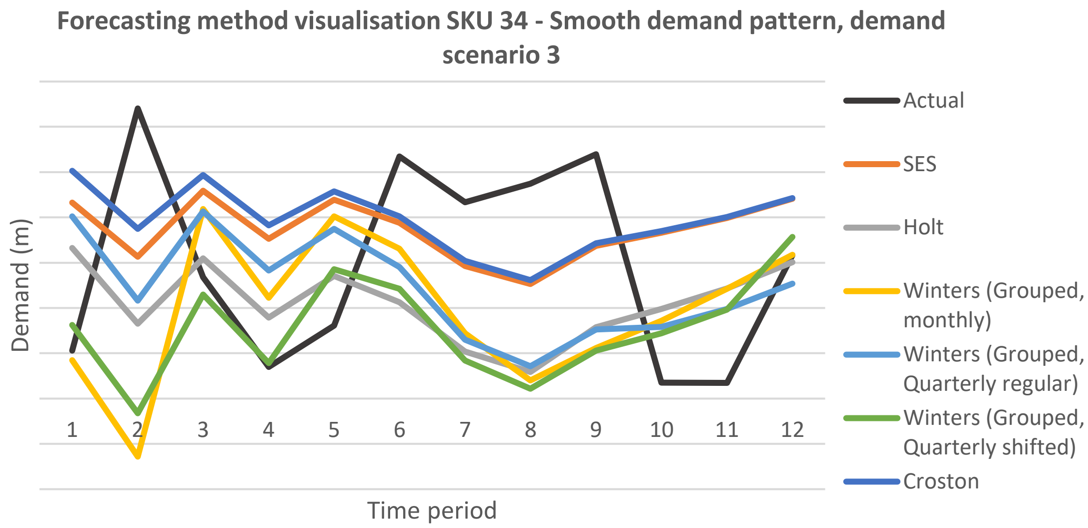

Figure 4.8. Forecasting method visualisation SKU 34 – Smooth demand pattern, demand scenario 3.

In case of conducting a graphical analysis on the forecasting performance measures, several similarities are observed. Often, the forecasting performances of the forecasting methods are more or less comparable. If not the case, then the performances of SES and Croston are comparable and often outperform the Holt and Winters method in case of SKUs with relatively high performance measure values in general. Also, in most cases the Holt and Winters method show a comparable performance among each other. In order to illustrate these observations, an example of the bias (%) as performance measure is provided in Figure 4.9. These performance values correspond to the SKUs classified as smooth in demand scenario 2. As could be observed, SES and Croston outperform Holt and Winters in case of a relatively high forecasting performance in general, e.g. SKU 110 and 126.

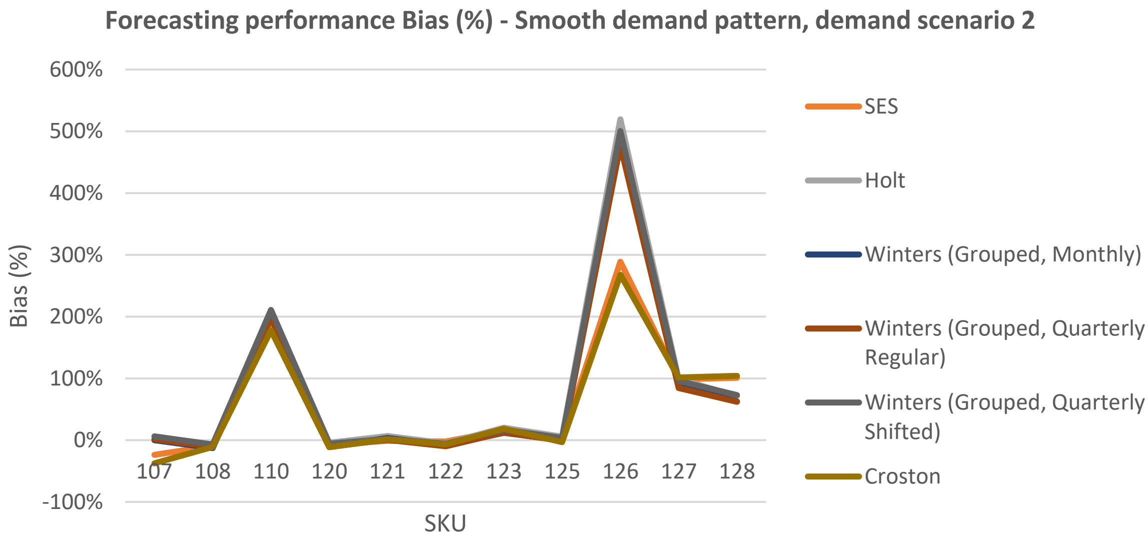

Figure 4.9. Forecasting performance evaluation of the Bias (%) - Smooth demand pattern, demand scenario 2.

In addition to the graphical analysis, a **statistical analysis** of the forecasting performance measures has been performed. A repeated measures ANOVA is conducted in order to evaluate whether there is a significant performance difference among the remaining forecasting methods. Within this repeated measures ANOVA H_0 equals *there is no significant difference between the performance measure values of the remaining forecasting methods for a specific DP-class and demand scenario combination* and the corresponding significance level equals 0.05. The results are provided in Table XI.16 in Appendix XI. From Table XI.16 it can be observed that there are relatively few significant differences.

With the information obtained from both the graphical and statistical analysis, a best forecasting method is selected for each combination of a DP-class and demand scenario. When selecting the best method, the following is considered;

- In case an outperforming forecasting method remains absent, the simplest method is selected as best performing forecasting method, taking into consideration that a slightly positive bias is preferred over a slightly negative bias as indicated in Section 3.3.
- The Holt and Winters forecasting methods are solely considered in case the forecasted values do not tend to drop below a value of 0 for a specific SKU in a certain DP-class and demand scenario.
- In case the SES and Croston method perform equally and a typical intermittent demand pattern is observed for a specific SKU, either classified as intermittent or lumpy, the Croston forecasting method is preferred over the SES method considering the information provided in literature. On the contrary, the SES forecasting method is preferred over Croston in case SKUs are classified as either smooth or erratic.

The best performing forecasting method and corresponding smoothing parameter value(s) for each DP-class and demand scenario are provided in Table 4.10.

Table 4.10. Best performing forecasting method and corresponding smoothing parameter value(s).

			Smoothing parameters		
	DP-Class	**Forecasting method**	*Alpha*	*Beta*	*Gamma*
Demand scenario 1	*Smooth*	SES	0.15	-	-
	Erratic	SES (Holt SKU 35)	0.25 (0.05)	(0.1)	-
	Intermittent	Croston (SES SKU 23, 24)	0.15 (0.25)	-	-
	Lumpy	Croston	0.25	-	-

			Smoothing parameters		
	DP-Class	**Forecasting method**	*Alpha*	*Beta*	*Gamma*
Demand scenario 2	*Smooth*	SES	0.15	-	-
	Erratic	SES (Holt SKU 23, 33)	0.25 (0.1)	(0.1)	-
	Intermittent	Croston (SES SKU 19, 55)	0.25 (0.3)	-	-
	Lumpy	Croston (SES SKU 30)	0.05 (0.15)	-	-

			Smoothing parameters		
	DP-Class	**Forecasting method**	*Alpha*	*Beta*	*Gamma*
Demand scenario 3	*Smooth*	SES (Holt SKU 128)	0.3 (0.3)	(0.05)	-
	Erratic	SES (Holt SKU 107)	0.2 (0.1)	(0.05)	-
	Intermittent	Croston (SES SKU 31, 36)	0.25 (0.3)	-	-
	Lumpy	Croston (SES SKU 30)	0.05 (0.1)	-	-

As could be observed from Table 4.10, a different best performing forecasting method is determined for some SKUs within a specific class of SKUs. From both the graphical and statistical analysis a better forecasting performance is observed in case of selecting the alternative forecasting method as best performing forecasting method for these specific SKUs. A cause for this observation could be the change in the demand pattern in the period following the period used for training the model and, thus, for the item classification. As aforementioned in Section 4.1.4, some external factors, e.g. the RM availability, are affecting the historic demand pattern. Eventually such a matter is affecting the availability of a product and influences the demand pattern. As a consequence, the demand pattern of a specific SKUs may be classified as e.g. erratic instead of smooth when considering the test data solely.

4.3 Forecasting performance evaluation

In Table 4.10 in Section 4.2.2 the best statistical forecasting method is provided for each DP-class and demand scenario. In order to evaluate the impact of the application of a statistical forecasting method, the performances of the **current** and the **statistical** forecasting method are compared with each other in this section. In addition, the **Naive** forecasting method is included in the performance evaluation and applied as a benchmarking method solely. The Naive forecasting method is a basic and simple forecasting method in which the demand of the current period equals the forecast for t periods ahead, i.e. the forecasting horizon τ (Hyndman & Athanasopoulos, 2018).

Considering the fact that all demand, independent of the order size or demand type, is considered in the current forecasting method, the forecasting performance of demand scenario 3 is solely considered in the performance comparison; i.e. all demand is incorporated in demand scenario 3. For 7 of the 34 SKUs, the current forecasting performance cannot be defined as these current forecasts are on a more aggregated level, i.e. combined product types, or the forecast for a specific SKUs is absent within the current forecasting procedure of VFA; Section 2.2.1 further elaborates on this topic. For this reason, the forecasting performance of 27 SKUs is compared within this section. The values of each performance measure per SKU and forecasting method are provided in Table XI.17 in Appendix XI, whereas a summarizing overview of these values is provided in Table 4.11. Figure 4.10 visualizes the performances of the current, alternative and the Naive forecasting method for each performance measure and the 27 reviewed SKUs.

Table 4.11. Summarizing overview of the performances of the current and the alternative forecasting method.

Performance measure	Forecasting method								
	Current			Statistical			Naive		
	Min.	*Max.*	*Avg.*	*Min.*	*Max.*	*Avg.*	*Min.*	*Max.*	*Avg.*
MAD (m)	83	1.067	392	37	1.062	280	27	2.671	401
Bias (m)	-687	680	222	-591	337	39	-132	805	98
Bias (%)	-69%	720%	151%	-59%	296%	39%	-60%	244%	20%
sMAPE (%)	46%	163%	114%	36%	165%	104%	N.a.	N.a.	N.a.

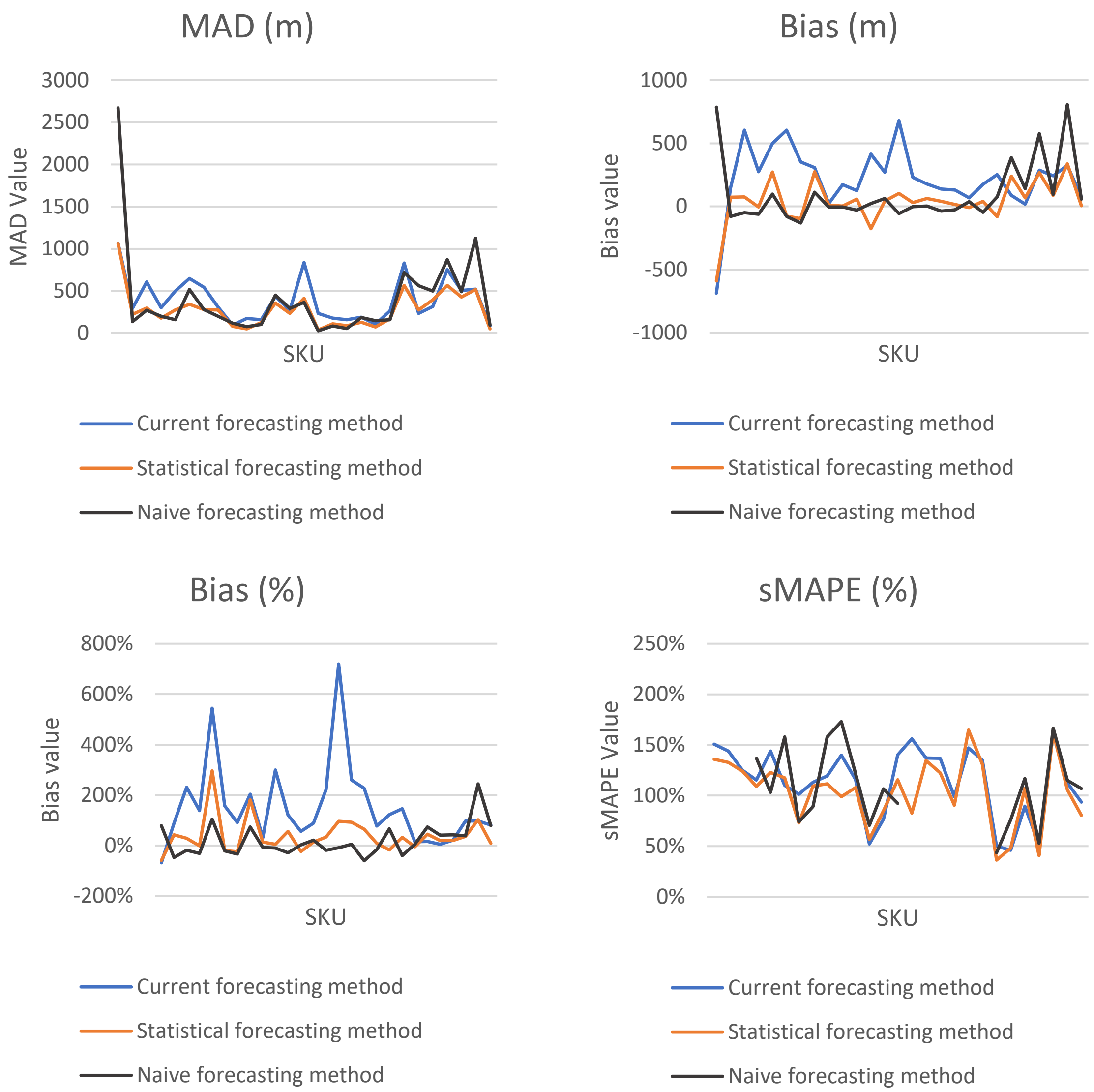

Figure 4.10. Forecasting performance comparison of the current method vs. the alternative method for demand scenario 3.

From Table 4.11 it could be observed that the statistical forecasting method outperforms the current forecasting method for any of the performance measure values, when reviewing the averaged values. When comparing the averaged values of the statistical forecasting method with the Naive method, the statistical method outperforms the Naive method for the MAD (m) and the bias (m). The Naive method outperforms the statistical method when reviewing the bias (%). For the Naive method several of the sMAPE (%) values cannot be determined due to a 0 by 0 division error. For this reason the average sMAPE (%) value is not given.

In addition, from Figure 4.10 it could be observed that the statistical forecasting method outperforms the current forecasting method for most SKUs when reviewing the MAD, bias (m), bias (%) and the sMAPE (%). When reviewing the sMAPE (%), it may be observed that the statistical and current forecasting method perform more or less equal, sometimes the alternative method outperforms the current forecasting method for several SKUs. When comparing the current forecasting method with the Naive method, it could be observed that both methods perform more or less equal when reviewing the MAD (m), the Naive method slightly outperforms the statistical method when reviewing the bias (m) and bias (%) and the statistical method outperforms the Naive method when reviewing the sMAPE (%).

These observations as described above are emphasized by means of a paired-sample, 2-tailed T-test between the performance measures of the different forecasting methods. The H_0 equals *there is no significant difference between the performance measure values of the forecasting methods* and the corresponding level of significance equals 0.05. The corresponding p-values are provided in Table 4.12. From this result it could be observed that the statistical method outperforms the current method and that the statistical and the Naive method perform more or less equal compared to the current method, with exception of the sMAPE. Considering the fact that the p-values of all performance measures are significant when comparing the current with the statistical forecasting method and this is not the case when comparing the current with the Naive forecasting method, it may be observed that the statistical forecasting method is a better alternative than the Naive method for the current forecasting method.

Table 4.12. Comparison of performance measure values of different forecasting methods: p-values of a paired-sample, 2-tailed T-test (level of significant = 0.05).

	p-Values of the compared forecasting methods		
Performance measure	*Current vs. Statistical*	*Current vs. Naive*	*Statistical vs. Naive*
MAD (m)	0.0001	0.9047	0.0694
Bias (m)	0.0002	0.1422	0.3245
Bias (%)	0.0002	0.0009	0.2114
sMAPE (%)	0.0114	0.1762	0.0082

When closely reviewing the averaged values for each demand scenario, as provided in Table 4.11, the impact of the statistical forecasting method compared to the current forecasting method is -112m, -183m, -112% and -10% for the MAD (m), bias (m), bias (%) and sMAPE (%), respectively. In addition, it could be observed that the performance measures of the statistical forecasting method remain relatively high. In order to determine whether certain SKUs are responsible for the relatively high values, the values of the performance measures are related to specific SKUs and to the fact whether the RM is supplied in colour or not. This analysis is visualized in Figures XI.21, XI.22, XI.23 and XI.24 in Appendix XI. From this analysis, it may be observed that the MAD (m) and bias (m) are slightly increased in case the RM is supplied uncoloured. When reviewing the bias (%) and the sMAPE (%), the performance measure values are more or less equal, independent on the supply state of the RM. Causes for the relatively high forecasting performance are observed to not be SKU characteristic dependent, but dependent on the present demand variability or on external factors such as the availability of the RM.

For the similar 27 SKUs, the forecasting performance of demand scenarios 1 and 2 is evaluated in addition. As these demand scenarios incorporate a different order size (m), the scale-dependent performance measures provide a biased view in case of a comparison among the demand scenarios, i.e. MAD (m) and bias (m). For this reason, the scale-independent performance measures can only be evaluated, i.e. the bias (%) and the sMAPE (%). For all demand scenarios and the current forecasting method the averaged values of both performance measures are provided in Table 4.13. As could be observed from these values, the statistical forecasting method outperforms the current forecasting method when considering any demand scenario. In addition, it could be observed that the bias is decreasing, while the sMAPE (%) is slightly increasing when reviewing the demand scenarios in increasing order; it would be expected for both performance measures to increase instead. Considering the formula of the bias (%) as provided in Equation (6) in Section 3.2.3, it makes sense that the averaged value of the bias (%) decreases in case the average forecast error stays more or less the same for each demand scenario, while the value of the actual demand increases. This effect will result in a smaller value of the bias when reviewing a larger demand scenario.

Table 4.13. Performance evaluation of each demand scenario with the scale-independent performance measures.

Demand scenario	Bias (%)	sMAPE (%)
1	93%	101%
2	66%	100%
3	39%	104%
Current situation	151%	114%

When evaluating the forecasting performance with the optimized smoothing parameters in general, as provided in Table 4.11 and in Appendix XI, it may be observed that some abnormal forecasting performances still occur for each of the forecasting methods considered. Section 4.1.4 elaborates further on the potential causes for these deviating forecasting performances. A consequence of a structural change in a demand pattern due to external factors for example, could cause a wrong classification of the SKU based on the demand pattern. The classification of the SKUs is based on the last 12 months of the train set, whereas the forecasting performance is measured over the test set. As described in Appendix IX, the best smoothing parameter values are based on the averaged performance measures for each DP-class and demand scenario. In case an SKU is classified wrongly, it could occur that the best smoothing parameters are actually not the best anymore for this specific SKU; resulting in high forecasting performance values. Also, the demand variability inherent to the demand VFA faces in combination with the period length on which the performance is measured, i.e. 6 months, may contribute to the relatively high values of the performance measures

4.4 Chapter conclusion

The result flowing from this chapter is an improved statistical forecasting method for the demand that VFA faces. As a consequence of the findings in Chapter 2, i.e. no distinction could be made between the regular and project demand, several demand scenarios have been established in order to imitate reality in 3 variants. In the previous sections a selection is made of 34 out of the 128 SKUs and each of these 34 SKUs are classified and forecasted. The main conclusions drawn in this chapter are provided in the following paragraphs.

The statistical forecasting method outperforms the current and Naive forecasting methods

From Section 4.3 it can be concluded that the statistical forecasting methods, as provided in Table 4.10 in Section 4.2.2, outperform the current forecasting method. Of these statistical methods, the adaptive variant outperforms the static variant. When reviewing the forecasting performance measures considered throughout this research, the impact of the statistical forecasting method compared to the current method is -112m, -183m, -112% and -10% for the MAD (m), bias (m), bias (%) and sMAPE (%), respectively. As indicated in Section 4.3, a significant performance difference is observed for each performance measure when comparing the performance values of the current forecasting method with the statistical method. This is not observed when comparing the performance values of the current forecasting method with the Naive method. For this reason, it can be concluded that the statistical forecasting method is the most suitable.

When reviewing the selected statistical forecasting methods, it can be concluded that the more simple forecasting methods such as SES and Croston outperform the more sophisticated methods such as Holt and Winters with the current data handling of VFA. Reason for this could be the demand variability inherent to the demand VFA faces. For several SKUs a trend is present and the Holt method is able to capture this trend correctly and therefore outperforms e.g. the SES method. For other SKUs, a trend is also present, but SES seems to outperform the Holt method. A reason for this could be the influence of the demand variability on the parameter value used to incorporate the trend in the Holt method. In some cases, the demand variability is high and a too high or too low value is assigned to the trend parameter, negatively affecting the forecasting performance; e.g. the forecasted value becomes negative. For none of the SKUs the Winters method is applied. As aforementioned in Section 4.1.1, seasonality appeared not to be significantly present in the graphical analysis. This observation is emphasized by the exclusion of the Winters method in the selected best forecasting methods.

The current data registration and storage is not optimal in terms of demand forecasting

As observed in Chapter 2 the demand type is currently not logged within VFA and sometimes the larger project orders are split into smaller project orders. Considering the current research setting, i.e. the establishment of demand scenarios, these smaller project orders are assumed to be regular orders and therefore generate a troubled demand pattern. Also, e.g. the unavailability of RM is not logged within VFA; also creating a troubled demand pattern for some instances. The absence of this kind of logged information, makes tracing these events and adjusting the demand pattern accordingly not possible. The demand patterns are the base of the DP-classification method and the chosen forecasting methods. As no corrections could have been conducted due to absence of data registration, the chosen forecasting method may not be optimal; eventually resulting in relatively high forecasting performance values.

Relatively high values of the performance measures remain

As aforementioned and observed in Section 4.3, it can be concluded that the values of the forecasting performance measures remain relatively high and that the SKU characteristics such as the supply state of the RM do not affect the performance measures. Potential causes that may affect these values are (1) the current inability to separate the demand types in the historic data, (2) the demand variability inherent to the demand VFA faces and (3) structural changes of the demand pattern occurred throughout the test set, resulting in wrongly classified SKUs. For each class of SKUs, the averaged smoothing parameters are optimized, potentially resulting in wrongly optimized smoothing parameters for an SKU that should have been assigned to another class. Section 4.3 further elaborates on this observation. This conclusion is also observed by means of the selection of two forecasting methods for some classes of SKUs, as provided in Table 4.10 in Section 4.2.2; Structural changes of a demand pattern may lead to wrongly classified SKUs.

Project demand accounts for approximately 35% to the yearly sales (€) of VFA

When reviewing the data used when establishing the demand scenarios in Section 4.1.2, it could be observed that the so-called project demand, i.e. the demand with larger order sizes, is of much importance to VFA. As shown in Table 4.1 and Table 4.2, 5% of the orders, i.e. the larger orders, account for approximately 35% to the yearly sales (€).

Approximately 20% of the SKUs have no demand over the past 4 years

When selecting the SKUs suitable for a statistical demand forecast in Section 4.1.3, it can be concluded that a relatively large part of the 128 SKUs faced no demand in the past 4 years. When reviewing demand scenario 1, approximately 24% (31 SKUs) of the number of SKUs within the scope of this research showed no demand in 2018 to 2021. When reviewing demand scenario 3, this number remains approximately 19% (24 SKUs). When reviewing the products characteristics that have no demand over the past 4 years, it is observed that only 4 of the 24 SKUs are delivered with uncoloured RM. Indicating that the largest part of which no demand occurs, of items still available in the product offer of VFA, is already specified on colour; i.e. the flexibility created with stocking semi-finished products is lost in advance. Considering the fact that the SKUs within the scope of this research cover approximately 91% of the sales (€) in 2021, as described in Section 2.1.1, it could be said that the scope covers relatively much of the product offer of VFA.

5 SOLUTION EVALUATION

The model solution, flowing as a result from Chapter 4, is evaluated in this chapter. Based on the generated demand forecasts, a required SS level is determined for each demand scenario; i.e. the SKU-individually required SS levels are summed for each demand scenario. Section 5.1 elaborates on the result of this evaluation. Next, Section 5.2 provides a conclusion of this chapter.

5.1 Required Safety Stock (SS)

As described in Section 3.3, the standard deviation of the forecast error during the review period and lead time (σ_{R+L}) should be derived from the demand forecast in order to establish a minimal required SS level per SKU. The formulas as provided in Equations (7) and (8) in Section 3.3 are used in order to determine σ_{R+L} and the required SS level, both provided below as a recap.

$$\sigma_{R+L} = \sigma_1 \sqrt{R+L}$$

$$SS = k\sigma_{R+L}$$

As indicated in Section 3.3, this calculation of σ_{R+L} tends to underestimate the actual value of σ_{R+L} and thus tends to underestimate the actual required SS level. In order to avoid this underestimation, it would be best to use observations of independent demand forecasts, i.e. only considering the forecast errors of non-overlapping periods in order to estimate σ_{R+L}. Considering the time period of the test set, 6 months in total, and the average length of the R+L-period, 4 months, this calculation method would result in only 1 forecasted value; not enough observations to derive σ_{R+L} from. The number of observations contributes to the certainty with which the value of σ_{R+L} can be determined. For this reason, an alternative approach as provided in Equation (8) is applied in order to determine σ_{R+L} with more certainty. An example of the aimed approach to estimate σ_{R+L}, as suggested above, and the alternative approach as provided in Equation (8) is provided in example *a* and *b*, respectively, of Figure 5.1. In this figure, the blue arrows indicate the forecast observations that can be used for the σ_{R+L} estimation.

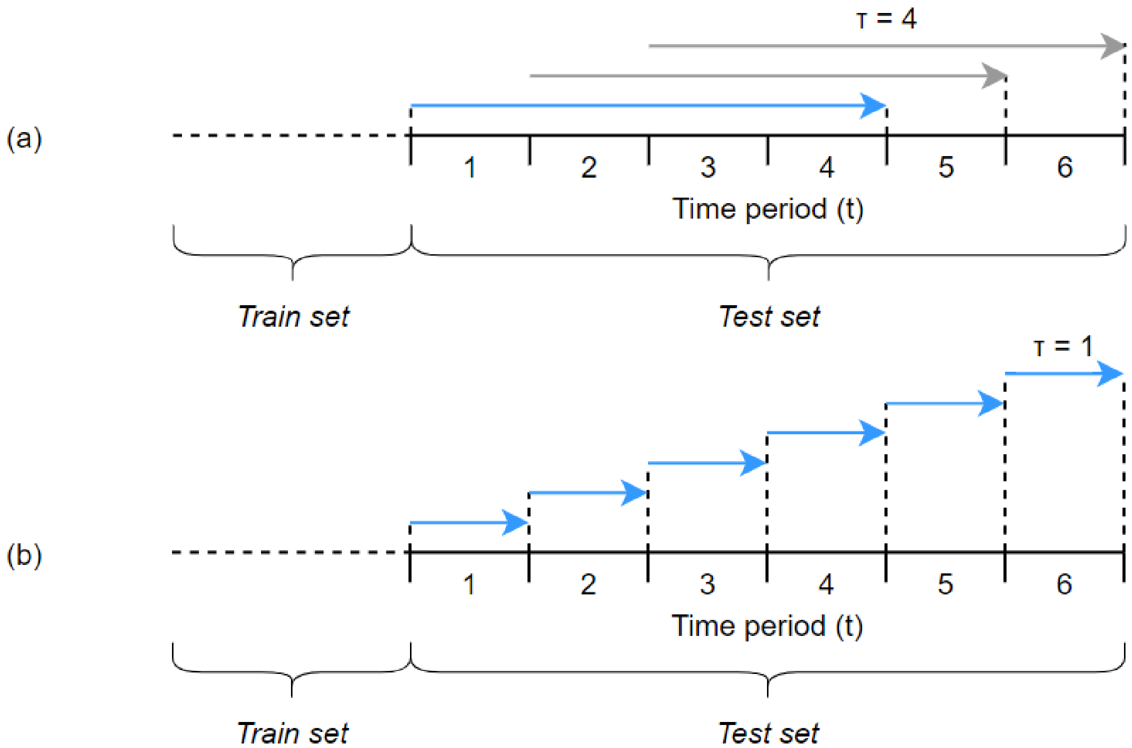

Figure 5.1. Observations used for the calculation of σ_{R+L}.

As aforementioned, the formulas as provided in Equations (7) and (8) will be used in order to determine the SS level with more certainty. In order to obtain a customer service level (S_1) of 96% as a minimum, k should be set to a value of approximately 1.75. The σ_{R+L} and the required SS level are determined for each of the 34 SKUs individually and summed for each demand scenario accordingly. In order to obtain insight in the sensitivity of the SS levels, the SS levels are also calculated for a customer service level of 94% and 98%, with a value of k set to approximately 1.55 and 2.05, respectively. The minimal required SS level per demand scenario is provided in Figure 5.2 and Table 5.1; i.e. the corresponding SS levels are provided as proportions of the current SS levels within VFA.

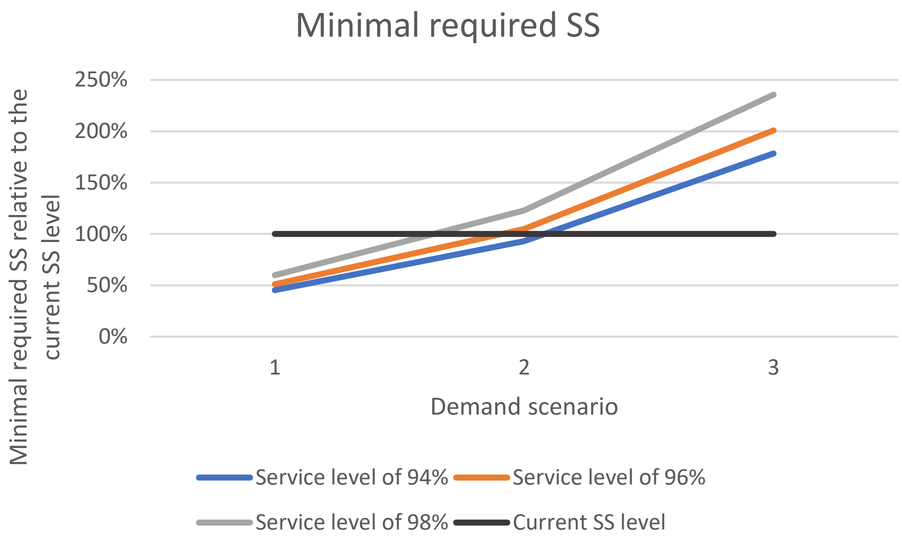

Figure 5.2. Evaluation of the required SS level per demand scenario and customer service level.

Table 5.1. Evaluation of required SS level per demand scenario and customer service level.

	Required minimum SS level as a proportion of the current SS level (%)		
Demand scenario	*Customer service of 94%*	*Customer service of 96%*	*Customer service of 98%*
1	45%	51%	60%
2	93%	105%	123%
3	178%	201%	236%
Current situation	100%	100%	100%

In order to evaluate the potential underestimation of the established SS levels, the aimed SS calculation approach is applied in addition to the alternative approach. As aforementioned, a minimum of two independent forecast errors is required. For this reason, the test set is extended to 12 instead of 6 months for this instance; the parameter optimization period is shortened in this case, the period on which the initial parameters are initialized is not shortened. From this analysis, it can be observed that this approach consistently results in lower SS levels than the alternative SS calculation approach. This observation is against the expectation as the aimed approach is expected to avoid an underestimation of the SS levels. Reasoning for this contradicting observation could be the relatively short parameter optimization period, i.e. 6 months, and the small number of independent forecast errors obtained for each SKU. For this reason, this aimed approach does not provide additional insights or corrections on the result of the alternative approach.

From both Table 5.1 and Figure 5.2 it could be observed that, in alignment with the expectation, the minimal required SS level increases in case the demand scenario increases. An increase of 106% and 92% occurred when reviewing the minimal required SS in demand scenarios 1 against 2 and demand scenarios 2 against 3 for a customer service level of 96%; this calculation is based on the actual numbers instead of the proportions as provided in Table 5.1. This increase could be partly assigned to the increase in the order size taken into account and to the increased demand variability when reviewing the demand scenarios in increasing order. The increase in demand variability among the demand scenarios is evaluated for the 34 SKUs by means of a calculation of the CV among the monthly demand, the corresponding formula is provided in Equation (2) in Section 2.2.2. The results of this evaluation are provided in Table 5.2. In addition, when reviewing Figure 5.2, it could be observed that the difference between the minimal required SS levels for each customer service level increases when reviewing the demand scenarios in increasing order.

Table 5.2. Development of the CV value of the monthly demand for each demand scenario.

	Demand scenario		
CV value	*1*	*2*	*3*
Avg.	0.60	0.71	0.76
Min.	0.24	0.05	0.05
Max.	1.26	1.32	1.41

In addition, the SKU-individual SS levels for a customer service level of 96% have been evaluated in order to visualize the impact of the demand variability. For each demand scenario, the SKU-individual SS levels are provided in Figure 5.3 for the 34 SKUs. As could be observed, several peaks in the SS appear when reviewing demand scenario 3 compared to the other demand scenarios and the current situation. In addition, it could be observed that the SS levels are more or less the same for SKU 18 to 55 and fluctuate more for SKU 17 and the SKUs from 107 onwards. When evaluating this observation, it could be observed that SKU 17 to 55 are stored as finished products and SKU 107 to 128 are stored as semi-finished products, i.e. aggregated on product and item level. In addition, it is observed that the SKUs with the more fluctuating SS level have abnormal peaks in their time series of 2021; e.g. relatable to project demand. When reviewing the time series of the SKUs with less fluctuating SS levels, a constant demand variability is observed, both a low or high variability. The difference relates to the fact that the abnormal peaks are not present in these time series. An example of both types of time series is provided in Figure 5.4, with SKU 17 having abnormal peaks, probably due to project demand, and SKU 122 having a constant demand variability.

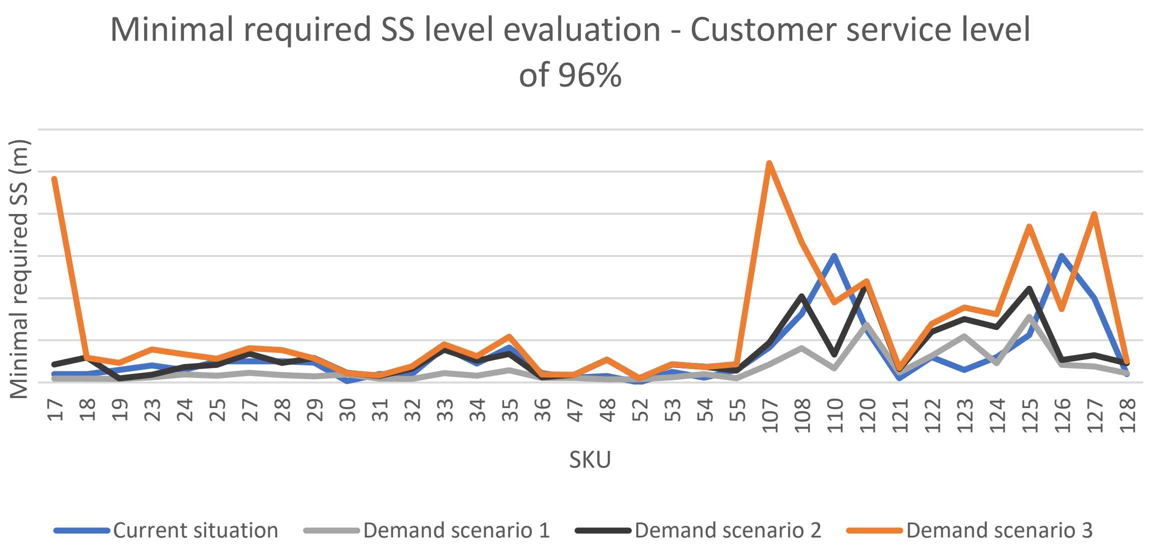

Figure 5.3. SKU-Individual SS levels for each demand scenario.

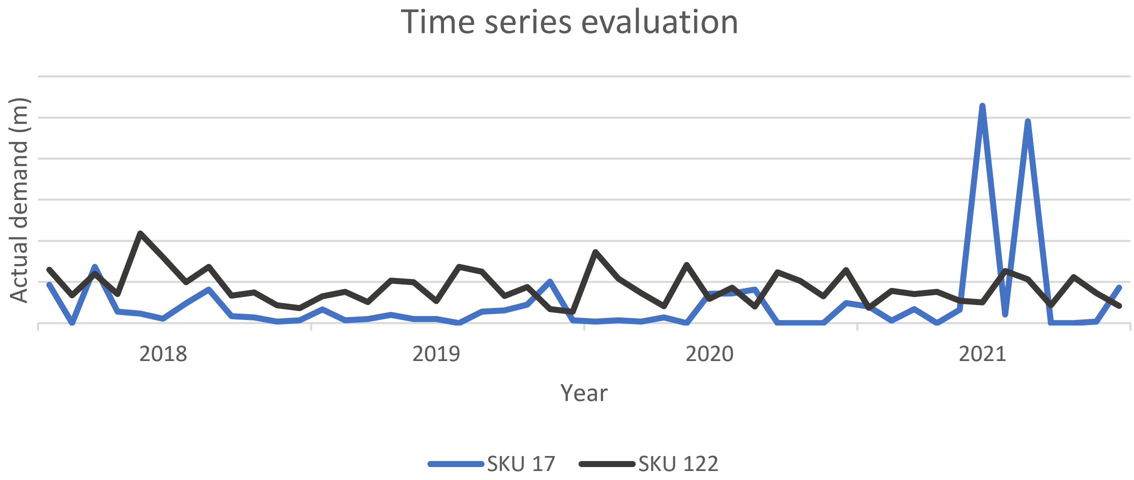

Figure 5.4. Actual demand time series of SKU 17 and SKU 122.

5.2 Chapter conclusion

Within this chapter the result flowing form the model is evaluated. The conclusions as provided in the following paragraphs are the result of this evaluation.

The current SS level of VFA is too low when considering all demand and a SS calculation based on S_1.

Considering the current approach towards demand forecasting and inventory control, i.e. the inclusion of both demand types and the stocking of semi-finished products for SKUs with RM supplied uncoloured and finished products for SKUs with RM supplied in colour, demand scenario 3 should be evaluated mainly when assessing the current SS level. When reviewing Figure 5.2 and Table 5.1, it appeared that the minimal required inventory levels should be approximately 200% larger than the current SS levels as documented in the ERP-system, when considering the SS calculation formula with the customer service level relating to a 4% chance of stock out per replenishment cycle (S_1).

The project demand has a relatively large effect on the minimal required SS levels

When the project demand is fully included in the demand forecast, represented by demand scenario 3, an increased demand uncertainty is incorporated in the demand forecast. As a consequence, the standard deviation of the forecast error becomes larger and the corresponding SS level increases. This observation is shown in Figure 5.3 and Figure 5.4.

The potential material flexibility is not optimally used when considering the current inventory control policy

When reviewing the currently established SS levels within VFA, it appeared that minimum inventory levels are also established for storage states that are not applicable for specific products. For example, as introduced in Chapter 2, it is sufficient to only maintain inventory on semi-finished product level for the RM supplied uncoloured as the colouring of the fabric does not take a significant amount of time. When reviewing the SKU selection of 34 SKUs, it is observed that for 5 of the 12 SKUs of which the RM is supplied uncoloured, a minimum inventory level is established for finished products in addition to the minimum inventory level for semi-finished products.

6 MODEL IMPLEMENTATION

Within this chapter the implementation of a statistical forecasting method within VFA is addressed. The steps to undertake for the implementation and the assignment of the corresponding responsibilities are addressed in the following paragraphs. Sections 6.1, 6.2 and 6.3 will elaborate on the implementation process, whereas Section 6.4 will provide a timeline of the implementation process and Section 6.5 provides the conclusions as a result of this chapter.

6.1 General implementation process

From the previous conclusions, e.g. as provided in Section 2.3, it may be observed that the current data registration does not include the information relevant for optimally establishing a statistical forecasting model; e.g. the demand type of an order. For this reason, Figure 6.1 provides a robust overview of the implementation process.

Figure 6.1. Robust overview of the implementation process.

In general, VFA should first make sure to process and store the sales data in another manner, in advance of implementing a statistical forecasting model. Section 6.2 further elaborates on the processing and storage of the sales data, whereas Section 6.3 further elaborates on the implementation of a statistical forecasting method and its monitoring afterwards. Both sections conclude with a RACI-matrix, i.e. an overview of the actions to be realised and the departments or employees hold responsible. These matrices are established in agreement with the Production Director of VFA. For each action, the responsibility is expressed in different roles; i.e. **Responsible** (R), **Accountable** (A), **Consulted** (C) and **Informed** (I). The roles represent the following types of responsibility:

Responsible	The person responsible for the execution of the action;
Accountable	The person bearing the final responsibility for a correct completion of the action. This role can only be assigned to 1 person per action;
Consulted	The person who is asked for advice in advance or when executing the action;
Informed	The person who is informed about decisions and the progress when executing the action;

6.2 Data processing

In advance of implementing the statistical forecasting methods as provided in Table 4.10 in Section 4.2.2 or any other statistical forecasting method, the current manner of data registration of VFA should be adjusted. The registered data should be logged in the ERP-system, as the information should be available among different departments, i.e. the Sales and Supply chain department. This change in registration solely relates to the sales data serving as input for the forecasting method and concerns the registration of (1) the demand type, (2) the process development of project orders and (3) the external factors affecting the demand; further elaborated on below.

Register the type of demand of each order, i.e. either regular demand or project demand
As aforementioned in Section 2.1.2, the larger project orders do not have to be delivered from inventory in case the CO-lead time of a project order exceeds the R+L period. For this reason, these orders can be excluded from the data serving as an input for the forecasting model. Currently, as described in Section 4.1.2, the demand types of orders are not logged and demand scenarios are established in order to imitate the split among the demand types. A more precise selection of the data, i.e. the logging of demand types, used as a foundation for the statistical demand forecast will eventually result in more accurate and lower minimal inventory levels, solely functioning in order to fulfil the regular demand or the demand up to a certain order size threshold (m).

Register and store the development of project orders from the initial request to the final order placement
An evaluation of the project order characteristics could provide relevant and usable insights for demand forecasting, in addition to the result of the statistical forecast of demand up to a certain order size threshold (m). In order to obtain these insights, the following should be logged with regard to the project order development process: (1) the date the order is initially received, (2) the date the order is transformed into a final and confirmed order, (3) the initially requested order delivery date, (4) the confirmed order delivery date, (5) the realised order delivery date, (6) the order development in terms of probabilities, corresponding dates and order information such as the final colour in case of probability changes. As a result, it could e.g. be observed that a certain product type in a specific colour is part of the project demand each year. In addition to the obtained forecasting insights, these insights may be beneficial for the Purchasing department. Currently, the Purchasing department reserves a certain production capacity at their suppliers at the beginning of each year. This additional demand info may result in higher capacity reservation levels for example, in order to prevent the production capacity to become a bottleneck.

Register the external factors and corresponding time periods that potentially affect the demand VFA faces, i.e. the RM availability for example
As described in Section 4.1.4, the current time series of the SKUs are influenced by the demand variability, inherent to the demand VFA faces, and by external factors such as the availability of the RM. As a consequence, some time series show an abnormal demand pattern; e.g. SKU 126 as depicted in Figure 4.7 in Section 4.2.2. As these periods with no optimal RM availability are not registered, the time series cannot be adjusted accordingly in order to provide a more accurate base for the statistical demand forecast in the form of adjusting the time series for these time period to the “regular” demand pattern.

For each aforementioned action, the roles of the employee(s) and/or department(s) of VFA involved are specified according to the RACI-matrix in Table 6.1.

Table 6.1. RACI-Matrix data processing implementation.

PHASE I: Data processing				
	Responsible entity within VFA			
	Supply chain			
Task	*Head of department*	*Forecasting specialist*	**Purchasing**	**Sales**
Register demand type per order	I	I	-	A / R / C
Register and store project order development	I	I	-	A / R / C
Register external factors potentially affecting the demand pattern	A / R	I	I / C	I / C

6.3 Model implementation

Once the data registration is optimized in terms of the set purpose, i.e. the establishment of a statistical demand forecast, the forecasting model can be established and implemented. The following steps should be realized in the corresponding order: (1) collect data, (2) manage the SKUs included in the forecast, (3) assign the forecasting responsibility to an employee, (5) establish a standardized forecasting process and (6) establish an inventory control policy.

Collect the required data in order to serve as an input for the demand forecasting model

For a certain period of time, the data resulting from the adjusted data registration process, should be collected in advance of establishing a forecasting model. From a data analysis, it should become clear up to which order size threshold (m) to forecast demand and what data to include as input for the demand forecast. Next, a link should be established between the ERP-system and the forecasting model in order to make sure the input data for the forecasting model is up to date. The data should be aggregated in the time buckets as specified in the forecasting model, i.e. months within this research setting.

Manage the SKUs included in the statistical demand forecast

The SKUs and data should be managed in alignment with the set purpose of the demand, i.e. optimizing the delivery performance by means of optimizing the inventory control policy in this case. For example, the to be forecasted SKUs should be based on the products kept in inventory instead of the products purchased as mentioned in Section 2.3. As indicated in Section 4.1.3, a selection of 34 SKUs is currently included in the forecast. This selection is based on the amount of historic data available. In future periods, historic data of other SKUs will become available in addition. These SKUs should also be incorporated in the forecast once enough historic data is available.

Assign the responsibility for the demand forecasting to a single employee with the required knowledge and skills

The responsibility for an up-to-date forecasting model should be assigned to an employee with the knowledge and skills required to adjust the forecasting model if necessary. This knowledge should reach out to (1) the program in which the model is established and to (2) statistical forecasting in general. In this case, the forecasting model itself can be adjusted in case a hiccup is faced or a change in design is required. Also, the corresponding input data is checked, and corrected if necessary, the optimal forecasting method can be adjusted if necessary and the forecasting performance is monitored by this employee. This employee is a so-called *forecasting specialist* and part of the Supply chain department.

Establish a standardized forecasting process within VFA

A standardized demand forecasting process should be established in order to sustain its efficiency and reoccurrence. The layout of this process should be communicated among the departments of VFA, so every department and employee is aware of this process and his or her potential (indirect) contribution. Within the process overview, the following should be addressed and determined:

- When to review the demand forecasting results and what departments are involved? E.g. once every 2 weeks or once a week with an employee of both the Purchasing and Sales department.
- When and how to evaluate the forecasting performance? What performance measures are most important or what values are worrisome for specific performance measures for example and how often should these performance measures be evaluated.
- When and how to review the SKU classification? It should be determined how often the SKUs incorporated in the forecasting model should be reclassified and what new classification methods may be beneficial to incorporate in the forecasting model. Also the reoccurrence of this SKU reclassification should be determined, e.g. once per quartile or once per year.
- When to review the applied forecasting methods in order to determine whether another forecasting method performs better in the current situation? Other available forecasting methods should always be considered as well performing alternatives under changing conditions.

Establish an inventory control policy within VFA

Once a forecasting model and the corresponding standardized process are established and implemented, an inventory control policy can be established. In order to determine which inventory control policy may be suitable, literature should be consulted and approaches from practice should be obtained. This step could be an interesting topic of a master thesis for example. When establishing an inventory control policy, one should keep in mind that it may be interesting to set different customer service levels for each SKU class. As indicated in Section 1.2.1, a service level of 96% is set for all SKUs currently.

For each aforementioned action, the roles of the employee(s) and/or department(s) of VFA involved are specified according to the RACI-matrix in Table 6.2.

Table 6.2. RACI-Matrix forecasting model implementation.

PHASE II: Model implementation				
	Responsible entity within VFA			
	Supply chain			
Task	*Head of department*	*Single employee*	**Purchasing**	**Sales**
Establish, manage and monitor the forecasting model	A	R	I	C
Manage and adjust the input data for the forecasting model	A	R	I	C
Evaluate demand forecasting results	A	R	I	C
Evaluate demand forecasting performance	A C	R	I	I
Review SKU classification	A	R	C I	C I
Review forecasting methods	A	R	I	C

6.4 Timeline

In Figure 6.2, time periods are assigned to the robust overview of the implementation process as provided in Section 6.1. In this way, insight is obtained in the amount of time required to implement a forecasting model in the manner suggested as a result of this research.

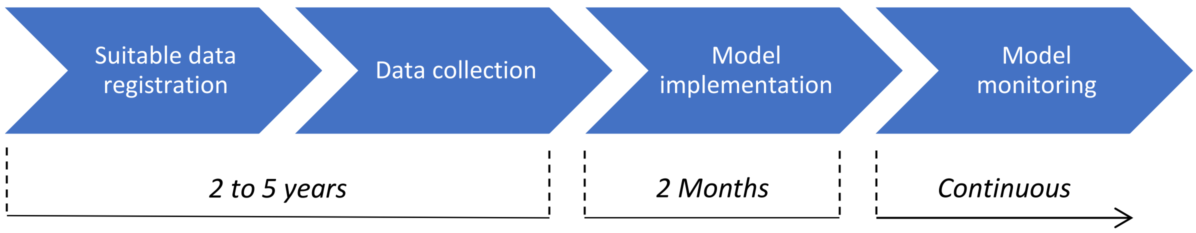

Figure 6.2. Implementation timeline.

As described in Section 6.2, the data should be correctly registered and stored. Sequentially, the data can be collected and evaluated. The length of the required data collection period depends on the forecasting method aimed to be implemented. When considering the forecasting methods reviewed in this research, i.e. SES, Holt, Winters and Croston, the establishment of SES and Croston requires 2 years of historic data; i.e. 1.5 year of train data and 0.5 year of test data. When establishing Holt or Winters, this period should be extended to a period of at least 5 years, as 3 or 4 seasonal cycles should be incorporated preferably. Again, 4.5 years can be used for training the model and 0.5 year functions as test data. Of course, while collecting the preferred data, the current historic data may already be used as input for a forecasting model. The fact that this data may affect the forecasting performance and reliability should be kept in mind obviously. In addition, it may be preferred to only collect the data up to a certain order size threshold (m); whether this is up to the regular demand threshold or a threshold up to which VFA wants to deliver from inventory.

Next, as described in Section 6.3, the forecasting model can be established and implemented. The model establishment incorporates the evaluation and classification of SKUs and applying a forecasting method in its most suitable form. This process will cover approximately 2 months.

Lastly, the established forecasting model should be monitored, i.e. evaluate its performance and adjust the model if necessary, and a standardized process should be incorporated in the daily operations of VFA. This monitoring of the forecasting model will be a continuously ongoing activity.

6.5 Chapter conclusion

The most important conclusions that could be drawn from Sections 6.1, 6.2 and 6.3 are provided below.

The data registration should be optimized preliminary to the optimal forecasting model implementation

As indicated in Section 4.4, the data registration and storage should be optimized in benefit of implementing an optimal statistical forecasting model. Until this moment, a statistical forecasting model using the historic data currently available can still be implemented in order to forecast demand; the statistical forecasting method outperforms the current forecasting method for any order size threshold as indicated in Section 4.4. The threshold of which order sizes to incorporate in the model should be determined in advance of establishing the model; this could be either up to an order size in which no project demand is expected or up to an order size upon which VFA wants to deliver from inventory.

The departments of VFA should stay in communication with each other

When the departments stay in contact with each other, relevant information can be exchanged as also indicated by the RACI-matrix. For example, the Sales department can timely inform their customers in case of an unavailability of RM as indicated by the Supply chain or Purchasing department. On the other hand, adjustments can be made to the demand forecasting data by means of input provided by the Sales department with regard to e.g. the type of demand that causes some peaks in demand. These peaks may be filtered out in case the forecast is solely for the regular demand or if abnormally high regular demand occurred once. In order to ease the communication process, logging of e.g. the demand type and the external factors affecting the RM availability should become part of the daily operational process among all considered departments. For future data analyses this data may also be beneficial and new insights may potentially be obtained.

7 CONCLUSION & RECOMMENDATIONS

Within this chapter the main conclusions, as a result of the full research period, are provided in Section 7.1. These conclusions are followed by the recommendations provided in Section 7.2 and suggestions for further research in Section 7.3.

7.1 Conclusion

As a result of this research, several conclusions may be drawn from the research findings. In the following paragraphs each conclusion is provided as a summarizing sentence, followed by a corresponding explanation.

The selected statistical forecasting methods outperform the current forecasting method

As described in Section 4.3, the selected statistical forecasting methods outperform the current forecasting method of VFA. When comparing the performances of demand scenario 3 with the current forecasting method, the impact is -112m, -183m, -112% and -10% for the MAD (m), bias (m), bias (%) and sMAPE (%), respectively.

The current sales data registration and storage is not optimal in the light of establishing a statistical forecasting model

In order to obtain the maximal benefit of the implementation of any statistical forecasting method, the current way of data handling within VFA should be adjusted and optimized in the light of the set purpose; serving as input data for a statistical demand forecasting model. When providing a concise overview, the following points with regard to data handling should be reviewed and adjusted: (1) the demand type of each incoming order should be registered, (2) the development of project orders should be logged and (3) the external factors that could potentially affect the demand pattern of an SKU should be registered, e.g. the RM unavailability, these factors could create a disturbed demand pattern and therefore a disturbed input for the forecasting model. Section 6.2 further elaborates on the required data handling adjustments in more details.

7.2 Recommendations

Next to the conclusions as provided above, several recommendations have also been formulated based on the research findings. In the following paragraphs each recommendation is provided as a summarizing sentence, followed by a corresponding explanation.

Review the product offer of VFA

As indicated in Section 4.4, approximately 20% of the SKUs that VFA currently offers to its customers did not face any demand in the period of 2018 to 2021. The largest part of these SKUs are items of which the RM is supplied in colour. This indicates that, in case a minimum inventory level is wished for these items, these items should be stocked as finished products; i.e. the flexibility related to colour and item type is lost. As a consequence, financial assets are assigned to inventory that does not move in case no demand is faced; i.e. the financial assets cannot be used for something else in the meantime.

Document the demand types

In order to obtain insight in the orders of each demand type that VFA faces, i.e. regular and project demand, this data should be logged for each incoming order. Once the historic data could be split on demand type, the characteristics of the project demand may be analysed and evaluated. From this analysis, beneficial insights may be obtained that could be incorporated in the statistical demand forecast as described in Section 6.2.

Document the development of the project orders

As indicated in Section 2.3, the historic data of the development of a project order is lost in the current data handling process. As a consequence, no insight can be obtained in the development of these orders. These insight may provide insight in both the project order characteristics and the corresponding CO-lead time. In case this information is available, the CO-lead time could serve as an order characteristic used to determine which data to include in the data set and which to exclude; i.e. fully specified orders with a development time longer than the specified forecast horizon do not have to be included in the demand forecast. The purchase of the RM of these orders can take place well ahead of time and the order can still be delivered to the customer on time.

Document the external factors that potentially affect the demand pattern of VFA

As observed during the research period, demand variability is inherent to the demand VFA faces and has its corresponding effect on the demand patterns and, thus, the forecast-ability. In addition to this variability, external factors such as RM unavailability also affect the demand patterns. As mentioned in Section 4.1.4, the presence or influence of such external factors is currently not logged. As a consequence, the effect could not be traced back in case of observing certain peaks or lows in a demand pattern. Accordingly, the root of this peak could not be traced back to an external factor in specific or to the fact that it is just part of the demand variability.

Vary with customer service level targets

In relation to the main purpose of this research, i.e. improve the current delivery performance, it is observed in Chapter 1 that the delivery performance target is set to 96% for all items. Following on the ABC-classification as provided in Section 4.2.1, a distinction in the delivery performance targets could be set, based on the specified class of an SKU. For example, the delivery performance target is set to 98%, 96% and 94% for the A-, B- and C-items, respectively. The realized delivery performance targets should together average e.g. to 96%. When this approach is implemented, the base of the ABC-analysis should be considered closely. For example, the financial impact could serve as a base of the ABC-analysis; the case within this research setting. In addition, the number sold of each SKU or the strategic value of an SKU could also serve as a base for the ABC-analysis. In the optimal case, each of these properties should be considered when determining the importance of an item.

Define a clear demand forecasting purpose

As stated in the research objective, the inventory control policy should be improved in order to eventually improve the delivery performance of VFA in the scope of this research. For this reason, the demand forecast should be established in the light of inventory control. As indicated in Section 2.3, currently, the forecasting purpose is a combination of inventory control and purchasing. Both contribute to an improved delivery performance of course, but the current forecasting approach did not fully supply the needs for either one of these purposes; making the current forecast non-optimal in the light of both purposes.

A combination of a statistical and a judgemental forecast should serve as demand forecasting model

Considering the relatively high value of the scale-independent forecasting performance measures bias (%) and sMAPE (%), as discussed in Section 4.3, it may be observed that it is not sufficient enough to use a statistical forecasting method solely for all demand combined; i.e. both demand types. A forecast that is partly statistical and partly judgemental could function beneficial for VFA. Within this forecast, the statistical forecast e.g. forecasts the regular demand and partly the project demand, i.e. a forecast of the project demand characteristics obtained from historic data. The judgemental forecast may focus on the additional project demand, not incorporated in the statistical forecasting method.

Log the forecasting performance

One of the findings as provided in Section 2.3 is the lack of a measured and logged forecasting performance. In order to enable an evaluation of the forecasting performance and a correction of the forecasting model if necessary, the forecasting performance should be measured, logged and evaluated.

When considering the 3 demand scenarios, continue with demand scenario 2 as initial guideline in order to distinguish between regular and project demand

Based on the insights obtained during the research period, demand scenario 2 appeared to be most suitable in order to distinguish between the demand types, i.e. deliver orders up to an order size of 350m from inventory. When considering the SS levels as provided in Table 5.1 in Section 5.1 in combination with the arguments of the employees of VFA as provided in Section 2.2.3, i.e. there is not enough warehouse space, demand scenario 3 is observed to be unsuitable as the current inventory levels should be doubled. Demand scenarios 1 and 2 appear to be suitable alternatives, considering the proportion of orders that are included, i.e. 80% and 95%, respectively. Considering the argument that too much inventory is kept currently, demand scenario 1 would be most suitable. Taking into account the corresponding order size threshold, i.e. 100m, it appears that this threshold conflicts with the current threshold that is assumed among the employees of VFA, more or less 500m² as indicated in Section 2.2.1. In addition, when reviewing Table 5.1 in Section 5.1, it appeared that approximately the same amount of inventory as in the current situation should be kept when assuming demand scenario 2 and a customer service level of 96%. Considering the number of orders included in demand scenario 2 and the minimal required SS level, it is recommended to continue with an order size threshold of 350m as a guideline to distinguish between regular and project demand. Considering the gap between the thresholds of demand scenarios 1 and 2, i.e. 250m, it may be expected that an optimal order size threshold can be found between the 100m and 350m. Further research is required in order to determine the optimal order size threshold, further elaborated on in the next section. Once a certain threshold is determined, this threshold should be clearly communicated both companywide and towards the customer of VFA.

7.3 Further research topics

Lastly, three topics for further research flowed from the research findings. Further research on these topics may be beneficial for the daily business of VFA and are described in the following paragraphs.

Clearly define up to which order size threshold to deliver from inventory

Within the alternative research approach, i.e. with demand scenarios as described in Section 4.1.2, it is assumed that the excluded project demand has a CO-lead time longer that the required forecasting horizon. As a consequence, the forecast established for each scenario indirectly states up to which order size to deliver from stock and the demand up to this order size is marked as regular demand. Once the new manner of data registration and storage reveals that the threshold between regular and project demand differs from this research approach or that the project demand occurs with a shorter CO-lead time than expected, it may be observed that the order size up to which to deliver from inventory also needs adjustments, i.e. not a full exclusion of project demand but an inclusion of project demand with a shorter CO-lead time. Once the data is correctly registered and stored, this insight may be obtained and a new order size threshold may be determined.

Evaluate the customer specific demand patterns

Next to the historic sales data per specific SKU, another view on the data may also provide additional information as input for the statistical demand forecast. This view relates to an evaluation of the demand pattern of each customer. The number of customers of VFA is relatively small, based on the historic sales data of 2018 to 2021. From this analysis it appeared that the largest part of the orders is placed by relatively few customers. When further developing a suitable forecasting method, the analysis of the demand pattern per customer may provide beneficial insight related to repeating orders with specific intervals or order characteristics and quantities. For example, of some customers it is known that they keep their own inventory of the products supplied by VFA. Once in a while, they will place larger orders of specific fabrics they offer to their customers. Such demand may result in a specific and maybe in a more easy-to-forecast demand pattern.

Establish a suitable inventory control policy

As indicated in Section 6.3, the establishment of an inventory control policy follows once the data registration and storage is optimized and a suitable forecasting model and procedure is implemented in the operational business of VFA. Further orientation and research on potential inventory control policies is required.

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I Product characteristics

At first Table I.1 provides an overview of the product offer of VFA within the scope of the research. The product offer is provided on SKU level. In addition, Table I.2 provides information with regard to the level of SKU-aggregation for each product type. Lastly, Table I.3 provides product type specific information with regard to the fabric composition, the supply state of the RM, the corresponding state of storage and the delivery time.

Table I.1. Product offer VFA on SKU-level.

Product family	**Product type**	**SKU**												**#SKUs**
		Widths (cm) & colours							*Application*					
		190	*200*	*240*	*275*	*280*	*300*	*320*	*31*	*32*	*34*	*35*	*37*	
Silverscreen	202		EB01 EB02 EB03 EC02 ED01 ED02 ED03 ED04			EB01 EB02 EB03 EC02 ED01 ED02 ED03 ED04						x		16
	205		EB01 EB02 EB03 EB04 EC01 EC02 ED01 ED02 ED03 ED04	EB01 EB02 EB03 EB04 EC01 EC02 ED01 ED02 ED03 ED04		EB01 EB02 EB03 EB04 EC01 EC02 ED01 ED02 ED03 ED04		EB01 EB02 EB03 EB04 EC01 EC02 ED01 ED02 ED03 ED04				x		40
	203		EB01 EB02 EB03 EC02 ED01			EB01 EB02 EB03 EC02 ED01						x		14

		ED02 ED03		ED02 ED03							
Omniascreen	293	EB01 EB02 EB03 ED01 ED02 ED03		EB01 EB02 EB03 ED01 ED02 ED03					x		12
Comfortscreen	103	EB01 ED01 ED03 ED04 7110 7130 7160 7190 7210 7430 7530		EB01 ED01 ED03 ED04 7110 7130 7160 7190 7210 7430 7530					x		22
Clearview	833	0000 0741 0765 0829 0936 0998 7100 7120 7180 7190 7240		0000 0741 0765 0829 0936 0998 7100 7120 7180 7190 7240					x		22
Enviroscreen	802	0000 0741	0000 0741	0000 0741	0000 0741				x		24

	803	0765 0829 0936 0998	0765 0829 0936 0998	0765 0829 0936 0998	0765 0829 0936 0998				x		24
	804								x		24
APO	825		7101 7131 7161 7191 7201 7431 7601 7701						x		8
Originals	812		0000 0105 0106 0119 0137 0162			x	x	x	x		144
	815		0221 0271 0292 0316 0323 0346			x	x	x	x		144
	816		0356 0367 0386 0441 0434 0450			x	x	x	x		144

	849	0552 0652 0661 0711 0734 0738	x	x	x	x		144
	850	0741 0765 0773 0778 0790 0823	x	x	x	x		144
	878	0829 0882 0920 0936 0998 0999	x	x	x	x		144
	890	0000 0741 0765 0829 0936 0998	x	x	x	x		24
Curtains	882	0000 0137 0162 0346 0367 0386 0441 0552					x	18

883	0661 0711 0738 0765 0778 0790 0823 0829 0936 0998					x	18

Table I.2. Aggregation levels product offer VFA.

Product family	Product type	Level of aggregation
Silverscreen	202	N.a.
	205	N.a.
	203	N.a.
Omniascreen	293	N.a.
Comfortscreen	103	N.a.
Clearview	833	Colour
Enviroscreen	802	Colour
	803	Colour
	804	Colour
APO	825	Colour
Originals	812	Colour, application
	815	Colour, application
	816	Colour, application
	849	Colour, application
	850	Colour, application
	878	Colour, application
	890	Colour, application
Curtains	882	Colour
	883	Colour

Table I.3. Information per product type within the research scope.

Product family	Product type	Notes	Composition	RM supply state	State of storage	Delivery time (assuming RM is in house at supplier)
Silverscreen	202		Glass fibre, PVC coating	Coloured	Finished Product	6-8 weeks
	205		Glass fibre, PVC coating	Coloured	Finished Product	6-8 weeks
	203		Polyester fibre, PVC coating	Coloured	Finished Product	2-3 months
Omniascreen	293		Polyester fibre, PVC coating	Coloured	Finished Product	2-3 months
Comfortscreen	103		Polyester	Coloured	Finished Product	2-3 months
Clearview	833		Polyester	Uncoloured	Finished Product /Semi- Finished Product	4-5 months
Enviroscreen	802	Same as product type 803 & 804; metallized	Polyester	Uncoloured	Finished Product /Semi-Finished Product	2-3 months
	803/804	Both same as product type 802; 803 is not metallized and coloured on 1 fabric side; 804 is not metallized and coloured on both fabric sides	Polyester	Uncoloured	Finished Product	2-3 months
APO	825		Polyester	Uncoloured	Semi-Finished Product	4-5 months
Originals	812		Polyester	Uncoloured	Semi- Finished Product	4-5 months
	815	Same as product type 816; not metallized	Polyester	Uncoloured	Semi- Finished Product	4-5 months
	816	Same as product type 815; metallized	Polyester	Uncoloured	Semi- Finished Product	4-5 months

	849	Same as product type 850; metallized	Polyester	Uncoloured	Semi- Finished Product	4-5 months
	850	Same as product type 849; not metallized	Polyester	Uncoloured	Semi- Finished Product	4-5 months
	878		Polyester	Uncoloured	Semi- Finished Product	4-5 months
	890		Polyester	Uncoloured	Semi- Finished Product	4-5 months
Curtains	882		Polyester	Uncoloured	Semi- Finished Product	4-5 months
	883		Polyester	Uncoloured	Semi- Finished Product	4-5 months

II Demand characteristics

Figure II.1 provides the demand pattern of VFA during 2021 in the form of a histogram. The occurrence of each order size (m) are categorized in bins of 50m. In addition, this Appendix provides argumentation with regard to why other sources than the historic order data are unsuitable for distinguishing between regular and project demand.

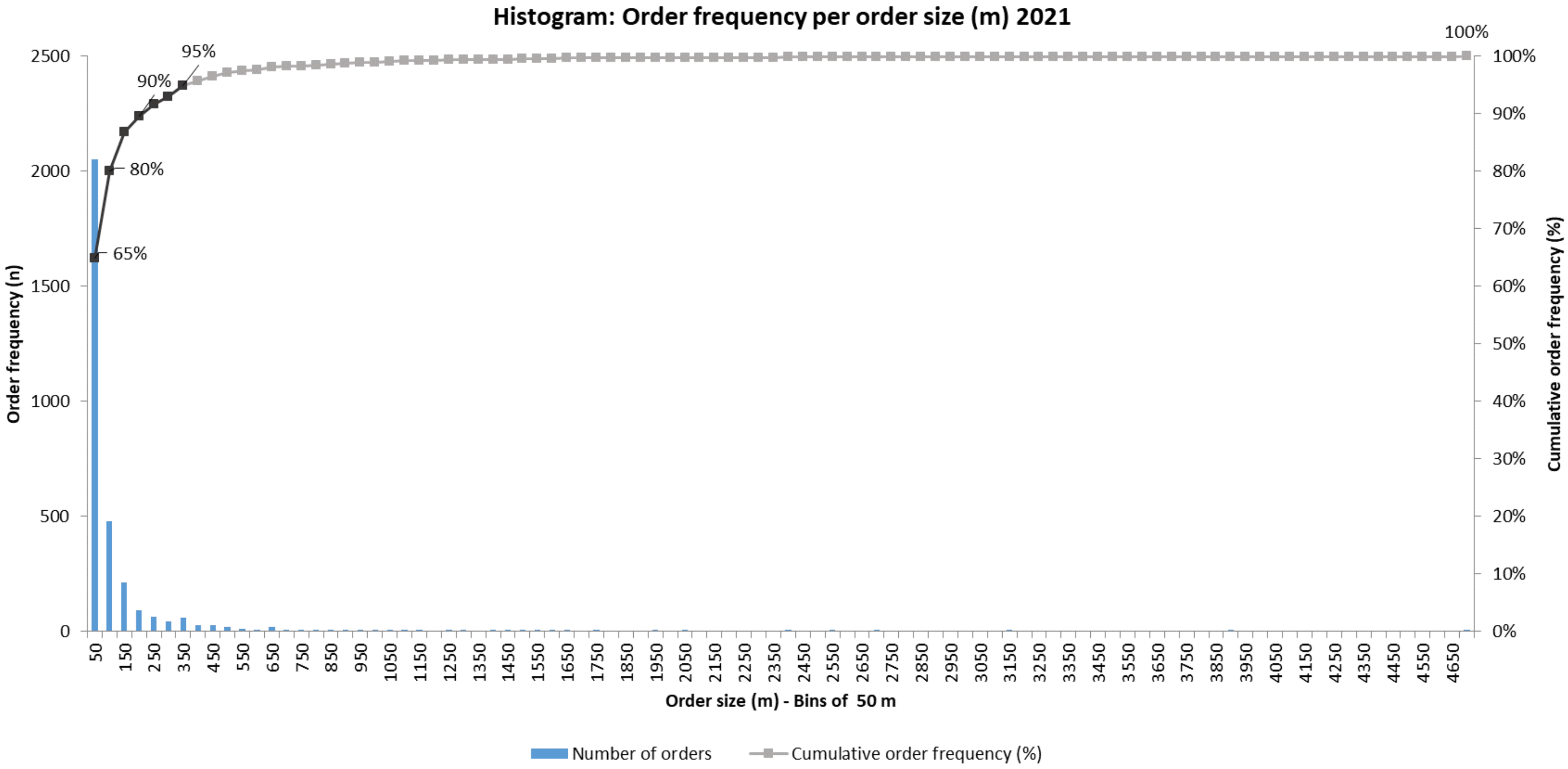

Figure II.1. Histogram of the order size (m) occurrences in 2021.

Evaluation of regular and project demand

As described in Section 2.1.2, the ERP-system does not provide information in order to enable a distinction among regular and project demand. For this reason, other sources have been consulted in order to review whether this distinction is still possible. In the following paragraphs an evaluation of the Customer Order (CO) lead time, the current sales quotation, the forecast lists provided by customers of VFA and backed-up information from a program currently out of use is provided.

At first, the **CO lead time** has been evaluated in order to distinguish between regular and project demand. The CO lead time represents the time between the moment the order becomes known to VFA and the initially requested date of delivery towards the customer. The expectation is that a larger CO lead time is connected to a larger order size (m) and therefore could indicate a project order. Figure II.2 depicts the order size against the corresponding CO lead time of the historic sales orders in 2021, the corresponding correlation coefficient is 0.27. The fact that a small CO lead time may also be connected to a larger order size (m) does not represent the situation in reality; VFA is in general not able to deliver large orders of e.g. 3,000m directly from inventory with a CO lead time of 8 days. This observation is confirmed by the sales and Purchasing department of VFA. Observing Figure II.2 and the correlation coefficient, it may be observed that there is no significant correlation between the order sizes (m) and the CO lead times.

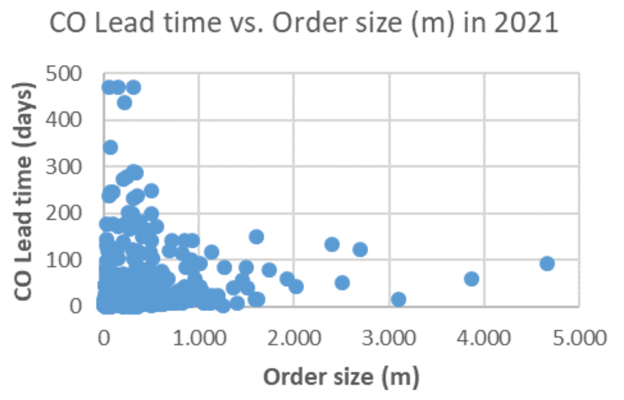

Figure II.2. Correlation plot of the CO lead time vs. the order size (m) in 2021.

A clarifying reason for this distorted view when evaluating the CO lead time, is the manual input and interference in the ERP-system when transforming a potential project order into a definite order. The potential orders are tracked and updated with information in the sales quotation and the definite orders are placed in the sales order list; both incorporated of the ERP-system. In the sales quotation a track is kept of the potential projects that may be assigned to VFA by means of different proportions, starting from 25% in case the order is just known and not specified in details yet up to 90% in case the order is almost sure to be assigned to VFA and the order is specified in detail. Once a project order is definitely assigned to VFA, the order is inserted in the sales order list and the order line is removed manually from the sales quotation; with a loss of data as a consequence. The moment the order becomes known at VFA is now represented by the moment the order was definitely assigned to VFA instead of the moment the project order became first known to VFA.

Because of (1) the lack of a link between the sales quotation and the sales order list in the ERP-system and (2) the lack of historic sales quotation data due to continuous removal of the potential order data, the CO lead time evaluation cannot be further specified or modified in order to represent reality in a more accurate way. In order to obtain useful data with regard to the distinction between regular and project demand, other data sources have been reviewed accordingly; the current sales quotation, the forecast lists provided by customers of VFA and historic order data from a program that is not used anymore within VFA.

As aforementioned, historic data of the sales quotation list is not available as the lines are removed once an order is definitely assigned to VFA or not. When reviewing the **current sales quotation** list, it can be concluded that no assumptions with regard to characteristics of the project demand could be made for the following reasons; (1) the Sales department indicates that the sales quotation list is not up to date w.r.t probabilities, order details (fabric type, width, colour and quantity) and dates and (2) the sales quotation list contains a relatively small amount of orders of which, for the larger part, the order details are not known (fabric type, width, colour and quantity).

The sales quotation list is partly based on the **forecast lists** provided by some of the customers of VFA. As indicated by the Sales department of VFA these forecast lists are not always up to date and are not shared structurally with VFA; the Sales department of VFA has to ask proactively for these forecast lists. Also indicated by the Sales department of VFA, is the fact that these forecast lists are often established from a positive point of view by the customers; making the content less reliable. In addition, when reviewing the latest forecast lists at this moment (mid-February 2022) the latest lists are provided in November 2022; indicating that the information on these lists is at least 3 months outdated. For these reasons, it can be concluded that the customer forecast lists are not a suitable source for reliable information.

Before the sales quotation was incorporated in the current ERP-system, an overview of the potential projects was kept in **another program**. VFA decided to stop using this program in 2019. A part of the data was backed-up and reviewed for potential usability when distinguishing between regular and project demand. At that time, a decision was made with regard to which information to back-up. For this reason, the creation date of a project and a development of the probabilities with the corresponding dates are missing in the backed-up data. In addition, the data does not contain order details in a large part of the data, even in case the project is transformed into an actual order and inserted in the ERP-system. Lastly, the program on which the assumptions would potentially be based is no longer used within VFA, creating the question whether this would be an interesting source for a future business operation such as a forecasting system at all. For these reasons, the backed-up data is not considered as a reliable and suitable source for information.

III Forecast performance

The results of the analyses with the different performance measures applied to each forecasted item are provided in Table III.4. In addition, Figure III.4 provides a more extensive overview by means of depicting the bias (%) for each forecasted item over the years 2020 and 2021. The result of the sMAPE and MAD as performance measures are provided in Figure III.3 and Figure III.5 in the form of a histogram accordingly. Lastly, Figure III.6 and Figure III.7 provide an evaluation of the sMAPE (%) and bias (%) as performance measures.

Table III.4. Results per year for each performance measure (Bias, sMAPE, MAD).

					Bias (m²)		Bias (%)		sMAPE (%)		MAD (m²)	
#	**Item**	**Product type**	**Width**	**Colour**	**2020**	**2021**	**2020**	**2021**	**2020**	**2021**	**2020**	**2021**
1	*35*	*202*	*200*	*0011*	-	34	-	26%	-	115%	-	148
2	*35*	*202*	*200*	*0012*	-	174	-	110%	-	128%	-	255
3	*35*	*202*	*200*	*0031*	-	-301	-	-47%	-	96%	-	614
4	*35*	*202*	*200*	*0032*	-	103	-	160%	-	100%	-	104
5	*35*	*202*	*200*	*0033*	-	183	-	58%	-	100%	-	313
6	*35*	*202*	*280*	*0011*	848	345	305%	107%	174%	93%	1,072	427
7	*35*	*202*	*280*	*0012*	761	381	124%	133%	120%	124%	947	506
8	*35*	*202*	*280*	*0031*	1,620	990	168%	146%	122%	123%	1,798	1,172
9	*35*	*202*	*280*	*0032*	501	226	93%	51%	104%	105%	630	483
10	*35*	*202*	*280*	*0033*	1,344	834	130%	100%	111%	100%	1,524	1,060
11	*35*	*205*	*200*	*0011*	29	-1,402	6%	-68%	143%	121%	571	1,996
12	*35*	*205*	*200*	*0012*	49	287	8%	76%	122%	118%	629	518
13	*35*	*205*	*200*	*0031*	149	1,248	11%	213%	112%	117%	1,246	1,253
14	*35*	*205*	*200*	*0032*	414	561	99%	128%	145%	113%	671	651
15	*35*	*205*	*200*	*0033*	487	721	64%	136%	113%	103%	911	770
16	*35*	*205*	*240*	*0011*	799	1,524	62%	156%	147%	101%	2,096	1,575
17	*35*	*205*	*240*	*0012*	328	1,101	19%	142%	75%	106%	1,120	1,329
18	*35*	*205*	*240*	*0013*	82	655	8%	128%	119%	113%	1,102	808
19	*35*	*205*	*240*	*0014*	112	20	82%	9%	173%	81%	294	163
20	*35*	*205*	*240*	*0021*	336	461	135%	378%	128%	142%	427	461
21	*35*	*205*	*240*	*0022*	560	299	205%	105%	148%	122%	710	460

22	*35*	*205*	*240*	*0031*	1,194	1,489	69%	104%	97%	78%	1,874	1,511
23	*35*	*205*	*240*	*0032*	472	736	40%	102%	90%	87%	981	802
24	*35*	*205*	*240*	*0033*	1,099	1,684	49%	206%	92%	127%	2,100	1,876
25	*35*	*205*	*240*	*0034*	216	567	35%	569%	150%	154%	842	567
26	*35*	*205*	*320*	*0011*	-82	638	-12%	327%	148%	135%	931	638
27	*35*	*205*	*320*	*0012*	20	330	6%	98%	192%	139%	562	633
28	*35*	*205*	*320*	*0031*	265	460	47%	85%	131%	108%	722	679
29	*35*	*205*	*320*	*0032*	83	181	25%	77%	160%	156%	490	430
30	*35*	*205*	*320*	*0033*	313	633	60%	172%	148%	129%	842	777
31	*35*	*203*	*200*	*0011*	-	122	-	96%	-	147%	-	251
32	*35*	*203*	*200*	*0012*	-	199	-	91%	-	129%	-	359
33	*35*	*203*	*200*	*0031*	-	79	-	23%	-	133%	-	446
34	*35*	*203*	*200*	*0032*	-	-63	-	-16%	-	128%	-	563
35	*35*	*203*	*200*	*0033*	-	180	-	55%	-	167%	-	776
36	*35*	*203*	*280*	*0011*	-503	144	-43%	26%	62%	78%	688	701
37	*35*	*203*	*280*	*0012*	-306	-86	-36%	-8%	68%	97%	659	1,162
38	*35*	*203*	*280*	*0013*	-	678	-	815%	-	162%	-	715
39	*35*	*203*	*280*	*0031*	-253	1,009	-18%	139%	87%	114%	1,465	2,404
40	*35*	*203*	*280*	*0032*	-18	1,101	-3%	324%	72%	118%	533	1,233
41	*35*	*203*	*280*	*0033*	-932	1,712	-49%	248%	82%	96%	1,878	1,712
42	*35*	*103*	*280*	*0011*	-467	761	-74%	1054%	128%	172%	595	761
43	*35*	*103*	*280*	*0031*	-1,813	167	-92%	25%	155%	164%	1,946	984
44	*35*	*103*	*280*	*0033*	-44	-537	-21%	-52%	140%	150%	258	1,134
45	*35*	*103*	*280*	*0034*	-1	-11	-1%	-4%	117%	121%	164	289
46	*35*	*103*	*280*	*7210*	-	317	-	318%	-	191%	-	441
47	*35*	*833*	*240*	*NA*	31	-	4%	-	138%	-	901	-
48	*35*	*833*	*275*	*NA*	-	251	-	43%	-	61%	-	398
49	*35*	*802*	*190*	*NA*	-928	1,420	-24%	52%	61%	89%	2,026	2,698
50	*35*	*802*	*240*	*NA*	1,985	1,652	39%	30%	53%	37%	2,892	2,100
51	*35*	*802*	*300*	*NA*	-2,428	3,638	-37%	166%	65%	110%	3,759	3,847

52	*35*	*812*	*240*	*NA*	96	-10	5%	-1%	45%	33%	748	480
53	*35*	*815*	*240*	*NA*	-265	142	-24%	21%	39%	55%	455	397
54	*35*	*849*	*240*	*NA*	231	240	38%	70%	74%	63%	463	262
55	*35*	*850*	*240*	*NA*	278	334	201%	404%	120%	144%	290	334
56	*35*	*878*	*240*	*NA*	361	-415	41%	-33%	56%	69%	557	838
57	*35*	*890*	*240*	*NA*	640	565	56%	82%	71%	122%	946	946
58	*31/32/34*	*812*	*240*	*NA*	-262	807	-8%	32%	27%	49%	830	1,354
59	*31/32/34*	*815*	*240*	*NA*	-316	421	-238%	587%	35%	49%	564	646
60	*31/32/34*	*849*	*240*	*NA*	-351	-370	-34%	-27%	50%	61%	491	721
61	*31/32/34*	*850*	*240*	*NA*	-422	-403	-63%	-45%	78%	74%	469	609
62	*31/32/34*	*878*	*240*	*NA*	53	651	2%	24%	31%	42%	1,031	1,206
63	*31/32/34*	*890*	*240*	*NA*	-25	-6	-100%	-100%	-	-	25	6
64	*37*	*882*	*240*	*NA*	-1,446	-115	-81%	-6%	113%	100%	1,446	1,661
65	*37*	*883*	*240*	*NA*	402	108	93%	35%	84%	94%	447	286

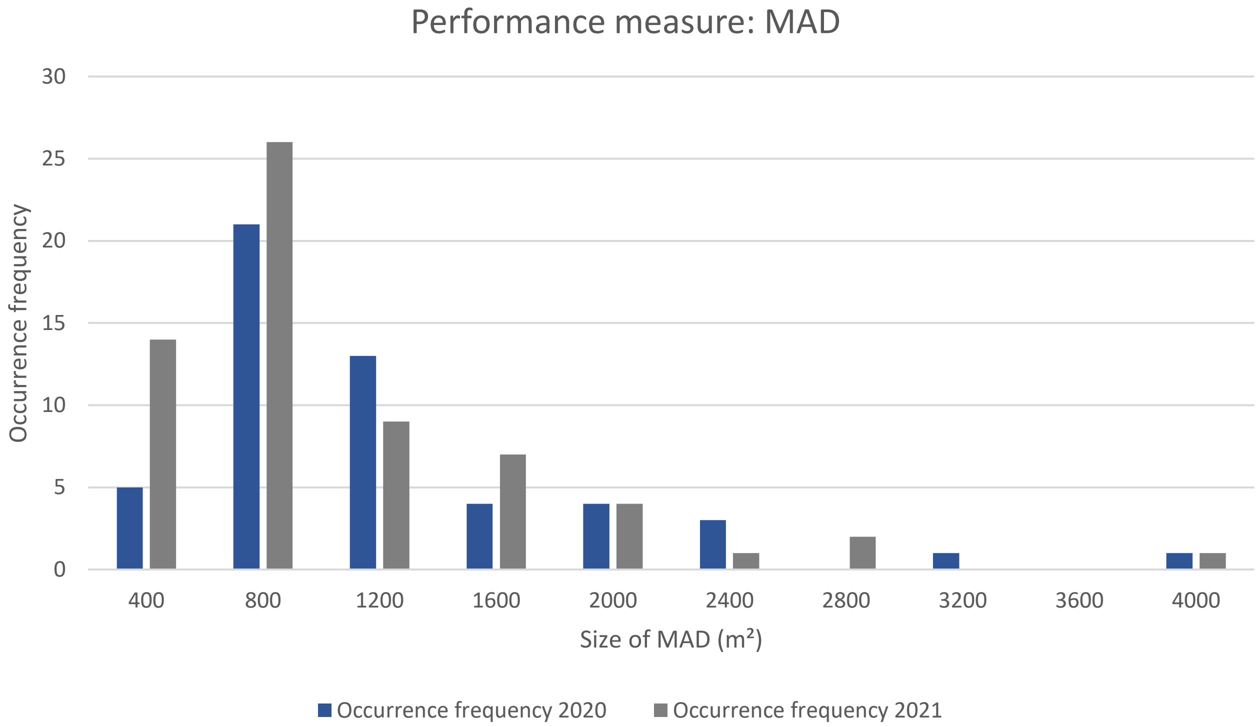

Figure III.3. Histogram of MAD (m²) for 2020 and 2021.

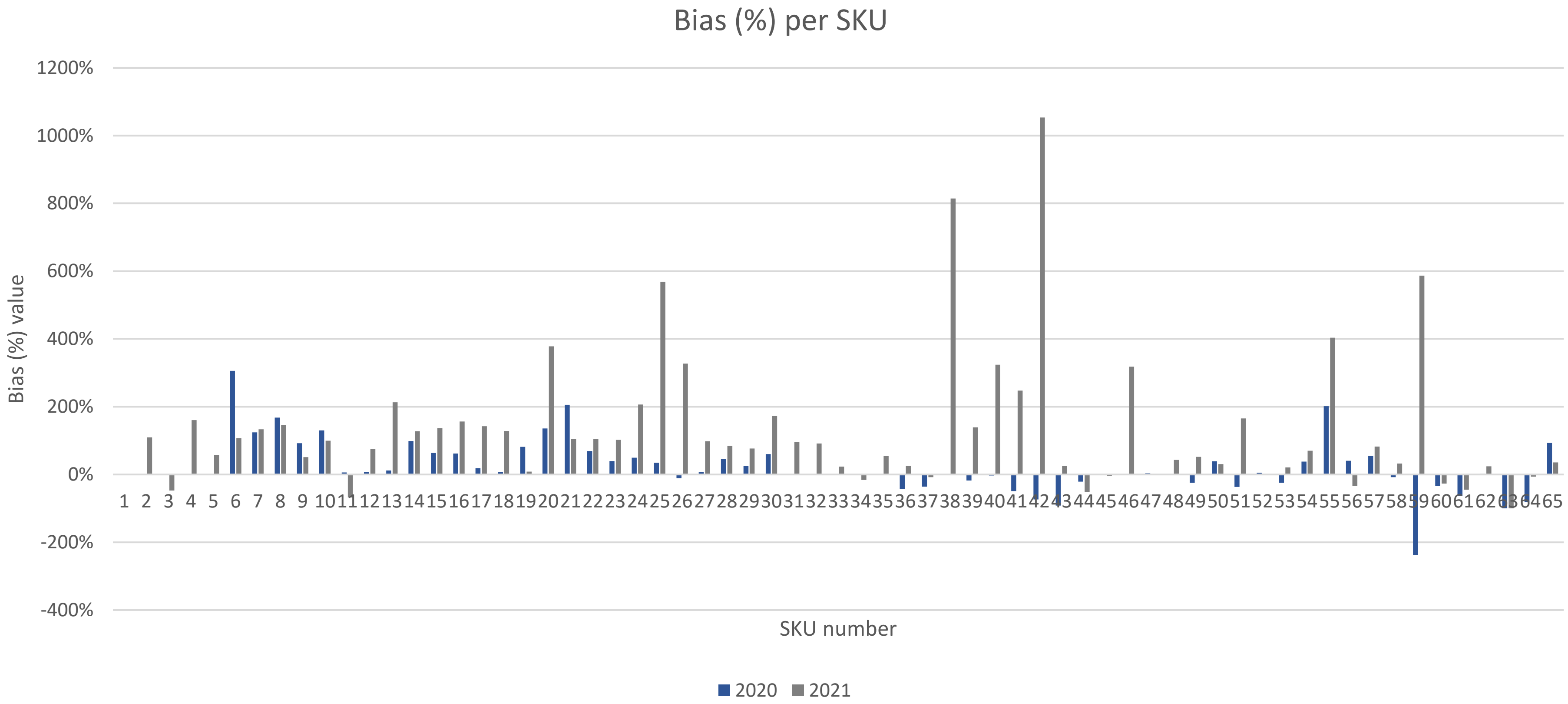

Figure III.4. Bias (%) per forecasted item for 2020 and 2021.

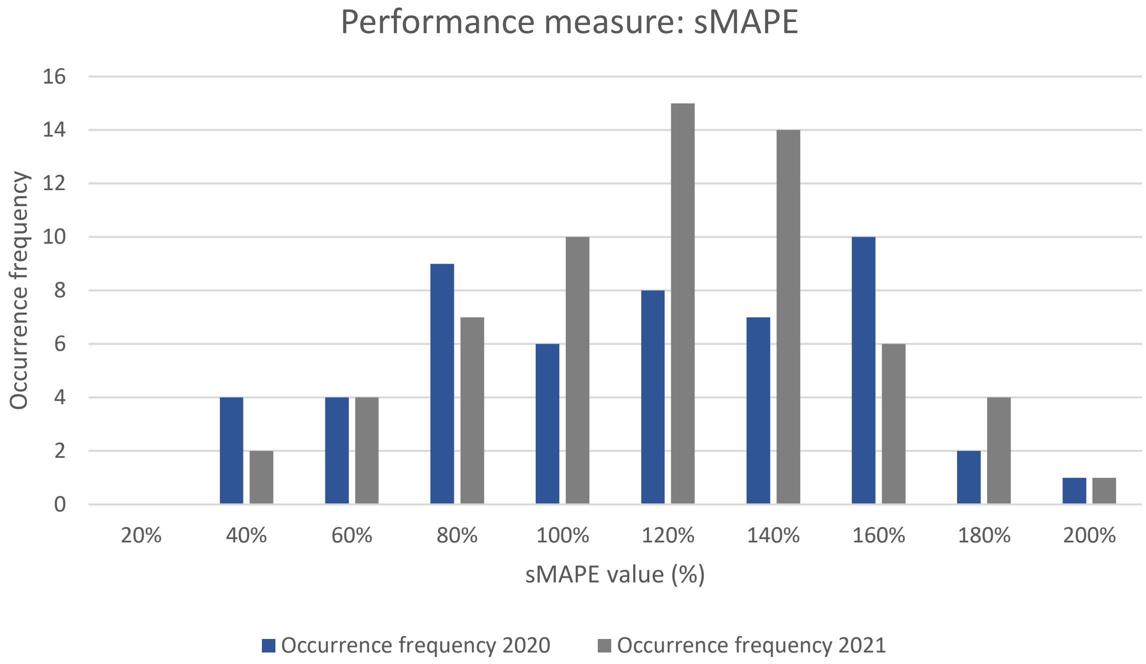

Figure III.5. Histogram of sMAPE (%) for 2020 and 2021.

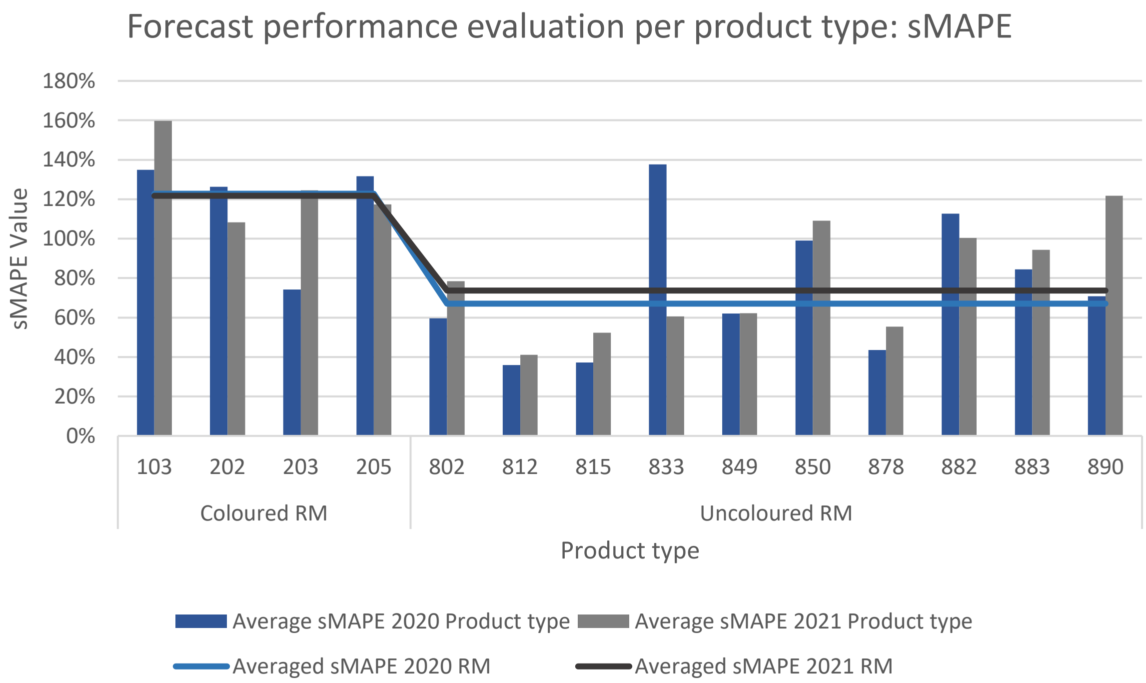

Figure III.6. Forecast performance evaluation per product type (sMAPE).

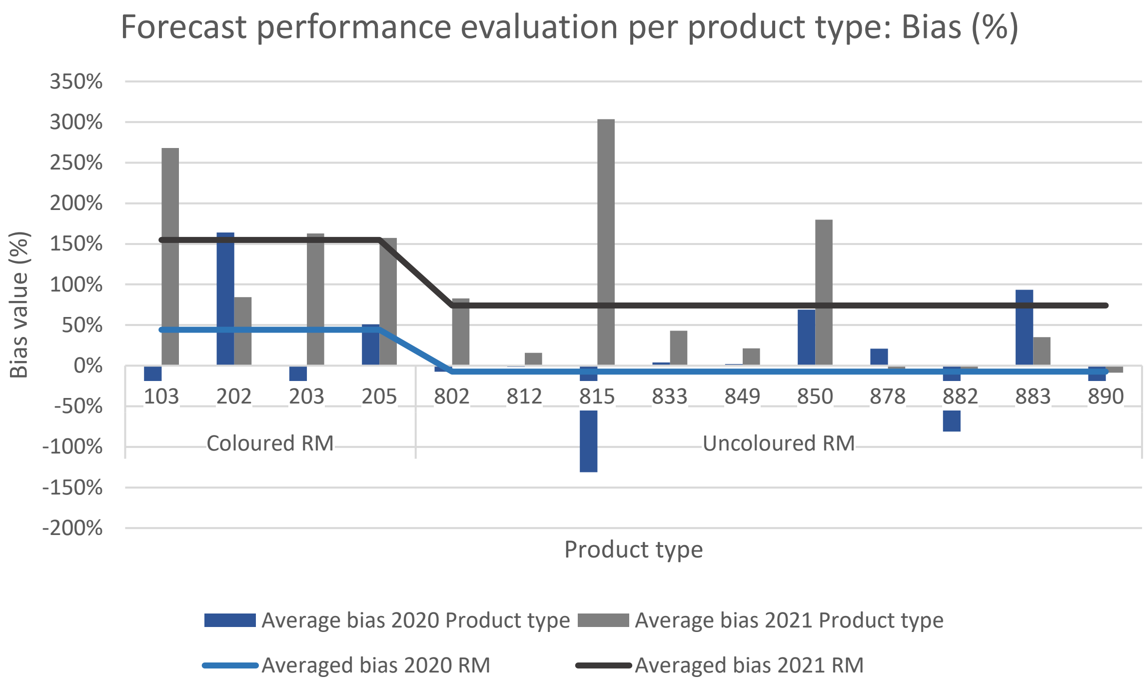

Figure III.7. Forecast performance evaluation per product type (bias (%)).

IV Forecasting methodology

As aforementioned in Sections 3.2.2 and 4.2.2, this section will further elaborate on the forecasting methodologies applied within the scope of this research. For each forecasting methodology the forecasting, the updating formula(s) and the initialization method are provided. Only for the Naive method no updating is required and therefore, no updating formulas are provided.

Naive method (N)
The N method does not require parameter updating while forecasting demand. For this reason, only Equation (9) is used when forecasting demand. The initialization of the N method only requires the actual demand of t-periods in advance of the to be forecasted time period.

Forecasting:

$$\hat{x}_{t,t+\tau} = x_t \tag{9}$$

Simple Exponential Smoothing (SES)
Equations (10) and (11) are used when forecasting according to the SES method. The initialization of the SES method requires the average demand over a certain time period, the last year of the training set in this case.

Forecasting:

$$\hat{x}_{t,t+\tau} = \hat{a}_t \tag{10}$$

Updating:

$$\hat{a}_t = \alpha x_t + (1-\alpha)\hat{a}_{t-1} \tag{11}$$

Holt's method (H)
For H method equations (12), (13) and (14) are used when forecasting demand. The initialization of the parameters a and b occurs with a linear regression on the deseasonalized demand as described by Chopra & Meindl (2013).

Forecasting:

$$\hat{x}_{t,t+\tau} = \hat{a}_t + \tau\hat{b}_t \tag{12}$$

Updating:

$$\hat{a}_t = \alpha x_t + (1-\alpha)(\hat{a}_{t-1} + \hat{b}_{t-1}) \tag{13}$$

$$\hat{b}_t = \beta(\hat{a}_t + \hat{a}_{t-1}) + (1-\beta)\hat{b}_{t-1} \tag{14}$$

Winter's method (W-Indv$_{M}$, W-Indv$_{RS}$, W-Indv$_{SS}$, W-Grp$_{M}$, W-Grp$_{RS}$, W-Grp$_{SS}$)
Winter's method is the most specific method as the value of 3 parameters should be established based on historic data. As with Holt, the value of a and b should be determined. In addition, the value of the F should be determined. Within the scope of this research the seasonality is established in 2 manners; SKU individual and based on aggregated demand data, thus grouped SKUs. For each manner 3 definitions of seasonality have been established as aforementioned in Section 4.2.2; monthly seasonality, quarterly seasonality with yearly quarters and shifted seasonality with seasonal quarters. The quarters and the corresponding months, with month 1 representing January, are provided in Table IV.5 for both types of quarterly seasonality.

Table IV.5. Months per quarter per quarterly seasonality definition.

	Seasonality definition	
Quarter	*Regular quarters*	*Shifted quarters*
1	1, 2, 3	12, 1, 2
2	4, 5, 6	3, 4, 5
3	7, 8, 9	6, 7, 8
4	10, 11, 12	9, 10, 11

As a consequence, this forecasting method resulted in 6 separate forecasting methodologies; W-Indv$_{M}$, W-Indv$_{RS}$, W-Indv$_{SS}$, W-Grp$_{M}$, W-Grp$_{RS}$ and W-Grp$_{SS}$. For these 6 methodologies a distinction is made in the updating formulas. For the grouped seasonality, the level and trend are updated on both group and SKU level, while the seasonality is only updated on group level; the corresponding formulas are provided in Equations (19), (20), (21), (22), (23) and (24). For the SKU individual seasonality the level, trend and seasonality are all updated on SKU level; the corresponding formulas are provided in Equations (15), (16), (17), (18) and (19). As with Holt's method, the initialization of the parameters a, b and F occurs according to the method provided by Chopra & Meindl (2013).

Forecasting:

$$\hat{x}_{t,t+\tau} = (\hat{a}_t + \tau\hat{b}_t)F_{t+\tau-P} \tag{15}$$

Updating (SKU individual seasonality):

$$\hat{a}_t = \alpha(\frac{x_t}{\hat{F}_{t-P}}) + (1-\alpha)(\hat{a}_{t-1} + \hat{b}_{t-1}) \tag{16}$$

$$\hat{b}_t = \beta(\hat{a}_t + \hat{a}_{t-1}) + (1-\beta)\hat{b}_{t-1} \tag{17}$$

$$\widehat{F'}_t = \gamma(\frac{x_t}{\hat{a}_t}) + (1-\gamma)\hat{F}_{t-P} \tag{18}$$

Forecasting:

$$\hat{x}_{t,t+\tau} = (\hat{a}_t + \tau\hat{b}_t)F_{t+\tau-P} \tag{19}$$

Updating (grouped seasonality):

<u>Group level</u>

$$\hat{a}_t = \alpha_{Group}(\frac{x_t}{\hat{F}_{t-P}}) + \left(1-\alpha_{Group}\right)(\hat{a}_{t-1} + \hat{b}_{t-1}) \tag{20}$$

$$\hat{b}_t = \beta_{Group}(\hat{a}_t + \hat{a}_{t-1}) + \left(1-\beta_{Group}\right)\hat{b}_{t-1} \tag{21}$$

$$\widehat{F'}_t = \gamma_{Group}(\frac{x_t}{\hat{a}_t}) + \left(1-\gamma_{Group}\right)\hat{F}_{t-P} \tag{22}$$

<u>SKU level</u>

$$\hat{a}_{j,t} = \alpha_j(\frac{x_{j,t}}{\hat{F}_t}) + \left(1-\alpha_j\right)(\hat{a}_{j,t-1} + \hat{b}_{j,t-1}) \tag{23}$$

$$\hat{b}_{j,t} = \beta_j(\hat{a}_{j,t} + \hat{a}_{j,t-1}) + \left(1-\beta_j\right)\hat{b}_{j,t-1} \tag{24}$$

Croston (CR)

Equations (25), (26) and (27) are used when forecasting according to the CR method. The initialization of the CR method requires the average demand, if demand occurs, over a certain time period and the average length of a 0-demand interval.

Forecasting:

$$\hat{x}_{t,t+\tau} = \frac{\hat{z}_t}{\hat{n}_t} \tag{25}$$

Updating:

$$\hat{z}_t = \alpha x_t + (1-\alpha)\hat{z}_{t-1} \tag{26}$$
$$\hat{n}_t = \alpha n_t + (1-\alpha)\hat{n}_{t-1} \tag{27}$$

Croston's method contains 1 smoothing parameter (α), used in 2 formulas. Schultz (1987) indicated that the use of 2 different smoothing parameters (α, β) could be beneficial. In the literature following Schultz (1987), Croston's original method with 1 smoothing parameter is most often applied and it appeared to outperform the use of different smoothing parameters (mukhopadhyay, Solis, & Gutierrez, 2021) (Zied Babai, Syntetos, & Teunter, 2014). For this reason, CR method with 1 smoothing parameter is applied within this research.

V New Product Introductions

In Table V.6 an overview is provided with regard to the historic data available for each SKU. For each SKU, the period of which historic data is available is highlighted in blue. The historic data period of SKUs for which substitute historic data could serve as an alternative is highlighted in grey.

Table V.6. Available historic sales data per SKU.

Fabric characteristic		# Of SKUs	Time period															
Type	Width		2018				2019				2020				2021			
			Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
202	200	8																
	280	8																
205	200	10																
	240	10																
	280	10																
	320	10																
203	200	7																
	280	7																
293	200	6																
	280	6																
103	200	11																
	280	11																
833	200	1																
	275	1																
802	190	1																
	240	1																
	275	1																
	300	1																
803	190	1																
	240	1																
	275	1																
	300	1																
804	190	1																
	240	1																

	275	1				
	300	1				
825	240	1				
812	240	1				
815	240	1				
816	240	1				
849	240	1				
850	240	1				
878	240	1				
890	240	1				
882	240	1				
883	240	1				

VI SKU Selection

Table VI.7 provides an overview of the SKU characteristics of the selected SKUs. In addition, Table VI.8 provides a description of the specific characteristics affecting a time series, if applicable, as described in Section 4.1.4.

Table VI.7. SKU Characteristics of the selected SKUs.

SKU	Product type	Product width	Colour	Item type
17	205	200	0011	35
18	205	200	0012	35
19	205	200	0013	35
23	205	200	0031	35
24	205	200	0032	35
25	205	200	0033	35
27	205	240	0011	35
28	205	240	0012	35
29	205	240	0013	35
30	205	240	0014	35
31	205	240	0021	35
32	205	240	0022	35
33	205	240	0031	35
34	205	240	0032	35
35	205	240	0033	35
36	205	240	0034	35
47	205	320	0011	35
48	205	320	0012	35
52	205	320	0022	35
53	205	320	0031	35
54	205	320	0032	35
55	205	320	0033	35
107	802	190	10000	35
108	802	240	10000	35
110	802	300	10000	35
120	812	240	10000	31/32/34/35
121	815	240	10000	31/32/34/35
122	816	240	10000	31/32/34/35
123	849	240	10000	31/32/34/35
124	850	240	10000	31/32/34/35
125	878	240	10000	31/32/34/35
126	890	240	10000	31/32/34/35
127	882	240	10000	37
128	883	240	10000	37

Table VI.8. Potential causes affecting the time series.

Product type	Product width	Potential cause affecting the time series
205	200/240/320	Availability of RM is limited due to production capacity supplier; causing an average decrease of the demand in 2020 and 2021
812	240	Availability of RM is limited; causing a decrease of the demand in the beginning of 2018
890	240	Availability of RM is limited due to quality issues of the fabric; causing an irregular time series, not only affected by the irregularity of the actual demand
882	240	New customer in 2021; causing an increase in the average demand for 2021

VII Item classification

First, the ABC-classification of all 128 SKUs is provided in Table VII.9. In addition, Table VII.10 provides an overview of the ABC- and DP-class per SKU and Table VII.11 provides an overview of the SKUs per ABC- and DP-class for each demand scenario.

Table VII.9. Number of SKUs per class per demand scenario (selection of 128 SKUs).

Class	Demand scenario		
	1	*2*	*3*
A	32 (25%)	36 (28%)	35 (27%)
B	26 (20%)	22 (17%)	25 (20%)
C	70 (55%)	70 (55%)	68 (53%)
Total	128	128	128

From Table VII.9 it could be observed that the largest part of the 128 items is classified as a C-item (≈ 55%) for all demand scenarios, followed by the A-items and B-items. It could also be noted that the number of C-items is slightly decreasing, whereas the number of A-items is slightly increasing when reviewing the demand scenarios in increasing order. This distribution among the A-, B- and C-class deviates from the standard as class A would be expected to have the least SKUs.

Table VII.10. ABC- and DP-classification characteristics per SKU, per demand scenario.

	Demand scenario 1		**Demand scenario 2**		**Demand scenario 3**	
SKU	*ABC-Class*	*DP-Class*	*ABC-Class*	*DP-Class*	*ABC-Class*	*DP-Class*
17	C	Lumpy	B	Lumpy	B	Lumpy
18	B	Intermittent	A	Lumpy	A	Lumpy
19	C	Lumpy	B	Intermittent	B	Erratic
23	B	Intermittent	B	Erratic	A	Erratic
24	C	Intermittent	B	Intermittent	B	Intermittent
25	B	Smooth	B	Erratic	A	Erratic
27	A	Intermittent	A	Lumpy	A	Lumpy
28	A	Erratic	A	Erratic	A	Erratic
29	A	Lumpy	A	Lumpy	A	Lumpy
30	B	Lumpy	B	Lumpy	C	Lumpy
31	B	Intermittent	B	Intermittent	B	Intermittent
32	B	Intermittent	B	Lumpy	B	Lumpy
33	A	Smooth	A	Erratic	A	Erratic
34	A	Erratic	A	Erratic	A	Smooth
35	A	Erratic	A	Erratic	A	Erratic
36	A	Intermittent	A	Intermittent	A	Intermittent
47	B	Lumpy	A	Lumpy	A	Lumpy
48	B	Lumpy	B	Intermittent	B	Intermittent
52	B	Lumpy	B	Lumpy	C	Lumpy
53	B	Intermittent	A	Lumpy	A	Lumpy
54	B	Intermittent	C	Intermittent	B	Lumpy
55	B	Lumpy	A	Intermittent	A	Intermittent
107	A	Smooth	A	Smooth	A	Erratic
108	A	Smooth	A	Smooth	A	Smooth
110	A	Smooth	A	Smooth	A	Smooth
120	A	Smooth	A	Smooth	A	Smooth
121	B	Smooth	B	Smooth	B	Smooth

122	A	Smooth	A	Smooth	A	Smooth
123	A	Smooth	A	Smooth	A	Smooth
124	A	Smooth	A	Erratic	B	Erratic
125	A	Smooth	A	Smooth	A	Smooth
126	A	Smooth	A	Smooth	A	Erratic
127	A	Smooth	A	Smooth	A	Erratic
128	A	Smooth	A	Smooth	B	Smooth

Table VII.11. SKU per ABC- and DP-class.

Demand scenario 1

		ABC-Class	
DP-Class	*A*	*B*	*C*
Smooth	33, 107, 108, 110, 120, 122, 123, 124, 125, 126, 127, 128	25, 121	
Erratic	28, 34, 35		
Intermittent	27, 36	18, 23, 31, 32, 53, 54	24
Lumpy	29	30, 47, 48, 52, 55	17, 19

Demand scenario 2

	ABC-Class		
DP-Class	*A*	*B*	*C*
Smooth	107, 108, 110, 120, 122, 123, 125, 126, 127, 128	121	
Erratic	28, 33, 34, 35, 124	23, 25,	
Intermittent	36, 55	19, 24, 31, 48,	54
Lumpy	18, 27, 29, 47, 53	17, 30, 32, 52	

Demand scenario 3

		ABC-Class	
DP-Class	*A*	*B*	*C*
Smooth	34, 108, 110, 120, 122, 123, 125	121, 128	
Erratic	23, 25, 28, 33, 35, 107, 126, 127	19, 124	
Intermittent	36, 55	24, 31, 48	
Lumpy	18, 27, 29, 47, 53	17, 32, 54	30, 52

VIII Forecasting variants performance evaluation

Figure VIII.8, Figure VIII.9, Figure VIII.10 and Figure VIII.11 depict the average performance value for each SKU for demand scenario 1, averaged over the applied forecasting methodologies for each forecasting variant. The applied forecasting methodologies are SES; H; W-Indv,M; W-Indv,RS; W-Indv,SS; W-Grp,M; W-Grp,RS; W-Grp,SS and CR with τ = 1, α = 0.19, β = 0.053 and γ = 0.1. The applied forecasting variants are static and adaptive. Subsequently, Figure VIII.12, Figure VIII.13, Figure VIII.14 and Figure VIII.15 provide the same information for demand scenario 2 and Figure VIII.16, Figure VIII.17, Figure VIII.18 and Figure VIII.19 for demand scenario 3. Lastly Table VIII.12 provides the results of the T-tests, conducted in order to determine whether the static and adaptive forecasting performance differs significantly from each other. The p-values highlighted in blue are below the significance level of 0.05, indicating a significant difference between the performance measure values of the static and adaptive variant.

Demand scenario 1

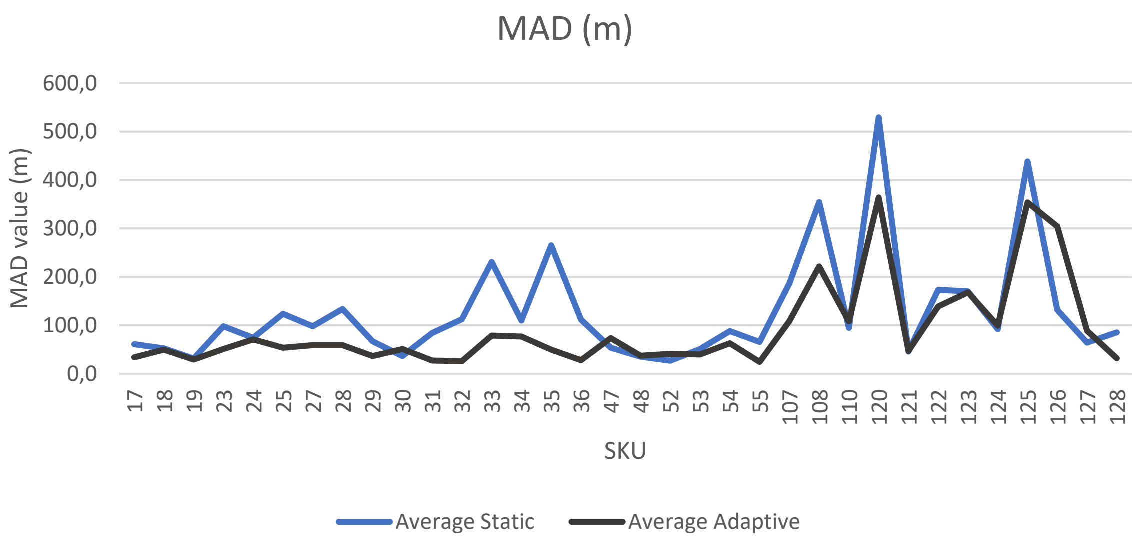

Figure VIII.9. Averaged MAD (m) of the static and adaptive forecasting variant in demand scenario 1.

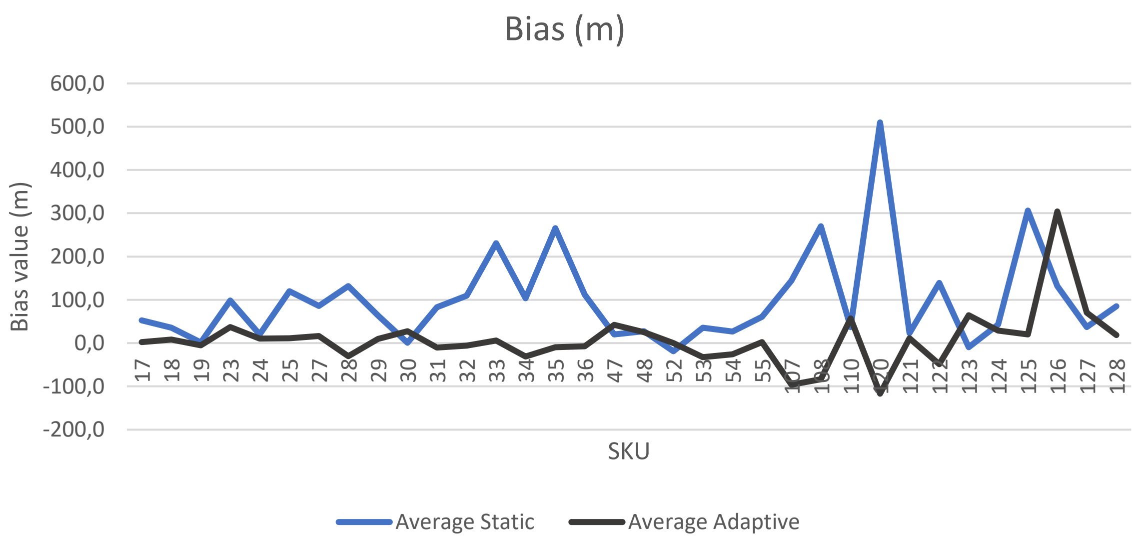

Figure VIII.8. Averaged bias (m) of the static and adaptive forecasting variant in demand scenario 1.

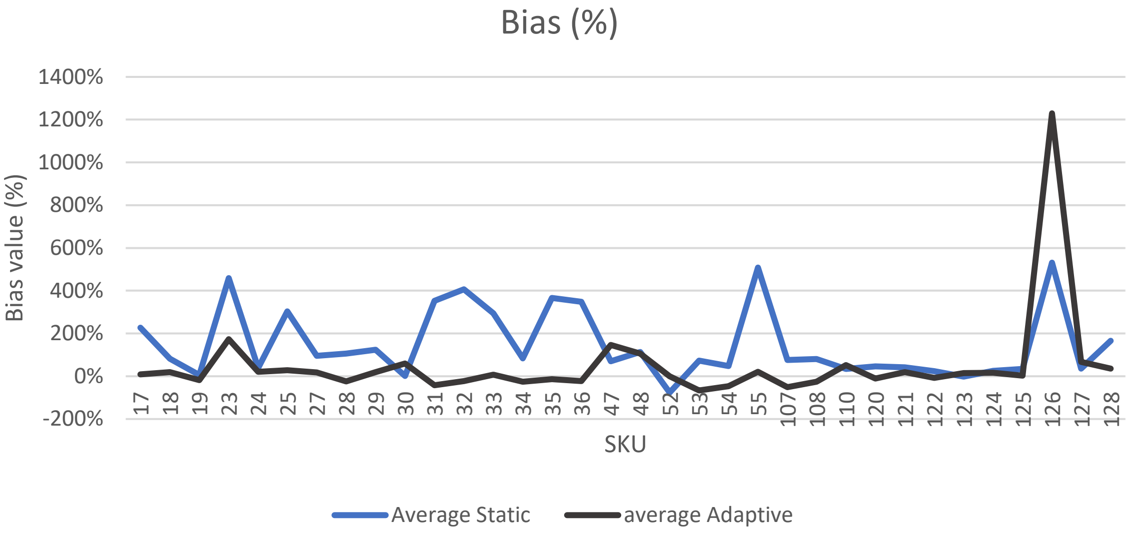

Figure VIII.10. Averaged bias (%) of the static and adaptive forecasting variant in demand scenario 1.

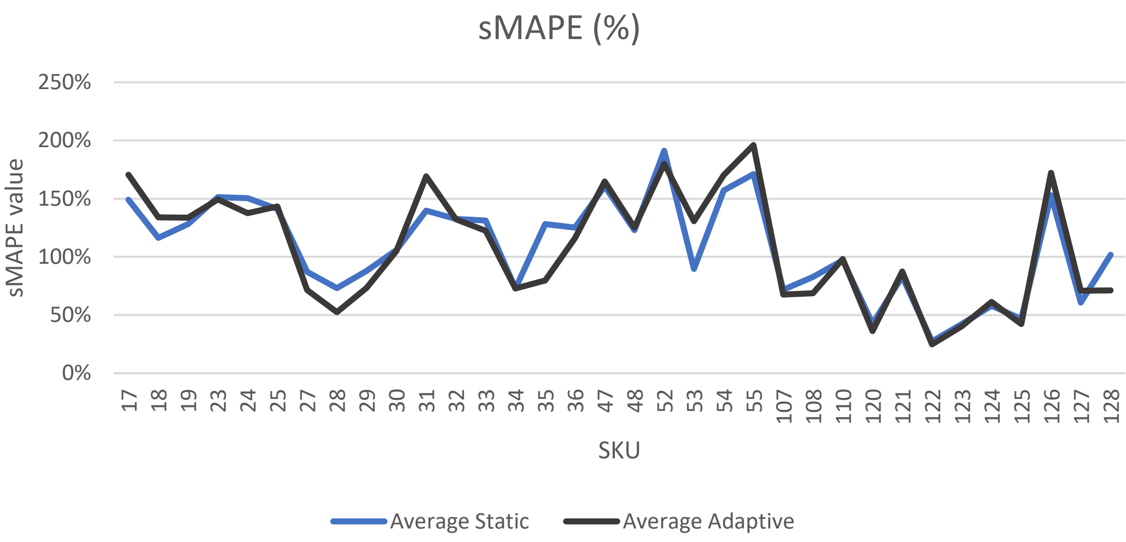

Figure VIII.11. Averaged sMAPE (%) of the static and adaptive forecasting variant in demand scenario 1.

Demand scenario 2

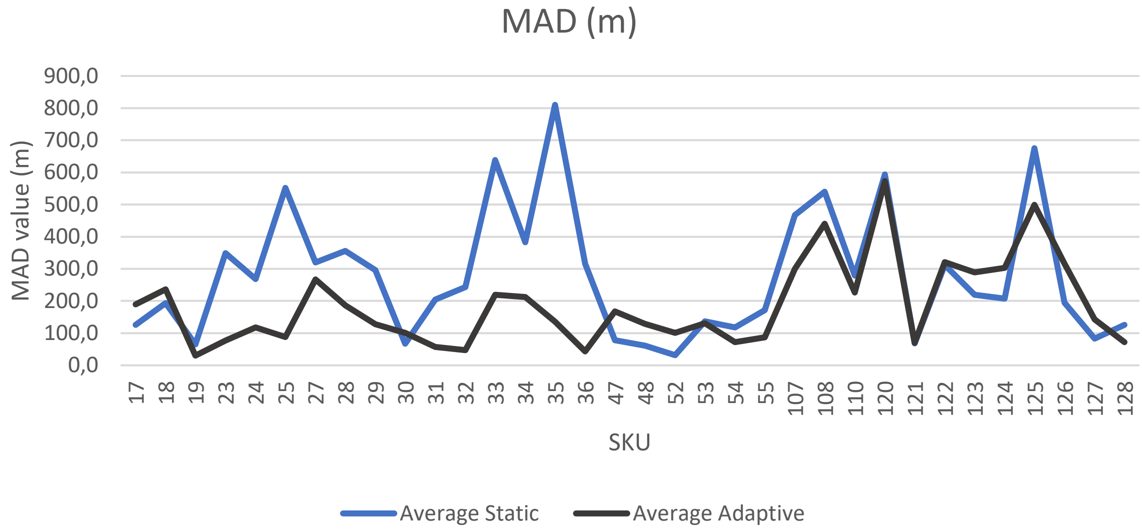

Figure VIII.13. Averaged MAD (m) of the static and adaptive forecasting variant in demand scenario 2.

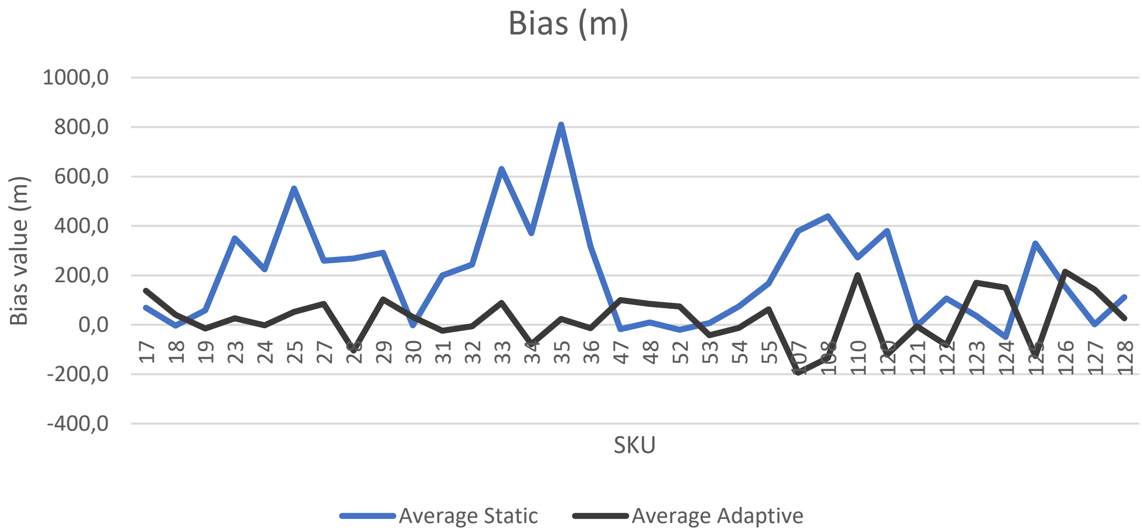

Figure VIII.12. Averaged bias (m) of the static and adaptive forecasting variant in demand scenario 2.

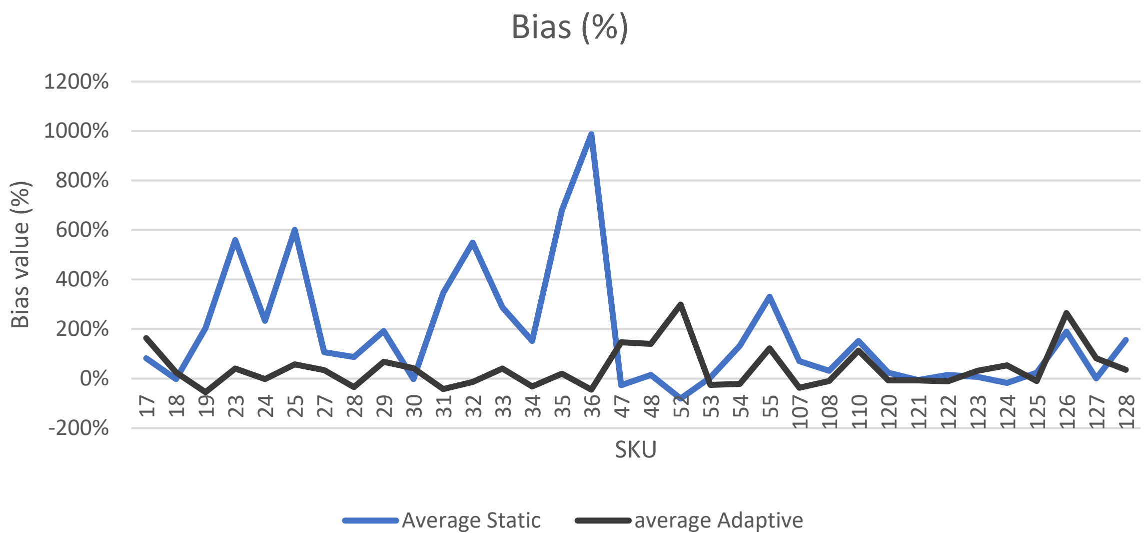

Figure VIII.15. Averaged bias (%) of the static and adaptive forecasting variant in demand scenario 2.

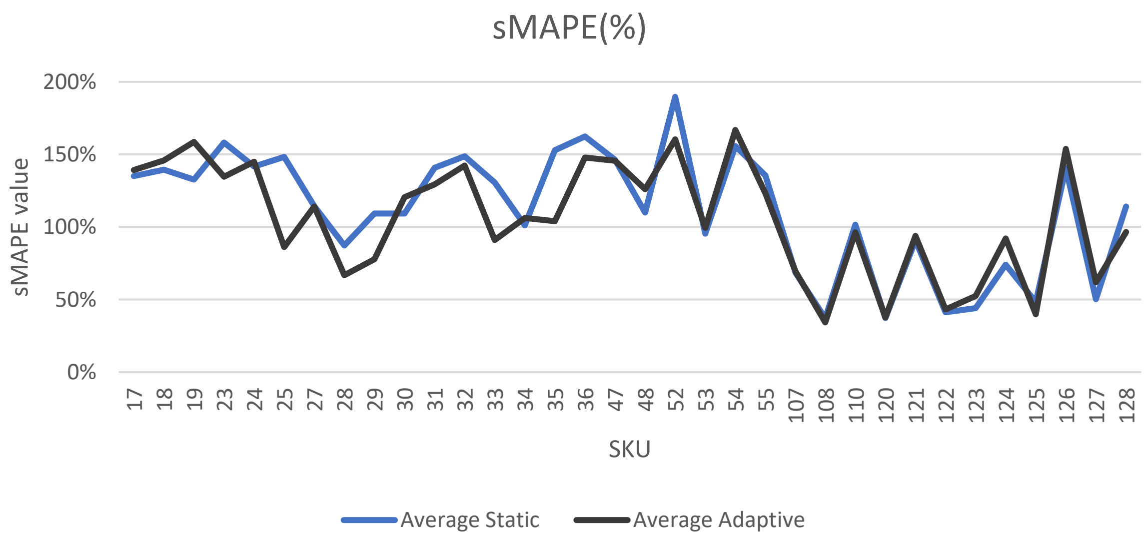

Figure VIII.14. Averaged sMAPE (%) of the static and adaptive forecasting variant in demand scenario 2.

Demand scenario 3

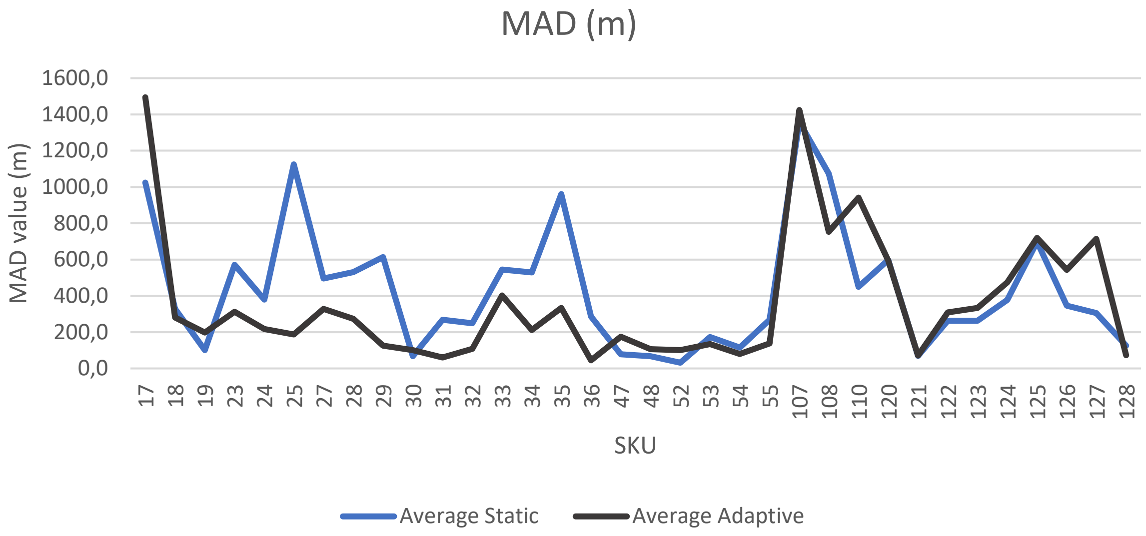

Figure VIII.17. Averaged MAD (m) of the static and adaptive forecasting variant in demand scenario 3.

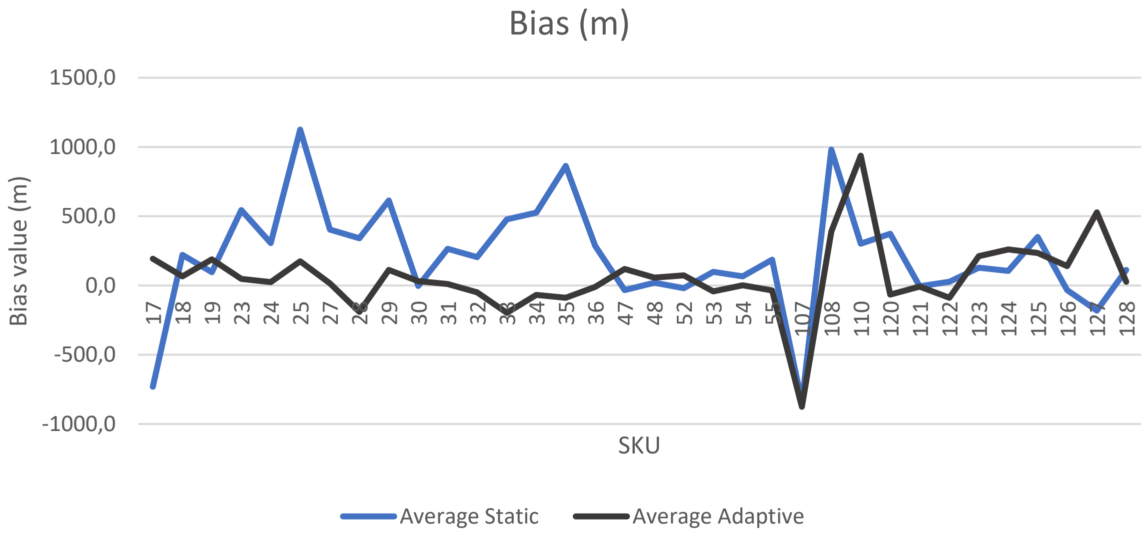

Figure VIII.16. Averaged bias (m) of the static and adaptive forecasting variant in demand scenario 3.

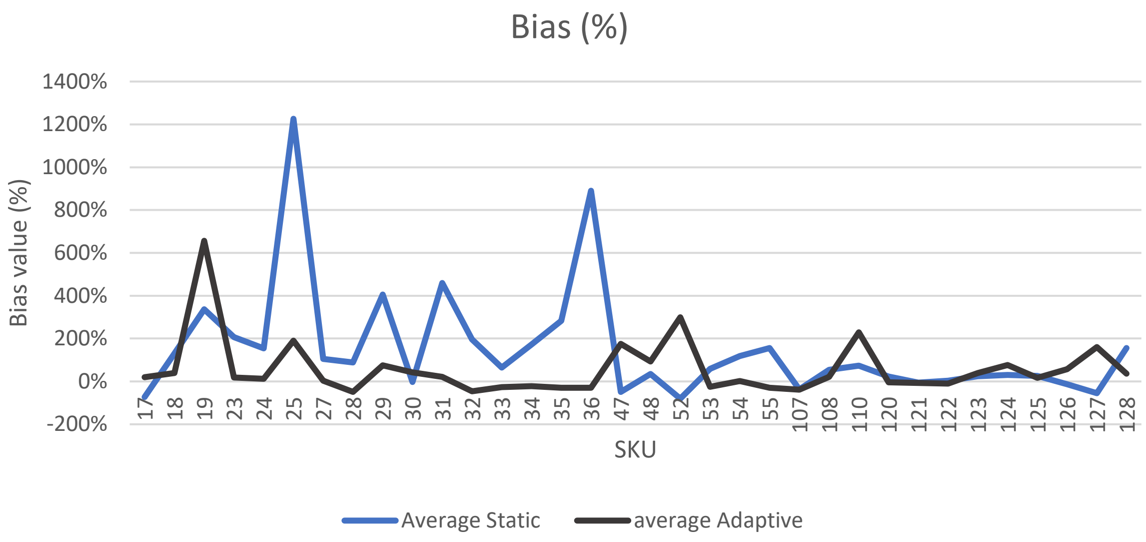

Figure VIII.18. Averaged bias (%) of the static and adaptive forecasting variant in demand scenario 3.

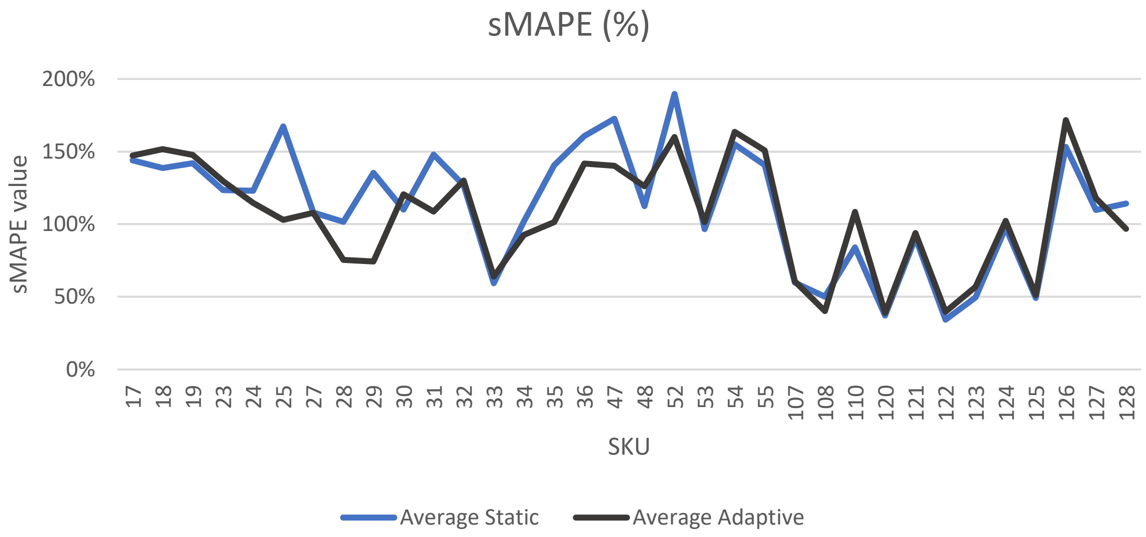

Figure VIII.19. Averaged sMAPE (%) of the static and adaptive forecasting variant in demand scenario 3.

Table VIII.12. Forecasting variant performance evaluation: p-value of a paired-sample, 2-tailed T-test (level of significance = 0.05).

		Performance measure			
	Forecasting method	*MAD (m)*	*Bias (m)*	*Bias (%)*	*sMAPE (%)*
Demand scenario 1	*SES*	0.000	0.000	0.000	0.028
	H	0.001	0.000	0.005	0.770
	W-Indv,M	0.046	0.008	0.256	0.623
	W-Indv,RS	0.086	0.005	0.238	0.907
	W-Indv,SS	0.020	0.002	0.083	0.705
	W-Grp,M	0.002	0.000	0.006	0.572
	W-Grp,RS	0.002	0.000	0.005	0.691
	W-Grp,SS	0.001	0.000	0.005	0.879
	CR	0.002	0.001	0.007	0.003

		Performance measure			
	Forecasting method	*MAD (m)*	*Bias (m)*	*Bias (%)*	*sMAPE (%)*
Demand scenario 2	*SES*	0.003	0.000	0.000	0.051
	H	0.002	0.000	0.006	0.144
	W-Indv,M	0.268	0.095	0.375	0.261
	W-Indv,RS	0.063	0.002	0.012	0.123
	W-Indv,SS	0.022	0.002	0.199	0.097
	W-Grp,M	0.004	0.000	0.006	0.281
	W-Grp,RS	0.004	0.000	0.006	0.211
	W-Grp,SS	0.003	0.000	0.005	0.158
	CR	0.024	0.000	0.001	0.264

		Performance measure			
	Forecasting method	*MAD (m)*	*Bias (m)*	*Bias (%)*	*sMAPE (%)*
Demand scenario 3	*SES*	0.090	0.006	0.001	0.139
	H	0.175	0.156	0.031	0.037
	W-Indv,M	0.538	0.598	0.464	0.322
	W-Indv,RS	0.399	0.530	0.158	0.039
	W-Indv,SS	0.465	0.321	0.495	0.098
	W-Grp,M	0.202	0.158	0.045	0.056
	W-Grp,RS	0.233	0.241	0.043	0.067
	W-Grp,SS	0.129	0.124	0.034	0.042
	CR	0.015	0.000	0.003	0.203

IX Smoothing parameter optimization

This section elaborates on the procedure to select the optimal combination of smoothing parameter values for the remaining alternative forecasting procedures; i.e. SES, H, W-Grp$_M$, W-Grp$_{RS}$, W-Grp$_{SS}$ and CR. Table IX.13 provides these optimal values per forecasting method for each DP-class and demand scenario. Several experiments have been conducted in order to optimize the smoothing parameter value(s) for each forecasting method per DP-class and per demand scenario. A search experiment is suggested in literature in order to determine suitable values for the smoothing parameters (Axsäter, 2006) (Silver, Pyke, & Thomas, 2017). In addition, Silver, Pyke & Thomas (2017) emphasize that an exact minimization of the performance measures is not required, because the effectiveness of certain smoothing parameter values appeared to be insensitive to small deviations of the best values for the smoothing parameters.

Literature has been reviewed in order to determine a suitable value range of the smoothing parameters to experiment with. As aforementioned, an optimal combination of the smoothing parameter values for Holt and the Winters method is provided by Silver, Pyke & Thomas (2017) and corresponds with 0.19, 0.053 and 0.1 for α, β and γ, respectively. Silver, Pyke & Thomas (2017) suggest the range of 0.01 – 0.3 as a value for α within SES to be often quite reasonable; the values of β and γ are based on the chosen value of α correspondingly. The aforementioned values of β and γ are emphasized by Axsäter (2006), when considering a forecasting procedure in which the parameters are updated monthly. In case the period length is 1 month, Axsäter (2006) mentions to use a value of α between 0.1 and 0.3 as commonly used in practice for SES. In general, the range of 0.1 to 0.3 for the smoothing parameters in exponential smoothing procedures is most frequently appearing in literature (Axsäter, 2006) (Silver, Pyke, & Thomas, 2017) (Chopra & Meindl, 2013) (Montgomery, Jennings, & Kulahci, 2015) (Kaya, Sahin, & Demirel, 2020) (Croston, 1978) (Zied Babai, Syntetos, & Teunter, 2014). A smoothing parameter value larger than 0.3 is described as an unusual large value by Silver, Pyke & Thomas (2017), indicating an unsuitability of the applied model.

In addition, the running time of the model should be acceptable when optimizing the smoothing parameters. The model running time increases in case the range of the potential smoothing parameter values is extended. The range to be reviewed is set to 0.05 to 0.3, considering the information provided by literature of the most common range of 0.1 to 0.3 and the optimal value combination as provided by Silver, Pyke & Thomas (2017), in which the β takes a value of 0.053. When reviewing the range of 0.05 to 0.3 with steps of 0.05, 6 values should be tried for each smoothing parameter; resulting in an experiment of $6^3 = 216$ possible combinations in case all 3 smoothing parameters are incorporated in the forecasting method.

These 216 experiments should be conducted for every DP-class and all demand scenarios, resulting in 216*4*3 = 2,592 experiments in total. Of all 34 SKUs, at most 14 are assigned to 1 DP-class within this research. When incorporating 14 SKUs, the corresponding running times for the most sophisticated forecasting method, i.e. Winters with monthly and SKU-grouped seasonality (W-Grp$_M$), are 153, 157 and 153 seconds for demand scenario 1, 2 and 3; approximately 2.5 minutes. 6 Of the 9 alternative forecasting methods incorporate all 3 smoothing parameters and therefore have a model running time of approximate the same. The running time of the remaining forecasting methods is negligible compared to these more sophisticated models.

Considering the fact that each forecasting method should be executed for every DP-class and for all demand scenarios, this would result in a model running time of approximately $2.5 * 4 * 3 = 30$ minutes for 1 forecasting method including 14 SKUs. When calculating the model running time for the 6 most sophisticated models, a period of $30 * 6 = 180$ minutes will be covered; approximately 3 hours. In reality, only 1 DP-class contains 14 SKUs for 1 demand scenario; the other classes contain less SKUs and therefore will result in a shorter running time. For this reason, it is observed that the total model running time, when considering all forecasting methods, DP-classes and demand scenarios, is at most 3 hours and for most instances it will be less.

Considering the running time of the most sophisticated forecasting method and the most common smoothing parameter range described in literature, the model running time is considered to be reasonable and the experimental range is set at 0.05 up to 0.3 with steps of 0.05 for α, β and γ.

In order to determine the optimal smoothing parameter values among this available range, the following steps have been taken;

1. Conduct a search experiment for each forecasting method, per DP-class and per demand scenario, with the smoothing parameter values ranging from 0.05 to 0.3 with steps of 0.05.
2. Select the optimal combination of smoothing parameter value(s) based on the minimization of performance measure MAD, averaged over the SKUs within a certain DP-class. Chopra & Meindl (2013) indicate that the performance measure to be minimized should be chosen among MSE, MAD and MAPE; the one a researcher or manager is most comfortable with. As the MSE and MAPE are not considered as performance measure within this research, the MAD, also a scale-dependent performance measure, is considered as main performance measure to minimize. When minimizing the MAD, equal weight is given to reducing all errors (Chopra & Meindl, 2013). The sMAPE and bias are not considered as performance measures to minimize for the following reasoning; the positive and negative bias values will cancel each other out when averaging the performance measure, resulting in a biased view when minimizing the bias, and the sMAPE is limited by means of an upper limit of 200%. In addition, when the MAD is minimized, the sMAPE value will be minimized accordingly as the sMAPE also depends on the difference between the actual and the forecasted value; likewise for the MAD value.
3. The optimal smoothing parameter values, in case of minimizing the MAD, are provided in Table IX.13 for each forecasting method per DP-class and per demand scenario.

Table IX.13. Optimal smoothing parameter value(s) per forecasting method per DP-class when minimizing MAD.

		Demand scenario 1			**Demand scenario 2**			**Demand scenario 3**		
DP-Class	**Forecasting method**	*Alpha*	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*
Smooth	*SES*	0.15	-	-	0.15	-	-	0.3	-	-
	H	0.05	0.05	-	0.05	0.05	-	0.3	0.05	-
	W-Indv,M	0.05	0.05	0.3	0.1	0.05	0.05	0.05	0.05	0.05
	W-Indv,RS	0.05	0.25	0.15	0.25	0.05	0.05	0.3	0.05	0.05
	W-Indv,SS	0.05	0.05	0.15	0.05	0.05	0.25	0.3	0.05	0.05
	W-Grp,M	0.05	0.05	0.3	0.05	0.05	0.3	0.3	0.25	0.3
	W-Grp,RS	0.05	0.05	0.3	0.05	0.05	0.3	0.3	0.05	0.25
	W-Grp,SS	0.05	0.05	0.3	0.05	0.05	0.3	0.3	0.2	0.3
	CR	0.2	-	-	0.25	-	-	0.3	-	-

		Demand scenario 1			**Demand scenario 2**			**Demand scenario 3**		
DP-Class	**Forecasting method**	*Alpha*	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*
Erratic	*SES*	0.25	-	-	0.25	-	-	0.2	-	-
	H	0.05	0.1	-	0.1	0.1	-	0.1	0.05	-
	W-Indv,M	0.15	0.05	0.05	0.05	0.25	0.25	0.05	0.05	0.05
	W-Indv,RS	0.1	0.05	0.05	0.15	0.05	0.3	0.3	0.05	0.15
	W-Indv,SS	0.25	0.3	0.05	0.2	0.05	0.3	0.05	0.05	0.05
	W-Grp,M	0.1	0.05	0.05	0.15	0.05	0.3	0.1	0.05	0.3
	W-Grp,RS	0.1	0.05	0.05	0.15	0.05	0.3	0.25	0.05	0.3
	W-Grp,SS	0.1	0.05	0.05	0.2	0.05	0.3	0.1	0.05	0.05
	CR	0.3	-	-	0.3	-	-	0.3	-	-

DP-Class	Forecasting method	Demand scenario 1			Demand scenario 2			Demand scenario 3		
		Alpha	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*
Intermittent	*SES*	0.25	-	-	0.3	-	-	0.3	-	-
	H	0.1	0.05	-	0.05	0.1	-	0.3	0.05	-
	W-Indv,M	0.05	0.15	0.3	0.05	0.05	0.3	0.3	0.1	0.3
	W-Indv,RS	0.25	0.3	0.1	0.05	0.1	0.05	0.3	0.2	0.15
	W-Indv,SS	0.1	0.05	0.3	0.05	0.1	0.2	0.1	0.2	0.15
	W-Grp,M	0.1	0.05	0.3	0.05	0.1	0.3	0.3	0.05	0.05
	W-Grp,RS	0.1	0.05	0.3	0.1	0.05	0.3	0.3	0.05	0.3
	W-Grp,SS	0.25	0.05	0.3	0.1	0.05	0.3	0.3	0.05	0.3
	CR	0.15	-	-	0.25	-	-	0.25	-	-

DP-Class	Forecasting method	Demand scenario 1			Demand scenario 2			Demand scenario 3		
		Alpha	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*	*Alpha*	*Beta*	*Gamma*
Lumpy	*SES*	0.2	-	-	0.15	-	-	0.1	-	-
	H	0.05	0.25	-	0.05	0.1	-	0.05	0.15	-
	W-Indv,M	0.05	0.05	0.15	0.3	0.05	0.3	0.05	0.05	0.05
	W-Indv,RS	0.1	0.05	0.1	0.25	0.3	0.2	0.05	0.05	0.1
	W-Indv,SS	0.05	0.1	0.05	0.3	0.05	0.05	0.2	0.2	0.25
	W-Grp,M	0.1	0.05	0.3	0.3	0.15	0.3	0.15	0.05	0.3
	W-Grp,RS	0.1	0.1	0.3	0.2	0.05	0.3	0.1	0.05	0.05
	W-Grp,SS	0.15	0.1	0.3	0.25	0.2	0.3	0.05	0.25	0.05
	CR	0.25	-	-	0.05	-	-	0.05	-	-

X Performance analysis of Winters methods variants

In Table X.14 the result of the paired-sample, 2-tailed T-test between the performances of Winters method with individual and grouped seasonality is provided. For each DP-class and demand scenario the T-test is performed for each performance measure. The test numbers as provided in Table X.14 represent the following forecasting methods:

1. Winters method with monthly seasonality; individual vs. grouped seasonality
2. Winters method with regular quarterly seasonality; individual vs. grouped seasonality
3. Winters method with shifted quarterly seasonality; individual vs. grouped seasonality

Table X.14. Forecasting performance evaluation between Winters method with individual and grouped seasonality: p-value of a paired-sample, 2-tailed T-test (level of significance = 0.05).

		Demand scenario 1				**Demand scenario 2**				**Demand scenario 3**			
DP-Class	**Test**	*MAD (m)*	*Bias (m)*	*Bias (%)*	*sMAPE (%)*	*MAD (m)*	*Bias (m)*	*Bias (%)*	*sMAPE (%)*	*MAD (m)*	*Bias (m)*	*Bias (%)*	*sMAPE (%)*
Smooth	*1*	0.24	0.65	0.38	0.13	0.09	0.27	0.23	0.15	0.32	0.07	0.12	0.71
	2	0.91	0.11	0.30	0.01	0.90	0.03	0.21	0.43	0.29	0.16	0.26	0.58
	3	0.50	0.62	0.36	0.69	0.77	0.75	0.57	0.74	0.27	0.13	0.21	0.83
Erratic	*1*	0.08	0.44	0.60	0.15	0.12	0.18	0.13	0.11	0.02	0.11	0.20	0.37
	2	0.23	0.80	0.99	0.33	0.46	0.68	0.78	0.33	0.97	0.63	0.55	0.84
	3	0.58	0.37	0.34	0.59	0.12	0.17	0.19	0.01	0.16	0.00	0.05	0.48
Intermittent	*1*	0.13	0.01	0.03	0.09	0.08	0.05	0.03	0.46	0.20	0.30	0.20	0.13
	2	0.92	0.57	0.60	0.55	0.81	0.17	0.13	0.05	0.86	0.95	0.97	0.69
	3	0.30	0.45	0.09	0.32	0.76	0.41	0.25	0.10	0.36	0.53	0.87	0.35
Lumpy	*1*	0.12	0.03	0.02	0.91	0.07	0.05	0.05	0.54	0.06	0.05	0.01	0.57
	2	0.50	0.30	0.18	0.19	0.53	0.20	0.97	1.00	0.78	0.74	0.95	0.75
	3	0.12	0.14	0.14	0.63	0.42	0.35	0.69	0.99	0.05	0.12	0.16	0.55

XI Forecasting methods performance evaluation

As aforementioned in Section 4.2.2, no best performing forecasting method could be determined based on the graphical analysis. For this reason, a repeated measures ANOVA is conducted with H_0 equal to *there is no significant difference between the performance measure values of the remaining forecasting methods for a specific DP-class and demand scenario combination* and a significance level of 0.05. The corresponding results are provided in Table XI.15, of which the significant differences are highlighted in blue.

In addition, the SKU individual performance measure values of the evaluated SKUs are provided in Table XI.16. The SKUs given in grey are not included in the forecasting performance comparison as the current forecasting performance could not be established. In addition, some values of the sMAPE with the Naive forecasting method resulted in a “division by 0” error; these errors are indicated with N.a., i.e. not applicable.

Lastly, Figure XI.20, Figure XI.21, Figure XI.22 and Figure XI.23 provide a visualisation of the SKU individual performance measures related to the fact whether the RM is supplied in colour or not.

Table XI.15. Forecasting performance evaluation with optimized smoothing parameters: p-value of a repeated measure ANOVA (level of significance = 0.05) between the performance measures of SES, H, W-GrpM, W-GrpRS, W-GrpSS and CR.

		p-value		
DP-Class	**Performance measure**	*Demand scenario 1*	*Demand scenario 2*	*Demand scenario 3*
Smooth	*MAD (m)*	0.508438	0.793928	0.515621
	Bias (m)	0.062906	0.003083	0.001874
	Bias (%)	0.61282	0.321451	0.022923
	sMAPE (%)	0.128949	0.858527	0.333313
Erratic	*MAD (m)*	0.006689	0.022273	0.354769
	Bias (m)	1.61842E-05	9.58E-05	0.030816
	Bias (%)	0.002938	0.001162	0.04131
	sMAPE (%)	0.990351	0.790547	0.487819
Intermittent	*MAD (m)*	0.34800	0.977535	0.908472
	Bias (m)	1.36E-05	0.277921	0.133015
	Bias (%)	6.59E-06	0.132078	0.376053
	sMAPE (%)	0.000714	0.001369	0.255085
Lumpy	*MAD (m)*	0.852802	0.797822	0.850551
	Bias (m)	0.480439	0.059223	0.620575
	Bias (%)	0.409706	0.151830	0.960861
	sMAPE (%)	0.072778	0.037062	0.317327

Table XI.16. Performance measure per forecasting method per SKU for demand scenario 3.

					MAD (m)			Bias (m)			Bias (%)			sMAPE (%)		
SKU #	**Product type**	**Width**	**Colour**	**Item type**	*Current*	*Statistical*	*Naive*	*Current*	*Statistical*	*Naive*	*Current*	*Statistical*	*Naive*	*Current*	*Statistical*	*Naive*
17	205	200	0011	35	1067	1,062	2671	-687	-591	786	-69%	-59%	78%	151%	136%	195%
18	205	200	0012	35	291	222	134	148	71	-81	88%	43%	-48%	144%	133%	N.a.
19	205	200	0013	35		113	128		113	91		396%	319%		144%	N.a.
23	205	200	0031	35	605	297	270	605	76	-50	230%	29%	-19%	125%	124%	N.a.
24	205	200	0032	35	298	177	199	274	-4	-62	138%	-2%	-31%	116%	109%	137%
25	205	200	0033	35	499	272	158	499	272	97	544%	296%	105%	144%	123%	103%
27	205	240	0011	35	646	339	516	603	-76	-80	158%	-20%	-21%	110%	118%	158%
28	205	240	0012	35	542	276	278	352	-97	-132	91%	-25%	-34%	101%	73%	74%
29	205	240	0013	35	308	275	200	308	275	113	203%	181%	74%	113%	110%	89%
30	205	240	0014	35	93	78	115	24	10	-5	31%	13%	-7%	120%	112%	158%
31	205	240	0021	35	172	50	74	172	3	-6	299%	5%	-10%	140%	99%	173%
32	205	240	0022	35	157	123	100	126	58	-30	121%	56%	-29%	116%	108%	122%
33	205	240	0031	35	433	358	450	415	-177	21	56%	-24%	3%	52%	57%	71%
34	205	240	0032	35	269	231	291	269	43	63	88%	14%	21%	77%	85%	107%
35	205	240	0033	35	839	412	363	680	102	-58	222%	33%	-19%	140%	116%	92%
36	205	240	0034	35	231	37	27	231	31	-3	720%	96%	-9%	156%	83%	N.a.
47	205	320	0011	35	178	108	84	178	63	4	259%	93%	5%	137%	135%	N.a.
48	205	320	0012	35	158	86	53	137	39	-36	227%	65%	-60%	137%	122%	N.a.
52	205	320	0022	35		41	41		26	-8		104%	-34%		144%	N.a.
53	205	320	0031	35	189	127	182	129	15	-27	78%	9%	-16%	99%	91%	N.a.
54	205	320	0032	35	106	71	147	68	-10	36	122%	-17%	65%	147%	165%	N.a.
55	205	320	0033	35	261	168	156	176	39	-48	146%	32%	-40%	135%	131%	N.a.
107	802	190	N.a.	35		1,244	1,427		-842	-1,200		-37%	-53%		52%	74%
108	802	240	N.a.	35		552	763		536	751		29%	41%		32%	36%

110	802	300	N.a.	35		764	633		764	510		187%	125%		109%	115%
120	812	240	N.a.	*	831	565	719	252	-82	74	15%	-5%	5%	50%	36%	44%
121	815	240	N.a.	*		60	64		-10	-18		-12%	-20%		85%	110%
122	816	240	N.a.	*		280	348		-94	-227		-11%	-27%		36%	46%
123	849	240	N.a.	*	234	272	561	88	239	388	16%	45%	73%	46%	48%	76%
124	850	240	N.a.	*	316	394	497	17	67	140	5%	20%	41%	90%	107%	117%
125	878	240	N.a.	*	751	564	870	286	266	577	21%	20%	43%	51%	41%	53%
126	890	240	N.a.	*	504	425	492	243	87	95	98%	36%	39%	163%	163%	167%
127	882	240	N.a.	37	522	517	1,124	323	337	805	97%	102%	244%	112%	106%	115%
128	883	240	N.a.	37	83	50	94	73	6	56	81%	8%	79%	94%	80%	107%

* 31/32/34/35

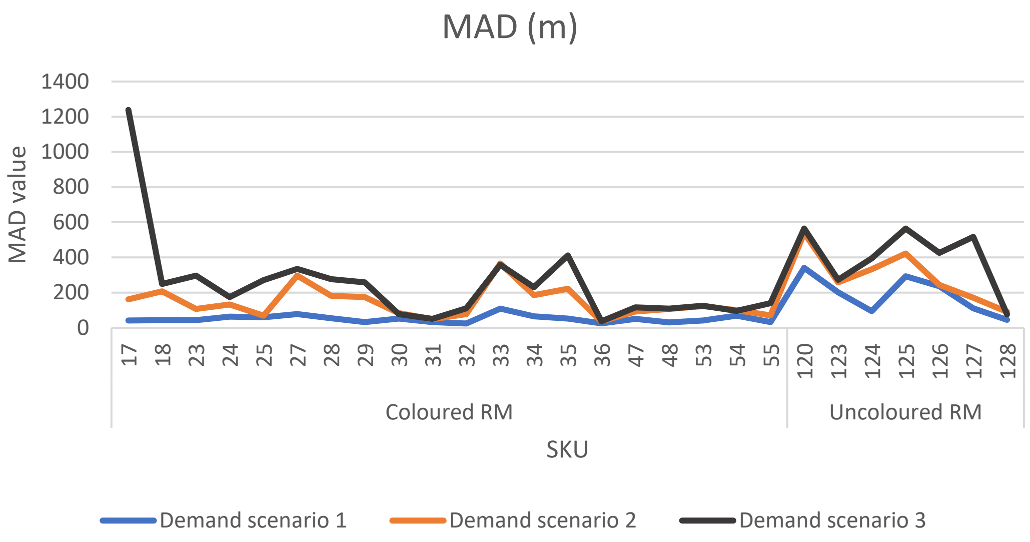

Figure XI.20. Effect of the RM supply state on the forecasting performance measure MAD.

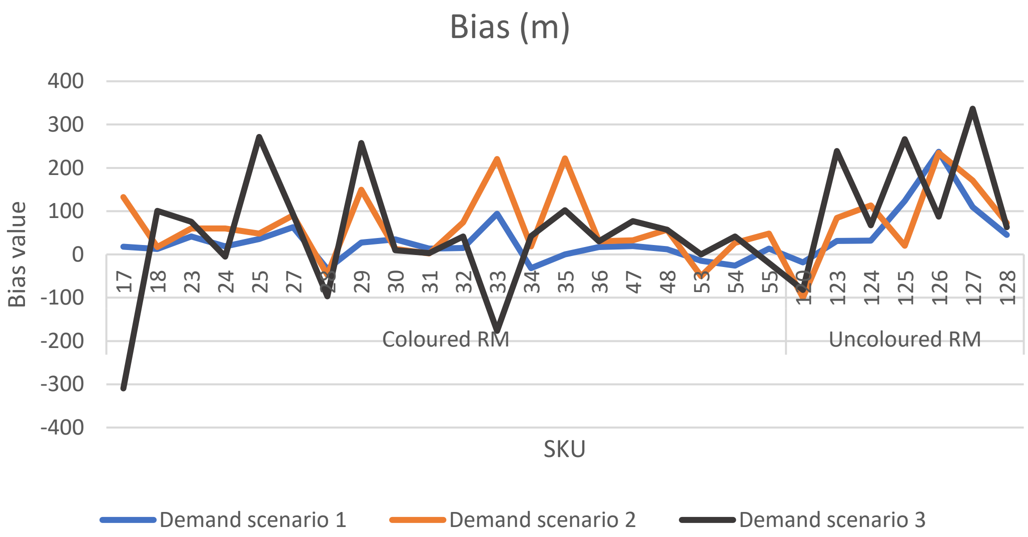

Figure XI.21. Effect of the RM supply state on the forecasting performance measure bias.

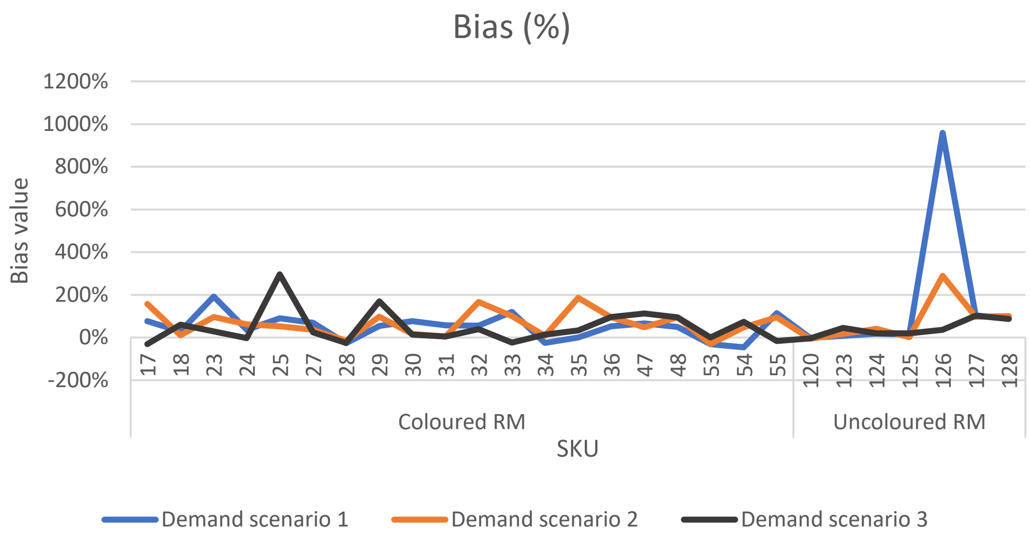

Figure XI.22. Effect of the RM supply state on the forecasting performance measure bias.

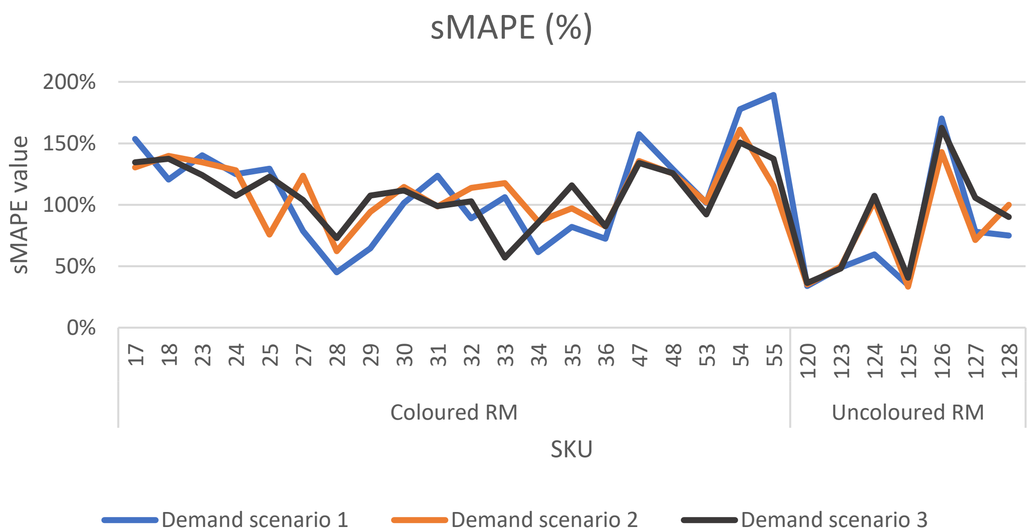

Figure XI.23. Effect of the RM supply state on the forecasting performance measure sMAPE.

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