MASTER

Quantifying the financial benefits of an improved forecast for inventory management

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Quantifying the financial benefits of an improved forecast for inventory management

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Abstract

This master thesis provides insights into the financial benefits of an improved forecast for inventory management. The interaction between the research fields forecasting and inventory control is explored to develop a prediction model that can quantify the financial benefits. An experimental study is conducted to identify the impact of the forecast accuracy, bias and other factors on the inventory control performance in a controlled setting. The results of the experimental study are used to develop a prediction model. The prediction model is used for a case study, where the financial benefits of improving statistical forecasting models are estimated. This research shows that the bias has more impact on the inventory control performance than the accuracy and that the benefits of accuracy improvements depend on the magnitude of the bias.

Executive summary

Introduction

The investments of companies in inventory are often enormous. Inventory control is needed to be competitive and to ensure product availability for customers while minimizing costs. A large part of the inventory control models assumes stationary demand. However, the assumption of stationary demand may not hold in reality. The demand can change over time due to trend, seasonality or product life cycles. To better anticipate the non-stationary demand patterns, dynamic inventory models can be used. The dynamic models integrate forecasts to update the inventory control parameters to better match supply and demand. This research focused on the interaction between forecasting and inventory control to identify the financial benefits of an improved forecast. The main research question is:

> *What are the financial benefits of an improved forecast for a forecast-based inventory control policy given a service level target?*

The research question is answered in four main steps. Firstly, a literature review is conducted to identify and select appropriate forecast methods and inventory control models. Secondly, an experimental study is used to explore the relationship between the forecast quality and inventory control performance. This is done in a controlled setting with simulation models to identify the impact of the forecast accuracy, bias and other factors. Thirdly, the experimental results were used to develop a prediction model that can quantify the financial benefits of an improved forecast. At last, the prediction model is used for a case study. The financial benefits of improving statistical forecasting models were quantified by the prediction model. The main research question is answered based on these four steps.

Experimental study

The forecasting methods and inventory control policies identified in the literature were combined to explore the financial benefits of an improved forecast. The ABC-XYZ analysis was used throughout this thesis to separate items with different demand characteristics. The ABC-XYZ analysis is a classification method that separates items using the business value (ABC) and demand stability (XYZ). The experimental study used the ABC-XYZ analysis to generated nine different items. This included stationary and non-stationary items with seasonality. Items with trends were excluded from the analysis in the experimental study.

The relationship between the forecast quality and inventory control performance was explored by simulating different scenarios. The forecast quality was determined with two criteria, namely the accuracy and bias. The forecasts with different accuracies and biases were generated using the forecast error and its distribution. This method was used to explore various what-if scenarios to determine the inventory control performance if a forecast error of a specified size would have been realized. The inventory control performance was determined by simulating the policies with the forecasts as input. The forecast-based inventory control policies assume unbiased forecasts. The inventory control performance was determined by summing the holding, backorder and ordering costs. The backorder costs were only incurred when the realized service level was below the target.

The added value of integrating forecasts into inventory control policies was determined by comparing the non-forecast-based and forecast-based inventory control performance. The results showed that the (s, Q) policy was not well suited for the integration of forecasts, and was left out of scope for further analyses. The (R, S) policy, on the other hand, was well suited for integrating forecasts. The integration of forecasts resulted in lower costs in every case, except for stationary demand with a high negative bias. Especially for non-stationary demand, huge costs reductions can be realized by using forecasts. The main analysis was done with the forecast-based inventory control policy. The results showed the importance of the forecast accuracy and bias. Especially, the impact of the negative bias on the total cost is significant. A negative bias also causes the total costs to increase with an increase in forecast accuracy because unbiased forecasts are assumed. The increase in forecast accuracy results in less safety stock and, therefore, more backorder costs as all the safety stock is used to compensate for the negative bias. Furthermore, the results showed that the impact of the accuracy and bias increased with the demand volume, lead time, target fill rate and item price. The impact of the accuracy and bias generally decreased with the review period because of the larger order quantity, needing less safety stock to reach the target fill rate. The high-volume and high-value items have the highest cost reductions when forecasts are improved. This is caused by the lower impact of the ordering costs, which are independent of the forecast accuracy and bias. The impact of the forecast accuracy, bias and other factors were used to develop a prediction model.

Prediction model

The results of the experimental study were used to develop a prediction model that can quantify the financial benefits. The simulation models could not be used because of computation time. Various machine learning models were tested for the development of a prediction model. The machine learning models were trained on a data set of simulations. A large number of simulations were done to get enough data for the machine learning models to learn the relationship between the identified input variables and total costs. The difference between the two predictions is used to quantify the financial benefits of an improved forecast.

The data set was used to train en test eight different machine learning models. The accuracy and bias of the machine learning models were compared to determine the best model. The best performing machine learning model was the CatBoost model, which reached an accuracy of 90.06% with a bias of -2.52%. The prediction model estimates the total costs of the old forecast and the new, improved forecast to determine the financial benefits. The prediction model is used in a case study, where the financial benefits of improving the forecast accuracy and bias of statistical forecasting models were estimated.

Case study

A case study is performed for one of the customers of EyeOn. The first step of the case study was performing the ABC-XYZ classification to get an idea of the items and their characteristics. Next, the historical demand data were pre-processed by aggregating the data to a weekly level and correcting outliers. Afterward, the forecast accuracy was determined by using several statistical models. The accuracy and bias of the best-performing model for each item were used. The weighted average forecast accuracy of the forecasting models was 57.2% and the bias -4.9%. So, overall was the forecasted demand lower than actual demand. The financial benefits of improving the achieved forecast accuracy and bias were estimated. The accuracy, bias and other identified factors were used to predict the financial benefits of improving the forecast.

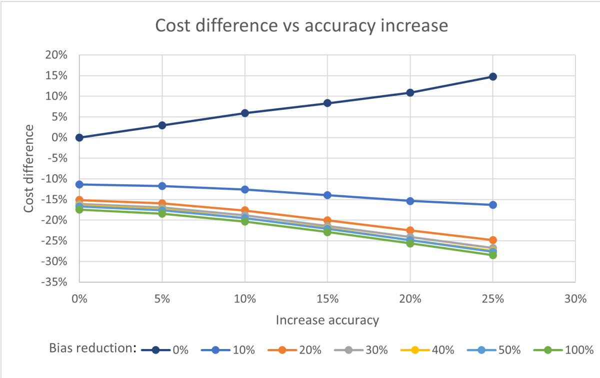

Figure 1: Results case study

The overall results show that the bias is the most important factor for this case and should be reduced as much as possible. Besides the financial benefits of reducing the bias, the benefits of improving the forecast accuracy also increase. The total costs can be reduced by approximately 17.5% if an unbiased forecast is realized. The costs can be further reduced to 20.31% and 25.64% if the forecast accuracy is increased by 10% and 20%, respectively.

Conclusion

Based on the findings of this research, a large opportunity for integrating forecasts into inventory control exists. The performance of the inventory control policies can significantly be improved by reducing the bias and increasing the accuracy. The prediction model can be used for other cases to quantify the financial benefits of an improved forecast. The results of this research show the importance of the bias. The assumption of inventory control policies that forecasts are unbiased does not hold in practice. Especially, the negative bias can be devastating for the inventory performance. The forecast accuracy can also significantly reduce the costs but only when there is no negative bias.

It is recommended to integrate the prediction model with an inventory or forecast assessment to quantify the financial benefits of improving the forecast accuracy and bias. The prediction model should be used for more cases to further explore the financial benefits of an improved forecast. It is recommended to validate the prediction model with, for example, business experts, customers or simulations. The bias should be reduced as much as possible, and it is recommended to explore methods that can reduce the bias or correct for biased forecasts.

Future research may focus on the forecast errors realized in practice and the impact of other distributions. The distribution of the forecast errors should maybe even be included in the validation of forecasting models as a key performance indicator. Another recommended topic for future research would be developing a method that can correct biased forecasts. Additionally, this research methodology can be used for more cases or inventory policies.

Preface

This thesis is the result of my graduation project conducted at EyeOn in Aarle-Rixtel, the Netherlands. The realization of this thesis for the master's program Operations Management & Logistics marks the end of my study at the Eindhoven University of Technology. After pursuing a bachelor's and master's degree, it is time to move on to the next stage of my life. Hereby, I would like to take the opportunity to show my gratitude to all the people who helped and supported me.

First of all, I would like to thank Nevin Mutlu, my first supervisor from the TU/e, for her guidance throughout the project. I highly appreciate your feedback and support from the start till the end. Secondly, I would like to thank Rob Basten, my second supervisor from the TU/e, for his helpful suggestions and feedback during our meetings. Also, thanks to Shaunak Dabadghao for his role as third supervisor. Further, I want to thank the Eindhoven University of Technology and the European Supply Chain Forum (ESCF) for providing this opportunity.

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Last but not least, I would like to thank my family for all their support and encouragement. You have made it possible for me to study and are always there for me. I am the person I am today because of you.

I would like to express my deepest appreciation and gratitude to all the people mentioned above and anyone else who contributed towards my master thesis.

Cas Roelants

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List of Abbreviation

ARIMA	Autoregressive Integrated Moving Average
BO	Backorders
CB	CatBoost
CDF	Cumulative Distribution Function
DES	Double Exponential Smoothing
EOQ	Economic Order Quantity
ESPRC	Expected Shortage Per Replenishment Cycle
HWES	Holt-Winters Exponential Smoothing
IP	Inventory Position
IT	In Transit
k	Safety factor
KNN	K-Nearest Neighbors
KPIs	Key Performance Indicators
L	Lead time
LGBM	Light Gradient Boosting Machine
MA	Moving Average
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
ME	Mean Error
MLP	Multi-layer Perceptron
MPE	Mean Percentage Error
MSE	Mean Squared Error
NGB	Natural Gradient Boosting
OH	On Hand inventory
PB	Percentage Bias
PDF	Probability Density Function
Q	order Quantity
R	Review period
RF	Random Forest
RMSE	Rooted Mean Squared Error
S	order-up-to-level
s	reorder level
SES	Single Exponential Smoothing
SKUs	Stock Keeping Units
sMAPE	Symmetric Mean Absolute Percentage Error
SS	Safety Stock
SVM	Support Vector Machine
XGB	eXtreme Gradient Boosting

Chapter 1

Introduction

1.1 General introduction

Inventory management is used in almost every company to ensure the availability of materials and products. The investments of companies in inventory are often enormous, and the use of inventory control models can have a large potential for improvement (Axsäter, 2006). Inventory control is needed to be competitive and to ensure product availability for customers. Balancing the trade-off between stock and availability is necessary to serve customers while minimizing costs. Inventory control models can be used to achieve a certain service level by determining the required safety stock to buffer against uncertainty. The service level is used to accept a degree of non-availability to avoid costly high stock levels. Demand forecasts can contribute to inventory management by supporting decision-making. Making predictions about future demand can decrease the uncertainty and help to get the right stock levels to anticipate changing demand patterns better. The added value of forecasting for inventory management depends on the quality of the forecasts and the demand patterns. The forecasts can contribute more when demand is more volatile or follows non-stationary demand patterns. These demand patterns have a higher level of uncertainty, which can be reduced with forecasts. The forecast accuracy and bias determine the quality of the forecast. The forecast accuracy is used to measure the deviation between the actual demand and forecasted demand and the forecast bias if a forecast is structural to low or high. The combination of the forecast accuracy and bias determines the quality of the forecast. Improving the forecast can result in a reduction of costs or an increase in service level for inventory management. This research aims to quantify the financial benefits of an improved forecast for inventory management.

1.2 Company introduction

This research is conducted at the consultancy company EyeOn. EyeOn is a company that specializes in realizing forecasting and planning improvements. With their expertise and knowledge, EyeOn helps its customers by designing, implementing and executing excellent planning processes. The customers of EyeOn are in four industries: complex products and systems, consumer products, process industry and life science. The focus of EyeOn is towards the European market, with offices in the Netherlands, Belgium, Switzerland and Ireland. With their head office located in Aarle-Rixtel, the Netherlands.

EyeOn provides a broad range of services for their customers to improve their planning and forecasting capabilities. EyeOn provides the following services:

- Consultancy & project management
- Data science
- Interim planning
- Planning systems
- Visual insights

To remain innovative, a close cooperation with Tilburg University, Erasmus University Rotterdam and Eindhoven University of Technology is maintained. EyeOn is continuously involved in research projects to provide state-of-the-art solutions for their customers. EyeOn also helps its customers by sharing their knowledge in one of their masterclasses.

1.3 Problem introduction

Two of EyeOn's services are forecasting and inventory management. The customers of EyeOn often have these processes already in place but have challenges or room for improvement. EyeOn can provide solutions by implementing high-quality forecasts to improve its inventory management. Forecasts can be improved in two ways, by increasing the accuracy or reducing the bias. The question is, however, what are the financial benefits of this improved forecast? This is the main topic of this research. The problem is addressed by identifying the relationship between the forecast quality, and inventory performance for different cases. The main influential factors, variables and parameters are identified so that the added business value of an improved forecast can be quantified to get better insights into the financial benefits. The goal is to develop a model that can accurately quantify the financial benefits of an improved forecast.

1.4 Background

Inventory control models are used to determine the right stock levels while minimizing the costs. The trade-off between demand and supply is one of the main concerns of inventory control. The inventory control models determine when an order should be placed and the size of the replenishment. A large part of the inventory control models assumes stationary demand. However, the assumption of stationary demand may not hold in reality (Axsäter, 2006). The demand can change over time due to trend, seasonality or product life cycles (Tunc et al., 2011). In the case of non-stationary demand patterns, a misalignment can be caused between the expected and actual demand. For example seasonality, the inventory model will overestimate the demand in the low season period and underestimate the demand in the high season. To better anticipate the non-stationary demand patterns, dynamic inventory models can be used. The dynamic models integrate forecasts to update the inventory control parameters to match supply and demand better.

The forecast-based inventory control models use forecasts and the distribution of its errors to determine the inventory parameters. The dynamic policy updates the inventory parameters with new forecasts every period. The performance of the dynamic forecast-based inventory models depends on the forecast performance. More accurate forecasts make it possible to anticipate the non-stationary demand better, improving the inventory performance. As mentioned in Section 1.1, the performance of forecasts can be divided into two main quality criteria, namely, forecast accuracy and bias. The accuracy is measured with the difference between the actual value and the forecasted value. On the other hand, the forecast bias measures if the forecasts are too high or low. Inventory control often assumes unbiased forecasts. The costs when this assumption is violated are determined, and the benefits of reducing the bias are quantified. A positive bias exists when overall, the forecasts are higher than the actual demand. This can result in overstocking due to the overestimation of demand. A negative bias is the opposite and exists when the forecasts are overall lower than the actual demand. This can cause lower customer service levels due to the underestimation of demand. The forecast accuracy and bias have a different impact on inventory management (Sanders and Graman, 2009). Therefore, the impact of the forecast accuracy and bias is studied in this research to identify the financial benefits of an improved forecast.

1.5 Problem definition

This research includes the fields forecasting and inventory control. The main focus is on the interaction between the two research fields. The literature on the interactions between forecasting and inventory control is limited (Gardner, 1990; Syntetos et al., 2009; Petropoulos et al., 2019). Therefore, this research is used to further investigate the interactions between forecasting and inventory control. The available literature is assessed and used as a basis to explore the interaction between the two research fields. The applicable forecasting and inventory models are combined to identify the financial benefits of an improved forecast. The research is used to address the absence of literature and challenges faced by EyeOn.

1.5.1 Research goal

The identified challenges and literature gap, which correspond to the financial benefits of an improved forecast, are addressed in this research. The goal is to develop a model that can quantify the financial benefits of an improved forecast, and apply this to a case. The goal results in the main research question, which is answered in this project. The goal and main research question are stated as follows:

> *Develop a model to quantify the financial benefits of an improved forecast for a forecast-based inventory policy given a service level target, and apply this to a case.*

This research goal results in the following main research question:

> *What are the financial benefits of an improved forecast for a forecast-based inventory control policy given a service level target?*

1.5.2 Research questions

In order to reach the research goal and answer the main research question, different research questions are introduced. The research questions are used to identify and develop forecasting and inventory control models, which are combined to explore the interaction between the two. An experimental study is used to identify the impact of the forecast accuracy, bias and other factors on the inventory control performance. The results of the experimental study are used to develop a prediction model that can quantify the financial benefits of an improved forecast. The developed prediction model is used for a case study. The following research questions are drawn up:

1. *Which forecasting models can be used for inventory control, and how can their performance be measured?*
    (a) *Which forecasting methods are available in the literature?*
    (b) *What are appropriate metrics for measuring the forecast accuracy and bias?*

(c) *How can forecasts of different qualities be made?*

Chapter 2 addresses this research question and is used to identify and develop forecasting models that can be used for this research. To answer the main research question, multiple forecasts with different accuracies and biases have to be generated. So, besides statistical forecasting models, another approach has to be developed to explore the impact of the forecast accuracy and bias. Also, appropriate metrics for measuring the forecast accuracy and bias have to be identified.

2. *What are appropriate inventory control policies, and how can forecasts be integrated?*

   (a) *Which stochastic inventory control policies are available in the literature?*
   (b) *How can forecasts be integrated into the inventory control policies?*
   (c) *In what way can the performance of the inventory control policies be determined?*

   This research question is answered in Chapter 3, by identifying and developing appropriate inventory control policies. The identified inventory control policies are modeled with and without the integration of forecasts. The forecast-based models are developed to compare the inventory control performance for different forecast accuracies and biases. The inventory control policies without the integration of forecasts are used as a baseline to identify the benefits of integrating forecasts. The forecast-based inventory policy only provides financial benefits when it also outperforms the non-forecast-based inventory control policy.

3. *How does the performance of the inventory control policies depend on the forecast accuracy, bias and other factors?*

   (a) *What are the financial benefits of integrating forecasts into the inventory control policies?*
   (b) *How does the forecast-based inventory control policy perform given a forecast accuracy and bias?*
   (c) *Which inventory control parameters are important for determining the impact of the forecast accuracy and bias?*

   This research question is answered in Chapter 4, with an experimental study. The forecasting and inventory models are combined in a simulation model and used in a controlled setting. The financial benefits of integrating forecasts are determined by comparing the inventory control performance with and without the integration of forecasts. The main analysis is done with the forecast-based inventory control models, used to determine the relationship between the forecast quality and inventory control performance. The impact of the forecast accuracy, bias and inventory control parameters is determined by simulating different scenarios. The important factors for quantifying the financial benefits of an improved forecast are identified in this chapter.

4. *How can a prediction model for quantifying the financial benefits of an improved forecast be developed?*

   (a) *What are appropriate prediction models for quantifying the financial benefits?*
   (b) *Which prediction model is the best suited for quantifying the financial benefits?*
   (c) *How accurate can the prediction model quantify the financial benefits?*

> Chapter 5 is used to answer this research question. The chapter is used to develop a prediction model that can quantify the financial benefits of an improved forecast. The forecast accuracy, bias and other identified factors are used by the model to predict the financial benefits of improving the forecast quality. The developed prediction model is used on a case study in Chapter 6.

The research questions are used to develop forecasting models and inventory control models that are used to explore the relationship between the forecast quality and inventory performance. This relationship and identified influential inventory control parameters are then used to develop a prediction model that can quantify the financial benefits of an improved forecast. The developed prediction model is used for a case study. By answering the research questions, the research goal will be reached, and the main research question answered.

1.5.3 Scope

The scope of this thesis is further explained in this section. To reach the research goal, forecasts of different qualities have to be used to determine the relationship between the forecast quality and inventory performance. This research does not focus on forecasting models and their performance but uses a more general approach, looking at what-if scenarios. Demand data are used to identify the inventory performance if a certain forecast accuracy would have been realized. This separates this thesis from a lot of other literature studies, where the inventory performance is determined for forecasting models.

The inventory control policies used in this research are stochastic, single-item and single-echelon. This research includes inventory control policies with and without the integration of forecasts. The inventory control policies are simulated to determine the cost performance of the policies. For the forecast-based inventory control policy, different forecasts are used as input.

Due to the time limit of this research, the impact of nine different items is explored in the analysis of Chapter 4. Because it is impossible to identify and present the results for a large number of items, nine items are generated with different demand characteristics using the ABC-XYZ classification. This research includes stationary and non-stationary items with seasonality. Items with trends are excluded from the analysis.

1.6 Outline

This section provides an overview of this thesis. The introduction and definition of the research problem are already provided in this chapter. Chapter 2 provides a literature review on the relevant subjects for demand forecasting and explains the models used in this thesis. Chapter 3 reviews the literature on inventory control and explains the used inventory control policies. The developed inventory control models with and without the integration of forecasts, mathematical formulations and assumptions are discussed. In Chapter 4 is the experimental study elaborated. The inventory control models are verified, and an analysis is performed in a controlled setting. Chapter 5 explains the prediction model that is developed to quantify the financial benefits of an improved forecast. In Chapter 6 is the prediction model used to perform a case study. Lastly, Chapter 7 concludes the main findings, results and discusses the limitations of this research.

Chapter 2

Demand forecasting

This chapter focuses on demand forecasting. The literature is used to identify applicable forecasting models and metrics. To explore the financial benefits of an improved forecast, different quality forecasts have to be generated, and the quality of the forecasts has to be measured with appropriate metrics. The identified and selected forecasting models and metrics are used to answer Research Question 1.

1. *Which forecasting models can be used for inventory control and how can their performance be measured?*

This chapter is organized as follows. Section 2.1 presents existing literature on demand forecasting. In Section 2.2 are forecasting models discussed. Section 2.3 explains several forecasting metrics used to measure the forecast accuracy and bias. In Section 2.4 is an alternative method for generating forecasts presented, which can be used to explore the impact of the forecast accuracy and bias independently. Section 2.5 concludes this chapter.

2.1 Literature review

Demand forecasting is used to predict future demand (Archer, 1980). Estimating future demand can support decision-making for operations management (Fildes and Beard, 1992). This makes forecasting very important for supply chain management but also one of the main challenges. Having inaccurate forecasts may result in poor decision making and can lead to shortages, low customer service levels or high stock levels (Beutel and Minner, 2012). Therefore are high-quality forecasts crucial for making the right decision at the right time. Improving forecasts can directly reduce inventory costs and improve customer service levels (Trapero et al., 2011).

Forecasting models are built on the assumption that future sales will behave the same as historical sales. Historical data are used as input and may require some pre-processing steps. First, the right data must be selected and put in the right format. Second, high-quality data must be used as input for the forecasting models. The performance of forecasting models can be significantly impacted by low-quality data (Zhang et al., 2003). To ensure high-quality data, data preparation is used to clean the data. Possible data preparation techniques that are often used in data mining are normalization, transformations, handling missing values, data smoothing and feature enhancement (Maaß et al., 2014).

The literature divides forecasting models into two groups: statistical models and machine learning models. Statistical models are for example, Moving Average (MA), Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Holt-Winters Exponential Smoothing (HWES), Autoregressive Integrated Moving Average (ARIMA) and Croston (Gooijer and Hyndman, 2006). Statistical forecasting models are often used in practice due to their simplicity and understandability. The researcher Spyros Makridakis contributed a great deal to the literature on forecasting. He is a researcher specializing in forecasting and organized five forecasting competitions, also known as the M-competitions. The M-competitions are open forecasting competitions that compare the forecast accuracies of different forecasting models. The M-competitions were firstly dominated by statistical forecasting models, but the 50 best models in the latest M-competition were machine learning models (Makridakis et al., 1993; Makridakis and Hibon, 2000; Makridakis et al., 2018a, 2020b). This shows that new, more advanced techniques may provide added value.

2.2 Forecasting models

Moving average

One of the simplest forecasting methods is moving average. Moving average uses the average of a fixed number of previous periods (m) to forecast the next value(s). The forecast generated for multiple periods ahead will be flat, meaning that the forecast for each period ahead will be the same. The moving average can be computed with the following formula (Nahmias and Olsen, 2015):

$$F_{t+1} = \frac{1}{m} \sum_{i=t-m+1}^{t} y_i \tag{2.1}$$

Exponential smoothing

Exponential smoothing is another statistical forecast method that uses a moving average but adds weight to the new observation and previous observations. The previous observations are weighted with the smoothing factor α and decrease exponentially over time. The recursive equation for the one-step-ahead forecast can be given with the following equation (Silver et al., 2016):

$$F_{t+1} = \alpha y_t + (1 - \alpha) F_t \tag{2.2}$$

The forecast is a weighted average of the new observation and the last forecast with $0 < \alpha < 1$ as smoothing parameter. The single exponential smoothing can be extended to double exponential smoothing. Double exponential smoothing uses a level and trend component to make a forecast. Double exponential smoothing uses two constants, α for data smoothing and β for trend smoothing. The double exponential smoothing can again be extended to triple exponential smoothing, also known as the Holt-Winters method. Triple exponential smoothing adds another component for seasonality. The constant γ is introduced to determine the seasonal index c used for the seasonality smoothing. The exponential smoothing models are widely used for forecasting (Gardner Jr, 1985; Ostertagová and Ostertag, 2011; Chatfield et al., 2001), and often perform well (Makridakis and Hibon, 2000).

ARIMA

Autoregressive integrated moving average models, also known as ARIMA models, are statistical forecasting methods introduced by Box and Jenkins (1970). ARIMA models can be used for forecasting time series with a trend. The models use autocorrelations to make the time series stationary by differencing (Chase, 2013). The ARIMA models can be extended to Seasonal ARIMA models, also called SARIMA models, which use additional seasonal factors (Vagropoulos et al., 2016). The ARIMA and SARIMA models can model trend, seasonality and other factors influencing demand but are often not used in practice due to their complexity (Chase, 2013).

Croston
The model introduced by Croston (1972) is a technique used to forecast products with intermittent demand. The Croston model uses simple exponential smoothing on the demand and time between demands to forecast. The model separates periods where there is no demand and demand to determine the model parameters. The Croston model can be summarized with the formulas given below (Shenstone and Hyndman, 2005). The exponential smoothing parameter (α) is used to determine the forecasts of the demand size (a_{t+1}) and inter-arrival time (p_{t+1}), which are combined to make a forecast. The inter-arrival time between D_{t-1} and D_{t1} is given by Q_t. The model parameters will not be updated when there is no demand.

$$\text{if } D_t > 0 \begin{cases} a_{t+1} = \alpha D_t + (1-\alpha)a_t \\ p_{t+1} = \alpha q_t + (1-\alpha)p_t \\ F_{t+1} = \frac{a_t}{p_t} \end{cases} \tag{2.3}$$

$$\text{if } D_t = 0 \begin{cases} a_{t+1} = a_t \\ p_{t+1} = p_t \\ F_{t+1} = F_t \end{cases} \tag{2.4}$$

Machine learning
Machine learning models can also be used for demand forecasting but take a different approach than the mentioned statistical models. Machine learning models use historical data to learn the dependency between input and output variables (Bontempi et al., 2012). Different machine learning models use different learning approaches to train the models and make predictions. The downside of machine learning models is that they require a relatively large amount of data in comparison to statistical models (Spiliotis et al., 2020). Another disadvantage of machine learning models is that these models are black boxes. The model learns patterns in the data without human intervention, making it more difficult to interpret the model's results. On the other hand, the advantage of machine learning models is that they can identify complex patterns in the data. Machine learning models can also use explanatory variables to improve the forecasting accuracy (Semenoglou et al., 2021). Examples of explanatory variables for demand forecasting are promotions, holidays and weather, for example. There are many different machine learning methods, and some examples are Neural Network (NN), Recurrent Neural Network (RNN), Long Short Term Memory Neural Network (LSTM NN), Classification And Regression Trees (CART), Support Vector Regression (SVR), K-Nearest Neighbor regression (KNN), eXtreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM). Makridakis et al. (2018b) explain the first six machine learning models, Chen and Guestrin (2016) the XGBoost model and Ke et al. (2017) the LightGBM model.

2.3 Forecast metrics

Numerous forecast metrics have been developed to measure the magnitude of the forecast error. The forecast error can be defined as the difference between the actual value (y) and forecasted value ($\hat{y}$). The forecast error for period t is denoted by e_t and can be calculated with the following equation:

$$e_t = y_t - \hat{y}_t \tag{2.5}$$

The different metrics have their own characteristics, advantages and disadvantages. Forecasting metrics are used to compare the performance of various forecasting models. The forecast metrics can be based on scale-dependent, percentage or relative forecast errors (Hyndman and Koehler, 2006). The scale-dependent metrics can be used to compare the performance of models on the same data set but not across data sets with different scales. The percentage errors are scale-independent and can be used to compare the forecast performance across data sets. The relative errors use a benchmark to scale the errors. The forecast errors are divided by the forecast errors of the benchmark model.

The scale-dependent metrics
The Mean Squared Error (MSE) is one of the three measures presented in Silver et al. (1998) and an often-used metric (Gooijer and Hyndman, 2006). The MSE takes the average of the squared forecast errors. The Rooted Mean Squared Error (RMSE) takes the squared root of the MSE and can be used in inventory management to determine the safety stocks. The Mean Absolute Deviation (MAD) is another commonly used forecast accuracy metric. The average absolute error is used to measure the forecast performance. The MAD can also be used for inventory control but is less widely applicable (Eppen and Martin, 1988).

The percentage metrics
The Mean Absolute Percentage Error (MAPE) is a forecast accuracy measure that is often used to compare different times series (Hyndman and Koehler, 2006). The MAPE is a percentage error and therefore, scale-independent. This is an advantage over the previously mentioned scale-dependent metrics (Hyndman, 2014). The Symmetric Mean Absolute Percentage Error (sMAPE) is a forecast accuracy measure that is often used as an alternative for the MAPE. The MAPE is undefined when the actual demand is zero and can take extreme values when the actual demand is very low. The sMAPE is one of the alternatives and has a lower and upper bound to avoid extreme values. The sMAPE is also used in the later M-competitions (Makridakis and Hibon, 2000; Makridakis et al., 2018a, 2020a). A disadvantage of the sMAPE is that the same absolute error does not result in the same sMAPE for different biases. The sMAPE is higher when the forecast is lower than the equal value (Hyndman and Koehler, 2006).

The relative metrics
The relative metrics use a benchmark to compare the performance of a forecast. The relative error is computed by dividing the forecast error by the benchmark forecast error. The mean relative absolute error is an example of a relative error, which takes the average absolute value of the relative error (Gooijer and Hyndman, 2006). The naïve forecasting method is an often used benchmark. The last observation is then used as a forecast for the next period. The relative metrics are also scale-independent.

Forecast accuracy
The RMSE and MAD are forecast metrics that estimate the standard deviation of the forecast error. The RMSE and MAD can both be used for inventory control to determine the safety stocks. The RMSE is more widely applicable and therefore, used in this thesis. The number of forecasts is represented by the letter n, the actual demand for period t with y_t and the forecast with $\hat{y}_t$. The RMSE is given by the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{2.6}$$

The MAPE and sMAPE are both scale-independent forecast metrics that are often used to determine the forecast accuracy. The advantages and disadvantages of the two metrics have been discussed above. The sMAPE is used in this research because it is less sensitive for low demand and also used in the later M-competitions (Makridakis and Hibon, 2000; Makridakis et al., 2018a, 2020a). One disadvantage of the sMAPE has to be highlighted. The sMAPE is higher when the forecast is lower than the actual value. This does have an impact on the forecast accuracy when there is a bias. The negatively biased forecasts have a lower accuracy than the positively biased forecasts. The sMAPE and accuracy can be computed with the following equation (Gooijer and Hyndman, 2006):

$$\begin{aligned} sMAPE &= \frac{1}{n}\sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{(y_t + \hat{y}_t)/2} \\ Accuracy &= 1 - sMAPE \end{aligned} \tag{2.7}$$

Forecast Bias

A forecast has a bias when the mean of the forecast error is not equal to zero. The bias can be calculated by taking the average difference between the forecast and actual value. In this case, a positive bias indicates that the mean of the forecast error is greater than zero. On the other hand, a negative bias indicates that the mean of the forecast error is smaller than zero (Sanders and Graman, 2009). A positive bias results in over forecasting and an increase in stock. A negative bias results in under forecasting and can reduce the inventory service levels and increase stock-outs. It is important to note the difference between the bias and the Mean Error (ME). The mean error takes the difference between the actual value and forecast. Having a negative mean error then indicates that there is an over-forecast and a positive mean error indicates an under-forecast. The same holds for the Mean Percentage Error (MPE). This forecast metric uses the percentages errors and can also be used to measure the bias. The disadvantage of the MPE is that it is undefined for actual values that are equal to zero or get very large for low demand. The Percentage Bias (PB) is an alternative for the MPE, which divides the sum of the forecasted demand by the sum of the actual demand and subtracts one to get a bias expressed in percentages. The PB is less sensitive for zero values or low demand.

The bias is measured with several metrics. The notation given in Equation 2.8 uses the difference between the forecast and actual demand. In this case, a positive bias indicates that the mean of the forecast errors is greater than zero. On the other hand, a negative bias indicates that the mean of the forecast errors is smaller than zero.

$$Bias = \frac{1}{n}\sum_{t=1}^{n} \hat{y}_t - y_t \tag{2.8}$$

The bias can also be expressed as a percentage. The formula used to measure the PB is the following:

$$PB = \frac{\sum \hat{y}_t}{\sum y_t} - 1 \tag{2.9}$$

It is important to note the difference between the bias and the Mean Error (ME). The mean error takes the difference between the actual value and forecast. Having a negative mean error indicates that there is an over-forecast and a positive mean error indicates an under-forecast. This is the opposite of the bias. The ME is the negative value of the bias.

$$ME = \frac{1}{n}\sum_{t=1}^{n} y_t - \hat{y}_t \tag{2.10}$$

The same holds for the Mean Percentage Error (MPE). This forecast metric uses the percentages errors and can also be used to measure the bias. The disadvantage of the MPE is that it can be undefined or get extreme values.

$$MPE = \frac{1}{n}\sum_{t=1}^{n} \frac{y_t - \hat{y}_t}{y_t} \tag{2.11}$$

2.4 Forecast error

There have been several studies investigating the impact of the forecast error on operations management. Petropoulos et al. (2019) use different forecasting models and compares their inventory performance. De Bodt and Van Wassenhove (1983), Lee and Adam Jr (1986), Enns (2002), Jeunet (2006), and Sanders and Graman (2009) used an alternative approach to experiment with the impact of the forecast accuracy and bias. These studies assume normal distributed forecast errors and use this property to experiment with forecasts by generating forecast errors and using the actual demand. So, the forecasts are based on the actual demand plus a forecast error of a specified size. The quality of the forecast can then be influenced by changing the parameters of the forecast error distribution. This method is used to overcome some limitations of forecasting models. Forecasting models will result in a forecast with a corresponding accuracy and bias, which cannot be controlled. The generated forecasts are, therefore, used to better experiment with the accuracy and bias. Forecasts with different accuracies and biases can be generated while not being limited by the forecast models and their outcomes.

The approach uses the forecast error mean and standard deviation to generate forecasts. A bias only exists when the mean of the forecast error is not equal to zero. So, a bias is generated by changing the mean of the forecast error. The forecast errors are added to the actual demand. Hence, having a positive mean results in a positive bias. The bias can also be negative, resulting in an under-forecast. The forecast uncertainty is determined with the standard deviation of the forecast error. The forecast uncertainty increases with the standard deviation. The forecast accuracy and bias can, therefore, be determined by changing the mean and standard deviation of the error. This method is used to get forecasts of different qualities that can be used as input for the forecast-based inventory control models. With the assumption of normally distributed forecast errors, forecasts can be generated with the following equation:

$$F_t = D_t + e_t \qquad e_t \overset{i.i.d}{\sim} \mathcal{N}(\mu, \sigma^2) \qquad \forall t \in \{1, ..., T\} \tag{2.12}$$

De Bodt and Van Wassenhove (1983), Jeunet (2006), and Enns (2002) used this method to investigate the effects of forecast errors on the lot-sizing process and material requirements planning systems. The study of Sanders and Graman (2009) investigated the costs of forecast errors in a warehouse environment. The results show that the forecast bias has significantly more impact on the costs than the forecast accuracy. An increase of the forecast error seems to have a linear cost increase, while the forecast bias results in a rapid exponential increase. The study is based on the inventory and labor costs of a labor-intensive warehouse. There has been no study identified, which uses this methodology for inventory control models.

2.5 Conclusion

In this chapter, has the literature on demand forecasting been reviewed to select several forecasting methods and metrics. Three sub-questions were developed to answer Research Question 1.

1a. *Which forecasting methods are available in the literature?*

1b. *What are appropriate metrics for measuring the forecast accuracy and bias?*

1c. *How can forecasts of different qualities be made?*

Research Question 1a. is answered by reviewing the literature. The literature has been used to identify multiple forecasting models. The statistical forecasting models are often used in practice and are widely applicable. The workings of several basic statistical models are given in

Section 2.2. The machine learning models, on the other hand, have a black box approach and require a large amount of data. Therefore, are these models less used in practice. However, the literature showed that machine learning models could outperform statistical models.

The quality of the forecasting models is measured with metrics for the forecast accuracy and bias. The literature has been used to identify several metrics, and the pros and cons are discussed. The metrics presented in Section 2.3 are used in this thesis. The forecast accuracy is measured with the sMAPE, and the RMSE is used to estimate the forecast error standard deviation. The forecast bias is measured with the PB. The used metrics are more widely applicable than the alternatives and therefore used in this thesis. This answers Research Question 1b.

The inventory control policy requires different forecast accuracies and biases as input to examine the impact of the forecast quality. The forecasting method presented in Section 2.4 is used to identify the impact of the forecast accuracy and bias independently. This method is used to get a general view of the impact of the forecast quality. The method uses the forecast errors and demand to create forecasts. So, looking at (historical) demand data, what would the forecast be when a forecast error of a specified size would have been realized. This method can be used to generate forecasts of different qualities, answering Research Question 1c.

Chapter 3

Inventory control

Inventory management is crucial for almost every organization (Jose et al., 2013). Inventory control is used to maintain the right amount of inventory at the right time, to meet demand. Inventory control models are used to optimize the trade-off between customer service levels and inventory costs. There are various inventory control policies developed to address this challenge. The literature is used to identify appropriate inventory control policies. The inventory control policies are integrated with forecasts so that the interaction between the forecast quality and inventory control performance can be explored. This chapter is used to address the following research question:

2. *What are appropriate inventory control policies and how can forecasts be integrated?*

The methods and models used for inventory control are presented in this chapter. In Section 3.1, a literature review on demand classification and inventory control policies is conducted. Next, in Section 3.2, are the standard inventory control policies explained in detail. Section 3.3 is used to explain the forecast-based inventory control policies. In Section 3.4, are the inventory control policies and simulation models further elaborated. Lastly, a conclusion is given in Section 3.5.

3.1 Literature review

3.1.1 Demand classification

Item classification can support the implementation of the correct forecasting methods and inventory control policies. The classification of Stock Keeping Units (SKUs) can help realize customer service levels and reduce inventory costs (Boylan et al., 2008). There are multiple classification methods in the literature. The ABC-XYZ analysis is an often-used method that combines two classification analyses, namely the ABC and XYZ analysis. The ABC analysis uses the Pareto principle and classifies demand based on the annual sales of an item (Scholz-Reiter et al., 2012). The second part is the XYZ analysis. This method categorizes the items according to their demand stability over time (Scholz-Reiter et al., 2012; Trubchenko et al., 2020).

The ABC-XYZ analysis is used to classify different items according to their main characteristics. The ABC analysis classifies items by their volume and the XYZ analysis according to the coefficient of variation. The three categories for the ABC classification with their criteria are shown below (Biswas et al., 2017; Stojanović and Regodić, 2017). The ABC classification is used to get an indication of the business value of items.

- A-items: approximately 20 percent of the products create 80 percent of the annual sales
- B-items: approximately 30 percent of the products create 15 percent of the annual sales
- C-items: approximately 50 percent of the products create 5 percent of the annual sales

Secondly, the XYZ classification is used to determine the stability of items over time. This gives a good indication of the forecasability of an item. The XYZ classification has the following three categories (Stojanović and Regodić, 2017):

- X-items: coefficient of variation < 0.5
- Y-items: coefficient of variation between 0.5 and 1
- Z-items: coefficient of variation > 1

Combining the ABC and XYZ classification results in nine item groups. The different item groups have different business value and forecastability. The items with a higher business value are of more importance, while the items with a lower coefficient of variation are easier to forecast. Trubchenko et al. (2020) showed that integrating the ABC-XYZ analysis and adapting your inventory management strategy per item group can reduce the inventory holding costs by approximately 20 percent. The implementation of the ABC-XYZ analysis can improve decision making and contribute to a reduction in inventory costs (Stojanović and Regodić, 2017). Besides the reduction in costs, better material ordering, handling and control can be realized by implementing the ABC-XYZ analysis (Pandya and Thakkar, 2016).

3.1.2 Inventory control policies

Inventory control policies are models used to optimize the inventory levels, replenishment quantities and achieve customer service levels. The literature distinguishes four classical inventory control policies, shown in Table 3.1 (Silver et al., 1998). The policies are distinguished by having periodic or continuous reviews and fixed or variable order quantities. The policies with periodic review use R to denote the time interval between two review moments. The policies that use a reorder level (s), order a replenishment when the Inventory Position (IP) is equal to the reorder level. The size of the replenishment order is Q for the fixed order quantity policies. The variable order quantity policies use an order-up-to-level (S). An order is placed such that the IP is raised to S. The four main inventory control policies are shown below in Table 3.1.

	Periodic review (R)	**Continuous review**
Fixed order quantity (Q)	(R, s, Q)	(s, Q)
Variable order quantity	(R, S) or (R, s, S)	(s, S)

Table 3.1: The four inventory control policies

The (s, Q) policy is one of these policies, using continuous review and a fixed order quantity. The reorder level is used to trigger a replenishment. Whenever the IP is below the reorder level, an replenishment of size Q is ordered. The (s, Q) policy assumes that an order is triggered when the IP is exactly equal to the reorder level. The (R, s, Q) policy uses periodic review instead of continuous review. Every Review period (R) are the stock levels determined, and if the inventory position is below the reorder level, a replenishment is triggered. The order of size Q arrives then after the Lead time (L). The (R, s, Q) policy is a more difficult policy because the assumption that the reorder level is exactly equal to the IP is violated. The difference between the reorder level and IP at the moment an order is placed is called the undershoot (De Kok, 2002). The undershoot has to be taken into account when determining the reorder level. The (R, S) policy is a method with a review period and an order-up-to-level. Every review period, an order is placed such that the IP is raised to the order-up-to-level. The (R, s, S) policy works the same but only places an order when the IP is below the reorder level at a review moment. The (s, S) policy uses a reorder level and order-up-to-level. The IP is raised to S when it drops below s. Van Donselaar and Broekmeulen (2014) developed another inventory control policy that uses a multiple of a batch-size for replenishments. The (R, s, nQ) policy uses a review period, reorder level and multiples (n) of a fixed batch-size (Q) for replenishments. This is often seen, for example, in the retail industry where case packages are used.

Demand distribution

The inventory control policies that assume stationary demand use a demand distribution to determine the inventory control parameters (Axsäter, 2006). The demand distribution and parameters have to be determined and estimated. This can be done by fitting historical demand on an identified distribution by using the maximum likelihood estimation or by calculating the demand parameters. The demand distribution is then used to calculate the relevant decision variables and Key Performance Indicators (KPIs). These decision variables are computed at the beginning of the horizon and remain constant. The normal and gamma distribution are often used distributions, especially when demand is high (Ramaekers and Janssens, 2008). The advantage of the gamma over the normal distribution is the non-negative property (Burgin, 1975). The poisson distribution is another alternative, often used when the demand is low (Axsäter, 2006). This seems to be a reasonable fit for low demand (Hasni et al., 2019).

The normal and gamma distribution are the most used to determine the safety stock for the inventory models. The Probability Density Function (PDF) of the distributions are given below:

$$PDF_{Normal} = f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \qquad x \in (-\infty,\infty) \tag{3.1}$$

$$\Gamma(k) = \int_0^\infty x^{k-1}e^{-x}dx \qquad x \in [0,\infty) \tag{3.2}$$

$$PDF_{Gamma} = f(x|k,\theta) = \frac{1}{\Gamma(k)\theta^k}x^{k-1}e^{-\frac{x}{\theta}} \qquad x \in [0,\infty) \tag{3.3}$$

The probability density function of the normal distribution requires values for the parameters μ and σ and the gamma distribution for k and θ. The parameters are determined based on historical demand and are used to calculate the reorder levels given a service level target. The parameters k and θ for the gamma distribution can be calculated with Equation 3.4.

$$\begin{aligned} k &= \frac{\mu^2}{\sigma^2} \\ \theta &= \frac{\sigma^2}{\mu} \end{aligned} \tag{3.4}$$

Stationary vs non-stationary models

Many inventory control policies assume stationary demand and use a demand distribution with known parameters. However, in the real world, neither the demand distribution nor the parameters are known, they have to be estimated or forecasted (Van Wingerden et al., 2014). The inventory control policies explained above assume stationary demand and use a demand distribution to determine the inventory control parameters. However, the assumption of stationary demand does often not hold in practice. Multiple factors such as trend, seasonality, promotions or other events can cause demand to be non-stationary (Tunc et al., 2011). Inventory policies for non-stationary demand require a different approach. The policy needs to be able to adapt to the changing demand. The stationary models determine the inventory control parameters once by assuming a known distribution or by fitting a distribution to the demand. Non-stationary inventory policies determine the inventory parameters for each period, anticipating the fluctuating demand.

To better anticipate non-stationary demand, forecast models can be used to enhance the performance of inventory management (Babaï and Dallery, 2005). The forecast-based inventory control policies use the forecasts and forecast errors to determine the inventory control parameters. The inventory control parameters are dynamic and updated every period. However, there is little research on the interaction between forecasting and inventory control in comparison to the research on the distinct research fields (Syntetos et al., 2009).

Safety stock
Inventory management uses safety stock to buffer against uncertain demand and supply to prevent stock-outs (Gonçalves et al., 2020). Most safety stocks are determined by fitting the normal or gamma distribution to historical demand. The distribution parameters are then used to determine the safety stock for a target service level. The forecast-based inventory control policies use another approach for the safety stocks. The safety stock is then based on the forecast error and its distribution. The RMSE can be used as an estimate for the standard deviation of the forecast error. When the forecast errors are assumed to be normally distributed, an approximation for the standard deviation can be made by using the MAD. The RMSE and MAD can be used for determining the forecast accuracy and be used for the safety stock calculations. Therefore, reducing the forecast error will directly impact the safety stock of the forecast-based inventory control policies.

Eppen and Martin (1988) argued that using the MAD when the forecast errors are not normally distributed can result in poor lead time demand variance. The error caused by using the MAD approximation can be between 15-30 percent when the forecast error is not normally distributed. The study of Trapero et al. (2019) provided an estimation method that relaxes the independence assumption of the forecast errors. Besides the forecast errors, the assumption of normally independently and identically distributed demand and lead times may also not always hold in practice. The paper of Prak et al. (2017) shows that the safety stocks require a correction factor when forecast models are used. A correction factor for MA and SES is presented to deal with auto-correlated forecast errors.

3.2 Standard inventory control policy

The literature was used to identify existing inventory control policies. The (R, S) and (s, Q) policy are used in this thesis, as these are often used in practice and the most applicable. The standard inventory control policies are explained in detail in this section. The policies assume stationary demand and fit a distribution on historical demand data. The demand distribution and its parameters are unknown. A demand analysis has to be performed to determine these. The distribution parameters are calculated based on historical demand data. The normal and gamma distribution are used as demand distributions. These demand distributions are the most used and often provide a good fit, especially when the items are fast-moving.

The Inventory Position (IP) is an important decision variable for inventory control and is used to determine the replenishments. The IP can be calculated by taking the On Hand inventory

(OH) plus the In Transit (IT) minus the Backorders (BO) of item i at time t. The IP is given with the following equation:

$$IP_{i,t} = OH_{i,t} + IT_{i,t} + BO_{i,t} \tag{3.5}$$

The assumption is made that the demand that cannot be satisfied immediately from stock is back-ordered. The backorders are fulfilled as soon as a replenishment arrives and new inventory is available.

3.2.1 (R, S) inventory control policy

The (R, S) policy uses a Review period (R) and order-up-to-level (S). Every review period, an order is placed such that the IP is raised to S. The (R, S) policy uses a dynamic order quantity, which depends on the IP. The Safety factor (k) is calculated by using the mean and standard deviation of the demand during L + R periods for the safety stock formulas. The following equation is used to determine the order-up-to-level:

$$S = \mu_{L+R} + k * \sigma_{L+R} \tag{3.6}$$

The S is for the standard inventory control policy determined once and not updated because the policy assumes the demand to be stationary. Therefore, the S stays the same for every period. The S can be plugged into the formula of Silver et al. (2016) to determine the expected OH, which is used to verify the simulation.

$$E(OH) \;=\; S - \mu_{L+R} + \frac{\mu_R}{2} \tag{3.7}$$

The mean demand during the review period is used as an estimate for the order quantity. The order quantity is needed for the safety stock calculations with a target fill rate. The order quantity is then for the (R, S) policy equal to μ_R and plugged into the safety stock formula.

3.2.2 (s, Q) inventory control policy

The (s, Q) policy assumes continuous review and uses a reorder level (s) and fixed order Quantity (Q). A replenishment is triggered when the inventory position is exactly equal to s. The s is determined by using the demand and standard deviation during the lead time. The s is calculated with the following formula:

$$s = \mu_L + k * \sigma_L \tag{3.8}$$

The Economic Order Quantity is used to determine the Q. The EOQ is most of the time very close to optimal (Silver et al., 2016). The EOQ uses a trade-off between the yearly holding costs (h) and the ordering costs (A). The order quantity can be calculated with the following formula:

$$Q = \sqrt{\frac{2AD_{yearly}}{h}} \tag{3.9}$$

The expected OH is used to verify the inventory on hand for the (s, Q) policy. The Q and Safety Stock (SS) are used as input. The expected inventory on hand can be calculated with the following equation (Silver et al., 2016):

$$E(OH) \;=\; \frac{Q}{2} + SS \tag{3.10}$$

3.2.3 Safety stock calculations

The two used demand distributions for determining the safety stocks in this thesis are the normal and gamma distribution. These distributions are used to determine the required safety stock to achieve the target service level. This research uses the fill rate as service level. The corresponding formulas for determining the safety stock are given below.

Normal distribution
The safety stock for normally distributed demand is computed using a target fill rate. The loss function of the unit normal distribution $Gu(x)$ is used to determine the safety factory k that will satisfy the target fill rate (TFR). The safety factor can be determined using (Silver et al., 1998):

$$Gu(k) = \frac{Q}{\sigma * (1 - TFR)} \tag{3.11}$$

The resulting safety factor can then again be used to determine the safety stock with the following equations for the (R, S) and (s, Q) policy:

$$SS = k * \sigma_{L+R} \qquad \text{and} \qquad SS = k * \sigma_L \tag{3.12}$$

An approximation for determining the safety stock with a target fill rate and normal distribution is used to speed up the simulation. This approximation is provided by Waissi and Rossin (1996) and explained in Silver et al. (1998). The full derivation of the approximation can be found in Appendix A.

Gamma distribution
The safety stock is also determined for gamma distributed demand and a target fill rate. The parameters of the gamma distribution can be determined with the mean and standard deviation of the demand during the protection interval. Determining the safety stock for a given fill rate for gamma distributed demand is a bit more complicated than for the normal distribution. Different safety stock values have to be tested until the safety stock satisfies $FR \geq TFR$. The fill rate for gamma distributed demand can be determined with Equation 3.13. The Expected Shortage Per Replenishment Cycle (ESPRC) has to be determined with the Cumulative Distribution Function (CDF).

$$\begin{aligned} &s = \mu + ss \\ &ESPRC = mean * (1 - cdf(s, k+1, \theta)) - s * (1 - cdf(s, k, \theta)) \\ &P2 = 1 - ESPRC/Q \end{aligned} \tag{3.13}$$

3.3 Forecast-based inventory control policy

The standard inventory control policies can be converted into dynamic forecast-based inventory control policies to better anticipate changing demand patterns. The forecast-based inventory control policies integrate forecasts to determine the inventory control parameters for each period. The forecasts and its errors are used to determine the safety stock and reorder level or order-up-to-level. The forecasts are made periodically and used to update the inventory control parameters. Using forecasts and updating the decision variables can reduce the amount of uncertainty. The required safety stock can, therefore, also be reduced. This can reduce the costs for non-stationary demand but may also reduce the costs for stationary demand.

3.3.1 (R, S) forecast-based inventory control policy

The (R, S) policy can integrate forecasts to determine the dynamic order-up-to-level. The (R, S_t) policy updates the decision variables every review period. A replenishment is made such that the inventory position is raised to the order-up-to-level. The protection interval is equal to the review period plus lead time. The forecasts horizon is, therefore, at least equal to the protection interval. The order quantity was already dynamic, so this does not change. Figure 3.1 shows the forecast-based (R, S_t) policy (Babaï and Dallery, 2005). Every review period, an order of size Q_t is released such that the IP is raised to S_t.

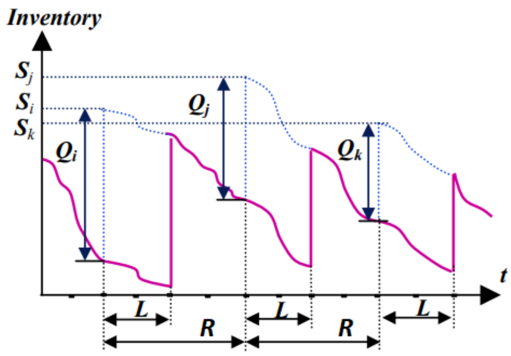


Figure 3.1: (R, S_t) forecast-based inventory policy

The S_t is determined with the forecasts and its errors for L + R periods. As explained earlier, the RMSE is used to estimate the standard deviation of the forecast error. The forecast (F_t) and RMSE at time t are used to determine the S and SS. The S is calculated with the following equation:

$$S_t = \sum_{i=1}^{L+R} F_{t+i-1} + k * \sqrt{MSE_t * (L + R)} \tag{3.14}$$

The forecast is updated at the start of each review period, and the RMSE is determined by looking a half year back. The forecasts errors are assumed to be normally distributed. So, the normal distribution is used for the safety stock calculations, even when the demand is not normally distributed. Equation 3.11 can be used to determine the safety factor. The forecast error standard deviation of the protection interval is used as input.

3.3.2 (s, Q) forecast-based inventory control policy

The (s, Q) policy can also integrate forecasts and change into a dynamic policy. The (s_t, Q_t) policy uses a dynamic reorder level (s_t) and order quantity (Q_t) for period t. The (s, Q) policy is based on continuous review. The (s_t, Q_t) policy however, requires a review period of one-time unit because of the discrete-time aspect (Babaï and Dallery, 2005). So, the (s_t, Q_t) policy does not really use continuous review.

The different decision variables of the forecast-based inventory policies depend on the time. Figure 3.2 shows the (s_t, Q_t) inventory control policy with dynamic reorder levels and order quantities. This inventory policy is based on the classical (s, Q) policy. The reorder point at period k is denoted with r_t and the order quantity with Q_t in the figure. The reorder levels are updated every period for this policy.

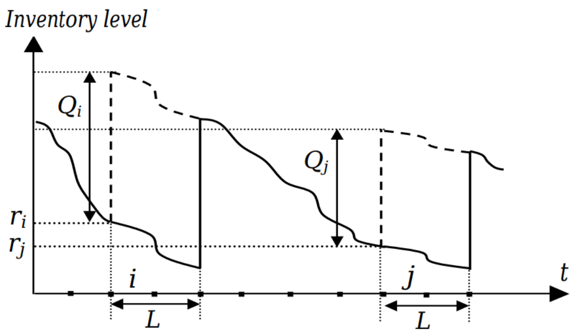


Figure 3.2: (s_t, Q_t) forecast-based inventory policy

The inventory control policy of Babaï and Dallery (2006) uses a review period of one period due to the discrete-time aspect. Continuous review assumes that a replenishment can be triggered every moment. The forecasts are, however, only updated every period. Therefore, a review period of one period is required to avoid misalignments between the forecasts and reorder levels. The resulting inventory policy is a $(1, r_t, Q_t)$ policy. The paper of Babaï and Dallery (2005) proposes to add an extra period to the protection interval to determine the reorder level. The reorder levels are then calculated by taking the cumulative forecast and forecast uncertainty for L+1 periods. This method is also used in Babaï and Dallery (2009) for stochastic lead times but results in significant deviations between the target and actual service levels. Therefore, another method is used to deal with the review period of one-time unit in this thesis.

The review period causes a violation of the assumption that the IP is exactly equal to the reorder level at the moment an order is released. The resulting difference is called the undershoot. This is the difference between the IP and reorder level at the moment a replenishment is triggered. The undershoot (U) has to be taken into account while determining the reorder levels. The mean and standard deviation of the demand is increased by the undershoot. The undershoot has to be determined from historical data or estimated. The new μ_D and σ_D can then be plugged in the safety stock formulas to determine the safety stock and reorder levels.

The undershoot is determined with the method of De Kok (2002) for a standard inventory control policy. The undershoot is a non-negative stochastic variable that depends on the demand (D). The undershoot is determined for gamma distributed demand, as this distribution is used in the experimental study. The gamma distribution parameters used for determining the undershoot are given in Equation 3.18. The following equation is used to determine the undershoot:

$$E[U] = \frac{\alpha + 1}{2 * \lambda} \tag{3.15}$$

$$E^2[U] = \frac{(\alpha + 1)(\alpha + 2)}{3 * \lambda^2} \tag{3.16}$$

$$Var(U) = E(U^2) - E^2(U) \tag{3.17}$$

With:

$$\alpha = \frac{E^2[D]}{\sigma^2(D)} \qquad and \qquad \lambda = \frac{\alpha}{E[D]} \tag{3.18}$$

The undershoot mean and variance is added to the mean lead time demand (μ_L) and variance (σ_L^2) to determine the mean and standard deviation of lead time demand (Schmidt et al., 2012).

$$\text{mean lead time demand} = \mu_L + \mu_U \tag{3.19}$$

$$\text{lead time standard deviation demand} = \sqrt{\sigma_L^2 + \sigma_U^2} \tag{3.20}$$

The resulting variables can be both assumed to be gamma distributed for the standard inventory control policies. Therefore, the gamma distribution would be the logical choice to determine the safety stock.

The same method is used for the forecast-based inventory control policy. The forecast-based control policy assumes normally distributed forecast errors, and the undershoot distribution depends on the demand. So, for gamma distributed demand are the forecast errors are normally distributed and the undershoot gamma distributed. The gamma distribution is used for the combination of the two stochastic variables, as this distribution has been identified as the better fit. So, including the undershoot changes the safety stock calculation from using the normal distribution to gamma distribution. The order quantity is also raised by the undershoot. This is used to raise the inventory levels to the correct level.

The s_t is without including the undershoot is determined with the forecasts and its errors during L periods. The RMSE is again used as an estimate of the standard deviation of the forecast error. The s_t is calculated with the equation below:

$$s_t = \sum_{i=1}^{L} F_{t+i-1} + k * \sqrt{MSE_t * (L)} \tag{3.21}$$

The order quantity for the (s_t, Q_t) policy is determined with the EOQ. Equation 3.22 is used to determine the order quantity in week buckets. The week buckets are then translated to an order quantity using the forecasts. The order quantity will always arrive after the lead time. Therefore, the forecast horizon is equal to the number of weeks buckets ordered after the lead time.

$$\begin{aligned} EOQ &= \sqrt{\frac{2AD_{yearly}}{h}} \\ Q_{weeks} &= int(EOQ/D_{weekly}) \\ Q_t &= \sum_{t=L+1}^{L+Q_{weeks}} F_t \end{aligned} \tag{3.22}$$

3.4 Inventory control approach

The literature review identified multiple inventory control policies. Two inventory control policies are used in this research to investigate the benefits of an improved forecast. The (R, S) and (s, Q) policy are identified as appropriate policies and are used in this research. The (R, S) and (s, Q) policy can both integrate forecasts and become a dynamic forecast-based policy. Instead of the demand distribution and corresponding parameters, forecasts and its errors are used as input to determine the inventory control parameters. The (R, S) uses a review period and is, therefore, well suited for the dynamic forecast-based policy. The order-up-to-level can be updated every review period. It is more difficult for the (s, Q) policy to integrate forecasts because it assumes continuous review. The (s, Q) policy is interesting because it can be used to explore the impact of the forecast-based policy on the order quantity. The forecasts have no direct impact on the replenishments of the (R, S_t) policy, as this policy already uses a dynamic order quantity. The forecasts are used to determine the order-up-to-level, which is used to determine the order quantity. The (s_t, Q_t) policy uses the forecasts to determine the order quantity. The forecasts are directly translated into a dynamic order quantity.

The inventory policies are simulated using a discrete event simulation. The generated forecasts using the method explained in Section 2.4 are used as input for the simulations to determine the costs and fill rate. Different forecast scenarios are then compared to determine the impact of the forecast accuracy and bias. The impact of the inventory parameters is identified by simulating different scenarios. The forecast-based policies are compared with the standard inventory control policies to identify the benefits of using forecasts for inventory management.

The (R, S) and (s, Q) policy are validated by using generated data with a known distribution and parameters. The results of the simulation are compared with the expected inventory on hand and target fill rate, which can be calculated. The length of the simulation is determined by plotting the average inventory on hand. The number of periods is set to the first moment the system appears to stabilize. The simulation is then n times repeated to determine the confidence intervals. The confidence intervals are used to determine if the results are significantly different.

Inventory costs
The holding costs, backorder costs and ordering costs are the three relevant cost factors for the inventory control simulations. The cost relation of Axsäter (2006) is used to determine the holding and backorder costs relation in this thesis. The backorder costs are hard to estimate, and the service level has to be included in the costs. Therefore, the relation given in Equation 3.23 is used.

$$\text{Fill rate} = \frac{\text{backorder costs}}{\text{backorder cost} + \text{holding cost}} \tag{3.23}$$

The target service level is used to determine the relationship between the two costs. The inventory holding costs are estimated between 10 and 25 percent depending on the industry (Vandeput, 2020). At EyeOn, 20 percent is used as an estimate for the inventory holding cost. This is also used in this research. The ordering costs are a fixed amount which is the same for all products.

The backorder costs can now be determined with the holding costs and target fill rate. These two variables are plugged into Equation 3.23 to determine the backorder costs. The backorder costs are the costs of having one backorder one unit of time. Because the holdings cost is on a yearly basis, the backorder costs are also yearly. In this research, the assumption is made that there are no benefits of having a higher service level than the target. Therefore, backorders costs are only incurred when for the backorders that are below the target fill rate. So, for example, with a given fill rate, five backorders are allowed per period. The actual amount of backorders per period is equal to six. The backorder costs for one backorder per period will then be incurred.

Simulation standard inventory control policy
The (s, Q) and (R, S) policy as described in Section 3.2 are used in this research as the standard inventory control policies. The standard inventory policies do not use forecasts and are non-dynamic because they assume stationary demand. Historical demand data are used to determine the demand distribution and its parameters. In the simulation, the warm-up period is used to determine the distribution parameters. Next, the distribution, mean and standard deviation of the demand are used to determine the inventory control parameters such as the safety stock and reorder level or order-up-to-level. The inventory control parameters are determined at the start of the simulation and stay the same over time. The inventory policy is simulated for T periods, which is equal to the simulation length. The simulation is repeated n times to get reliable results. An overview of the simulation is given in Figure 3.3. The demand, lead time, review period and target fill rate are used as input.

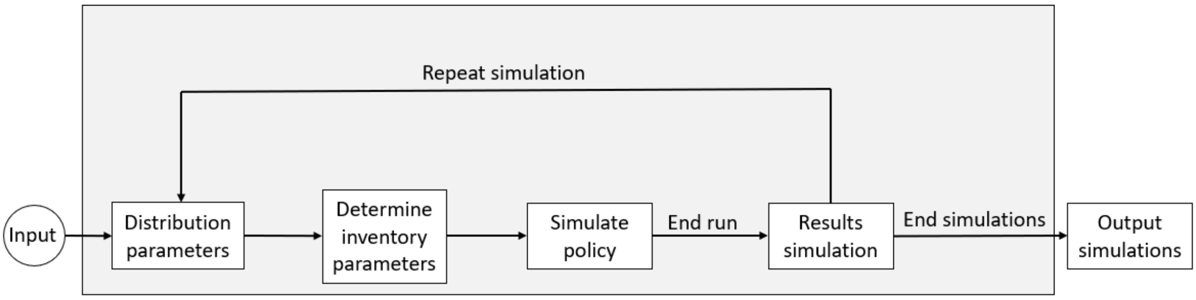


Figure 3.3: Standard inventory control policy simulation

Simulation forecast-based inventory policy
The (s, Q) and (R, S) policy can integrate forecasts to better anticipate non-stationary demand. The policies become dynamic, using the forecasts and its errors of period t to determine the inventory parameters. An overview of the approach for the forecast-based inventory control policy is given below in Figure 3.4. The demand data and forecast errors parameters are used as input. The forecasts are then generated based on the forecast error mean and standard deviation with the approach explained in Section 2.4. Next, the inventory control parameters such as the safety stock and reorder level or order-up-to-level are determined. These inventory control parameters are based on the forecasts and its errors. The forecast error standard deviation is estimated using the RMSE, as mentioned before. The dynamic policy updates the inventory parameters every period or review period. The same as for the standard inventory policy, the simulation has a length of T periods and is repeated n times to get reliable results.

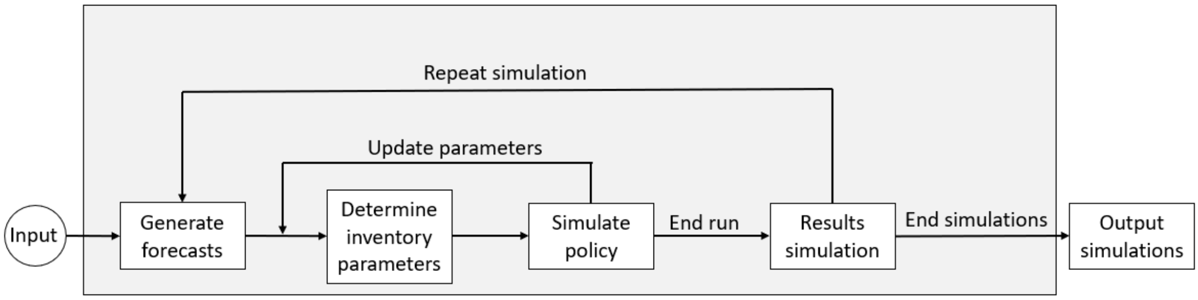


Figure 3.4: Forecast-based inventory control policy simulation

3.5 Conclusion

In this chapter, has the literature on inventory control been reviewed and are two inventory control policies identified for this research. Three sub-questions were developed to answer Research Question 2.

2a. Which stochastic inventory control policies are available in the literature?

2b. How can forecasts be integrated into the inventory control policies?

2c. In what way can the performance of the inventory control policies be determined?

The literature has been used to identify existing inventory control policies. The (R, S) and (s, Q) inventory control policy are often used in practice and can both integrate forecasts. These policies are used in this research to identify the financial benefits of an improved forecast for inventory management. The literature review on inventory control and the identified policies answer Research Question 2a.

The standard inventory control policies have been presented in Section 3.2. The inventory control policies assume stationary demand and use a demand distribution and corresponding parameters to determine the decision variables. The inventory control policies that integrate forecasts take a different approach. The forecast-based inventory control policies, presented in Section 3.3 use the forecasts and its errors to determine the decision variables. The methods developed for integrating forecasts into the inventory control policies answer Research Question 2b.

Simulation models have been developed to determine the inventory control performance. Three costs factors are used to compare the inventory control performance with the service level target included in the backorder costs. The simulation models for the standard and forecast-based inventory control policies are used to identify the value of demand forecasting. The developed approach and simulation models answer Research Question 2c. The forecasting method identified in Section 2.4 is combined with the forecast-based inventory control policies to explore the impact of the forecast accuracy and bias.

Chapter 4

Experimental study

In this chapter is an experimental study performed to explore the interaction between forecasting and inventory control. In Chapter 2 has a forecasting method been presented that can generate forecasts with different accuracies and biases. This method is combined with the inventory control models that are explained in Chapter 3. The forecasting and inventory control models are used to identify the impact of the forecast accuracy, bias and other factors on the inventory control performance. The following research question is answered in this chapter:

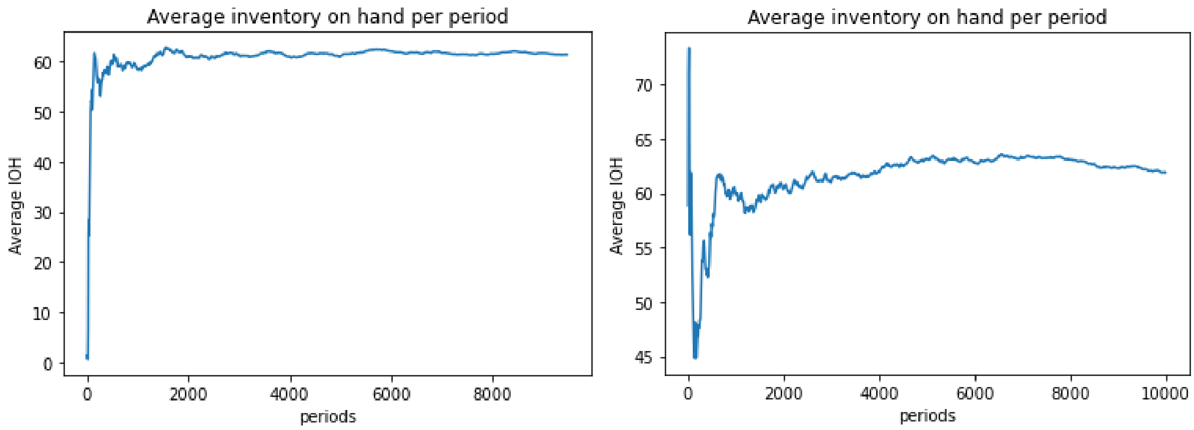
3. *How does the performance of the inventory control policies depend on the forecast accuracy, bias and other factors?*

This chapter is organized as follows. In Section 4.1 are the simulation models of the inventory policies verified. In Section 4.2, data are generated that is used for the experimental study. Section 4.3 is used to look at the forecast errors of statistical forecasting models. In Section 4.4 is the main analysis performed. The inventory control policies are simulated with different accuracies, biases and input variables. Section 4.5 is used to perform a small sensitivity analysis. Lastly, Section 4.6 concludes the results of the experimental study.

4.1 Model verification

The inventory control simulations used in this research are verified for the (s, Q) and (R, S) policies. These policies can be used to compare the outcome of the simulation and the expected outcome. To verify the simulation, demand is generated using the normal and gamma distribution. The results are compared to determine whether the simulation works as expected.

To verify the simulations, the expected inventory on hand is compared with the simulated inventory on hand, and the target service level is compared with the realized service level. The expected inventory on hand is calculated with the formulas given in Section 3.2. A warm-up period is used to avoid abnormal system behavior in the results due to starting parameters. Firstly, the number of periods for the warm-up period is determined. Figure 4.1a shows that the inventory on hand has no major changes anymore after 1,000 periods. Therefore, a warm-up period of 1,000 is chosen to ensure that the starting parameters have no impact on the results. Secondly, the number of periods required to get a good estimate of the simulation is determined. The average inventory on hand per period for 10,000 periods is determined. The inventory on hand stabilizes around the 5,000 periods, as can be seen in Figure 4.1b. The total simulation length is set to 6,000 periods to get a good estimation of the results.



(a) Inventory on hand without warm-up

(b) Inventory on hand with warm-up

Figure 4.1: Inventory on hand per period

The warm-up period and length of the simulation are used to validate the simulation. Normal and gamma distributed demand is generated to compare the target fill rate with the actual fill rate and expected inventory on hand with the simulated inventory on hand. The demand distribution parameters for the normal and gamma distribution are shown in Table 4.1.

Distribution	μ	σ
Normal	20	8

Distribution	Shape	Scale
Gamma	5	4

Table 4.1: Distribution parameters verification

To verify the simulation, a lead time of one period is chosen. The simulation is repeated ten times to determine a confidence interval for the inventory on hand. The following formula is used to calculate the 95% confidence interval:

$$\begin{aligned} Upper\ bound &= mean(IOH) + 1.96 * \frac{std(IOH)}{\sqrt{runs}} \\ Lower\ bound &= mean(IOH) - 1.96 * \frac{std(IOH)}{\sqrt{runs}} \end{aligned} \tag{4.1}$$

The results of the simulations for the (s, Q) policy are shown below in Table 4.2. Three target fill rates are used for each distribution to see whether the simulation behaves as expected. The expected, lower bound, average and upper bound of the inventory on hand is shown in the table below. The fill rates and inventory on hand are compared to determine whether the simulation is correct.

	Fill rate		**Inventory on hand**			
	Target	*Actual*	*Expected*	*Lower bound*	*Average*	*Upper bound*
Normal	95%	95.09%	28.50	28.35	28.44	28.53
	97.5%	97.92%	31.75	31.57	31.63	31.69
	99%	99.33%	35.50	35.23	35.30	35.37
Gamma	95%	94.68%	29.75	29.70	29.79	29.88
	97.5%	97.67%	34.42	34.07	34.28	34.49
	99%	99.24%	39.97	39.58	39.82	40.07

Table 4.2: Verification results (s, Q) policy

The verification results for the normal distribution show two things. The results for a 95% fill rate are as expected. The target and actual fill rate have a minimal difference, and the expected inventory on hand falls in the confidence interval. The results for the 97.5% and 99% fill rates are slightly higher than the target. The expected inventory on hand is, therefore, also slightly higher and falls outside the confidence interval. The results of the simulations for the gamma distributed demand behave as expected. The difference between the target and actual fill rate is small, and the expected inventory on hand falls within the confidence interval of the simulation. Besides the slightly higher fill rates and inventory on hand for the two mentioned cases, the system behaves as expected.

The same procedure is repeated for the (R, S) policy. To verify the simulation of this inventory control policy, the expected inventory on hand and fill rates are compared with the simulation output. The results of the (R, S) policy are shown in Table 4.3.

	Fill rate		**Inventory on hand**			
	Target	*Actual*	*Expected*	*Lower bound*	*Average*	*Upper bound*
Normal	95%	95.04%	30.957	30.75	30.99	31.23
	97,5%	97.44%	34.87	34.43	34.79	35.15
	99%	98.92%	39.45	38.84	39.27	39.69
Gamma	95%	94.88%	35.17	34.64	35.12	35.60
	97.5%	97.54%	40.74	40.43	40.87	41.31
	99%	99.03%	47.618	47.32	47.77	48.22

Table 4.3: Verification results (R, S)

As can be seen in Table 4.3, the system behaves as expected. The target fill rates are very close to the actual fill rates, and all the inventory on hand falls within the confidence intervals.

So, besides the two cases in the (s, Q) policy, all the results fall within the confidence intervals. The two cases that fall outside the confidence intervals show small deviations and just missed the confidence interval. This can be caused by the randomness in the simulation. Therefore, both the inventory control policies are assumed to be verified.

4.2 Experimental data

Experimental demand data have been generated to get a better understanding of the system and influential factors. The data are used to experiment in a controlled setting with the inventory control policies. The data have been generated using the gamma distribution. The gamma distribution is preferred over the normal distribution because of the non-negative property. The PDF of the gamma distribution is given in Section 3.1.2 and is used to generate data. Random samples of the distributions are drawn, given the parameters of the distribution. The generated data are used as demand data for the experimental study. The added value of a forecast-based inventory control policy depends on the forecast accuracy and demand characteristics. Seasonality is added to the demand to identify the impact of non-stationarity. Nine items are used in the experimental study. Each item represents an item group of the ABC-XYZ classification method. Three different coefficients of variations and volumes are used. The used distribution parameters are shown below in Table 4.4. The seasonality is added with the following equation:

$$Seasonal\ demand = Demand * seasonal\ index * (cos(\frac{t_j}{2C\pi} - \pi) + 1) \tag{4.2}$$

The seasonality is determined with the week of the year t_j and seasonality cycle C. The seasonality index indicates the amplitude of seasonality as a fraction of the mean. A seasonality index of 0.4 results in a 40% increase in the high season and a 40% decrease in the low season. A seasonality cycle of one year is used in this experiment, resulting in one high season and one low season per year.

Item	AX	AY	AZ	BX	BY	BZ	CX	CY	CZ
Mean	100	100	100	10	10	10	2	2	2
Std	50	75	100	5	7.5	10	1	1.5	2
Seasonality index	0	0.4	0.8	0	0.4	0.8	0	0.4	0.8

Table 4.4: Demand data experimental study

4.3 Forecast error

The experimental study uses a distribution for the forecast errors to generate forecasts with different accuracies and biases. This method is explained in Section 2.4. The forecast errors are often assumed to be normally distributed. The assumption of normally distributed forecast errors is tested using statistical forecasting models. So, instead of just assuming normal distributed forecast errors, statistical models are used to see whether the normal distribution is a good fit. The statistical forecasting models are used for a X, Y and Z item, as these items have a different forecastability. The forecasting errors and identified distribution are afterward used in the experiments to generate forecasts with different accuracies and biases.

Walk-forward validation

The forecasting models use a walk-forward validation method for determining the forecast errors. This method is shown in Figure 4.2. The walk-forward validation is used to evaluate time series in a realistic way. The method replicates the forecasting and validation steps used in practice. The first step is to split the data into a training and test set. The training data set is used to train the forecasting models and determine the parameters. The model is then used to predict the first test period. The test period is added to the training data after the prediction is made. Next, the model is trained again, and a new prediction is made. This process is repeated for the whole test data set. The resulting predictions are compared with the actual demand data to determine the forecast errors.

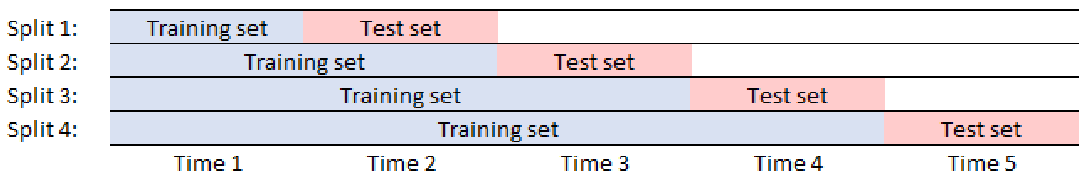
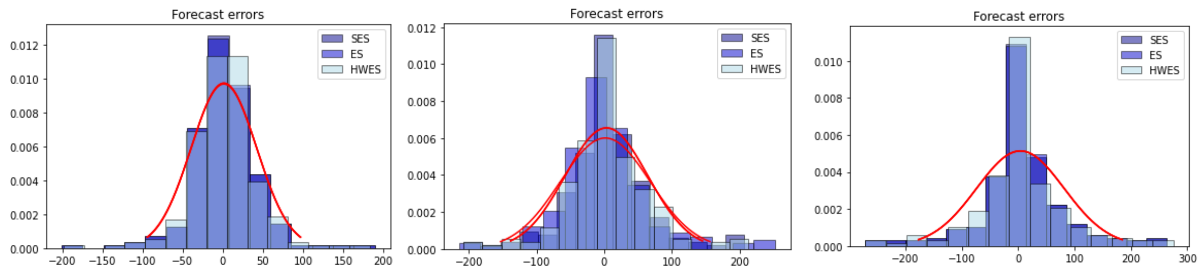


Figure 4.2: Walk-forward validation

Forecast error distribution

The forecasting models ES, ES and HWES are used to test the distribution of the forecast errors, as these models are also often used in practice. The forecast models are used to perform a walk-forward validation, and the forecast errors are plotted in a histogram. The forecasting errors for an X, Y and Z item are shown in Figure 4.3. The forecast errors for all the items and models have a bell-shaped distribution. The forecast errors are centered around 0, meaning there is no bias or only a small one. The standard deviation of the forecast errors increases for X, Y and Z, respectively. This is expected, as mentioned in the literature review, the XYZ analysis is used to determine the forecastability of items. The more volatile items are harder to forecast. The normal distribution is a good fit for the X and Y items. The forecast errors of the Z items are more centered around the mean. The forecast errors get heavier tails when the volatility increases.



(a) X item (b) Y item (c) Z item

Figure 4.3: Forecast error distributions

The assumption of the normally distributed forecast errors is validated and is a reasonable fit. The normal distribution is therefore used to generate forecasts. The sensitivity analysis is used to investigate other distributions for the forecast errors. A heavy-tailed distribution will be used to identify the impact of another forecast error distribution.

The mean and standard deviation of the forecast errors are used to generate forecasts with a bias or accuracy. The magnitude of the forecast errors is assumed to be equal over the forecast horizon. The mean and standard deviation of the forecast errors are assumed to stay equal over time because trend items are out of scope, and the seasonal items have a repeating cycle. Also, the assumption is made that the forecasts cannot be negative. When a distribution is used for generating forecasts, there is a probability of having negative forecasts, especially when the forecasts errors have a high standard deviation. All the negative forecasts are set equal to zero.

4.4 Inventory control policies

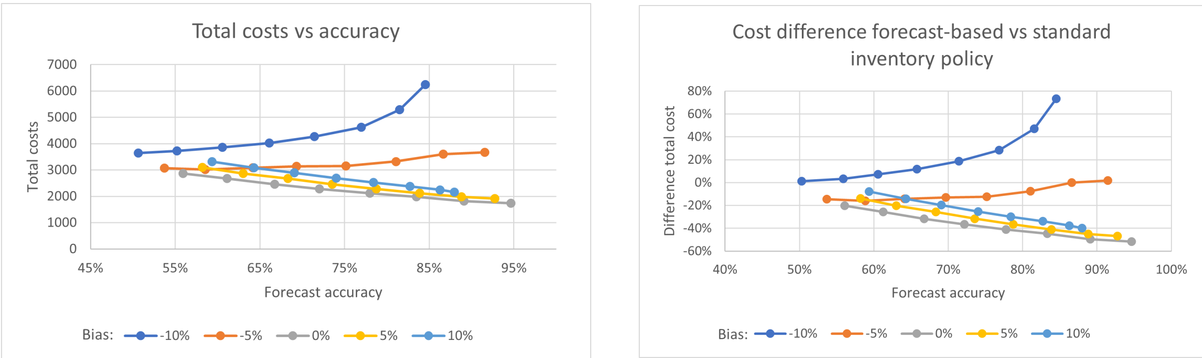
In this section are the results of the inventory control policies discussed. The assumption is made that the forecast errors are normally distributed with μ and σ. The forecasts are generated using Equation 2.12. Different forecast accuracies and biases are generated to identify the impact of the forecast on the forecast-based inventory policies. The mean of the forecast error ranges from -10% to 10%, resulting in different biases. The standard deviation of the forecast error ranges from 5% to 40%, resulting in different accuracies. The forecasts with different accuracies and biases are used as input for the inventory control policies. The total costs are determined by summing the inventory holding cost, backorder cost and ordering cost.

The base case in this experimental study has a target fill rate of 95%. This target fill rate is used in the experimental study to compare different accuracies and biases. The lead time and, if applicable review period, are equal to one period. The item price is equal to 100 for the base case. The resulting holding costs are 20 per item per year. The backorder costs can be determined by using Equation 3.23 with the holding costs and target fill rate. The resulting backorder costs per item per year are 380. The ordering costs are set at 20. So, the inventory control parameters for the base case are L = 1, R = 1, h = 20, b = 380, A = 20 and fill rate = 95%. The impact of several inventory parameters is determined. The forecast uncertainty for determining the safety stock levels is determined on the last half-year. So, 26 observations are used to determine the RMSE, which is used to determine the safety stocks. The sMAPE is used to determine the forecast accuracy and the PB to determine the bias.

4.4.1 Analysis (R, S) policy

Firstly, the (R, S) inventory control policy is used in this experiment. The (R, S) policy becomes the (R, S_t) policy, where the order-up-to-level is dynamic. The (R, S) policy already uses a dynamic order quantity, so the forecast accuracy does not directly influence the order quantity and replenishment policy. The order of events is the following. At the start of a review period, the order-up-to-level is updated. Afterward, the inventory levels are checked, and the order is released. Thirdly, demand is observed and deducted from the inventory levels.

The resulting costs for the AX item with a (R, S_t) policy can be seen in Figure 4.4a, the results for the other items are available in Appendix B. The observed results are combinations of biases and forecast uncertainties. The lines indicate different biases, meaning that the forecast is structural too high or low. The comparison with the standard (R, S) policy is made in Figure 4.4b, where the percentage cost difference between the forecast-based and standard inventory control policy is shown.



(a) Total costs vs accuracy

(b) Difference total costs vs accuracy

Figure 4.4: Costs vs forecast accuracy AX item

The results show that a positive bias and negative bias behave differently. The cost for a positive bias decreases when the forecast accuracy increases. This is logical, more accurate forecasts require less safety stock and have, therefore, less inventory costs. The costs of a negatively biased forecast show that the costs increase when the forecast accuracy increases. The reason for this unexpected behavior is that the safety stock increases when the forecast accuracy decreases. The safety stock calculations assume no bias, the extra unforeseen demand, because of the negative bias, results in the use of all the safety stock. The increase in safety stock results in a higher service level and in lower backorder costs, as can be seen in Figure 4.5. The decrease in backorder costs outweighs the increase in safety stock, as expected, because the holding costs are lower than the backorder costs. The lowest costs are reached when there is no bias and a high forecast accuracy. The costs increase for a positive and negative bias compared to no bias. Having a positive bias results in over-forecasting and more inventory costs. On the other hand, a negatively biased forecast results in under-forecasting and a lower service level. The lower service level realized with a negative bias increases the backorder costs. A negative bias also decreases the holding costs because there is less inventory. However, the increase in backorder costs outweighs the decrease in inventory costs. It is important to note that having very low backorder costs can change this. The lowest costs can then be achieved with a negative bias.

The (R, S_t) policy can decrease the costs by almost 50% compared to the (R, S) policy for an AX item. The cost increase when there is a high negative bias. The AX item does not have seasonality, the standard (R, S) policy can reach the target fill rate, but it requires more safety stock. The forecasts reduce the uncertainty and hence, the required safety stock. The negatively biased forecasts cannot reach the service level target and have high backorder costs. The impact of the forecast accuracy and bias on the service level can be seen below in Figure 4.5. The impact on the service levels is important because there are only backorder costs when the service levels are below target.

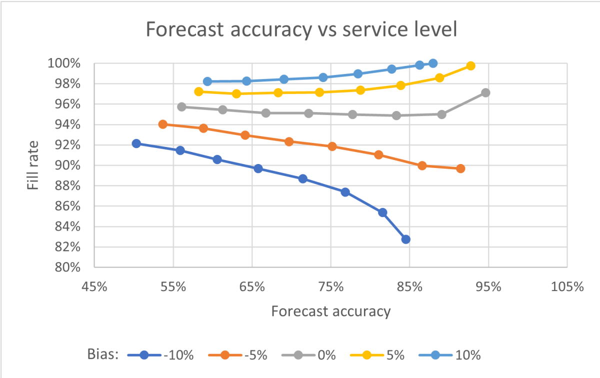


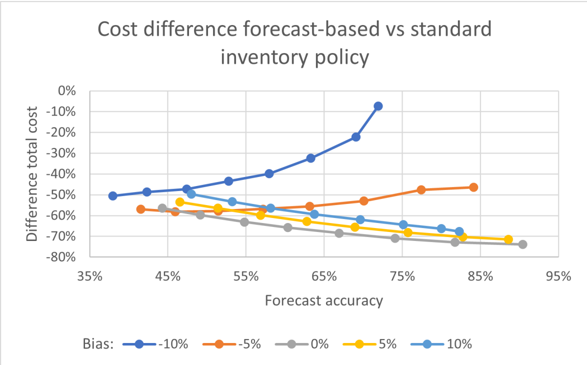
Figure 4.5: Service level vs accuracy AX item

The fill rates for different biases and forecast accuracies are shown above in Figure 4.5. The fill rates for forecasts without bias are approximately equal to the target. Only the last point, with high accuracy, is above target. Because of the very high accuracy, no safety stock is required, and a higher fill rate is achieved. As expected, a positive bias has a higher fill rate, and a negative bias has a lower fill rate. The fill rate for a negative bias increases when the forecast accuracy decrease, as mentioned before. When the negative bias is primarily responsible for the forecast inaccuracy, the lowest service level is achieved. The service level for a positive bias increases with the forecast accuracy. The positive bias compensates for periods when the forecast is lower than the actual demand. With a higher forecast accuracy, less compensation is possible, resulting in higher service levels.

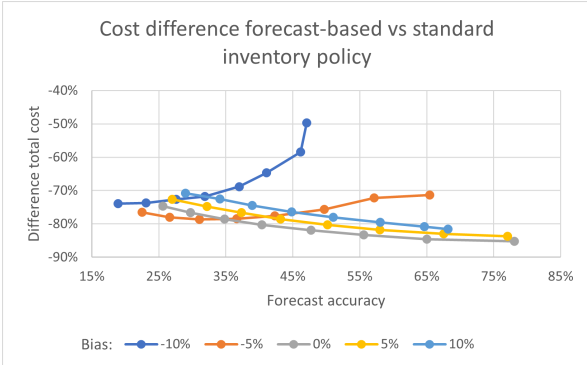
The same behavior is observed for the B and C items, but the reduction in costs decreases for the A, B and C items, respectively. The ordering cost becomes the dominant cost factor for the lower-volume items. Resulting in less impact on the backorder and holding costs, which are determined by the forecast accuracy and bias. The service levels increase for X, Y and Z, respectively. This can be explained by the assumption that the forecasts cannot be negative. The assumption results in a positive bias, which is higher for the more volatile items. The items with a higher forecast error standard deviation have a higher chance of negative forecasts. This effect also results in a difference between the generated mean of the forecast error and the realized mean of the forecast error.

The differences between the X, Y and Z items are also seen in the costs difference between the standard and forecast-based policy. The results of the percentage difference between the forecast-based and standard inventory policy of the AY and AZ items are shown in Figure 4.6. The lines show the same trend but have a clear difference in terms of cost reduction and accuracy. Also, the bias lines are shifted downwards. The reason for this shift is the difference in realized mean forecast error, as explained above. So, as a reminder, the lines indicate the generated bias, not the actual ones.

The results show an increase in potential cost reduction for the X, Y, Z, respectively. The increase in cost reduction has mainly to do with the increased costs of the standard inventory control policy. The Y and Z items have a seasonality pattern and are more volatile. The standard inventory control policy cannot reach the target fill rate, resulting in high backorder costs. This increase in costs in combination with only minor changes in the forecast-based policy results in a higher cost reduction when forecasts are integrated. The value of integrating forecasts increases when the demand is non-stationary. As mentioned earlier, the more volatile items have a lower accuracy.



(a) Difference total costs AY



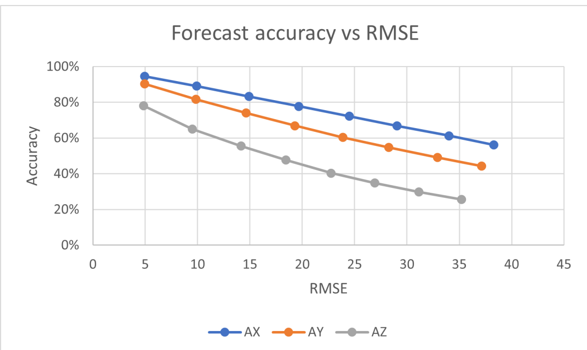
(b) Difference total costs AZ

Figure 4.6: Cost difference forecast-based vs standard inventory control policy

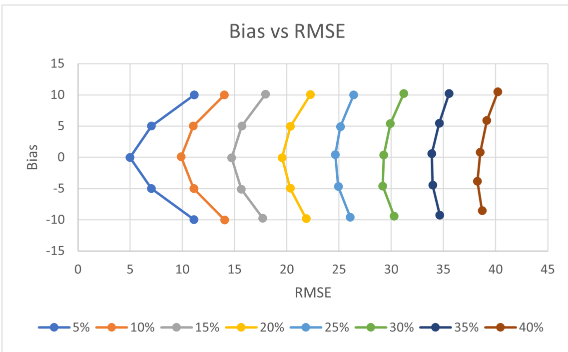
Forecast accuracy and bias

The forecast accuracy and bias have an impact on each other and depend on the item groups. This section is used to deep dive into the relation of the accuracy, bias and item groups.

The forecast accuracy is different for the XYZ item groups. The same absolute forecast errors result in different relative forecast errors. As explained earlier, low demand results in a higher sMAPE. The sMAPE is less sensitive for low demand than the MAPE but still results in a higher sMAPE when there are more low demand periods. The increasing standard deviation and seasonality for the Y and Z items result in more low demand periods and therefore, a larger sMAPE. Having a lower accuracy for the more volatile items is, however, logical. These items are, in practice, harder to forecast. The forecast accuracies for three items can be seen in Figure 4.7a. The bias also has an impact on the forecast accuracy. The relation between the bias and the RMSE is shown in Figure 4.7b. The impact of the bias on the RMSE decreases when the forecast error increases. This means that the difference between the safety stock also decreases for different biases when the forecast uncertainty increases.



(a) Forecast accuracy item groups

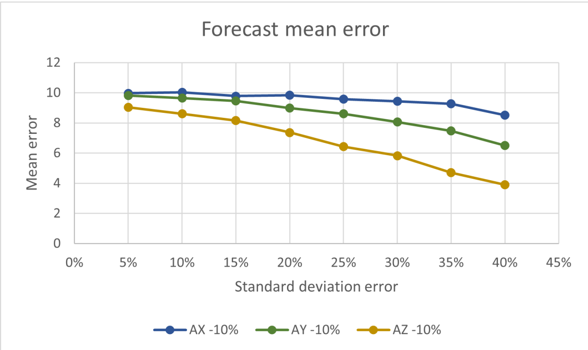


(b) Bias vs accuracy

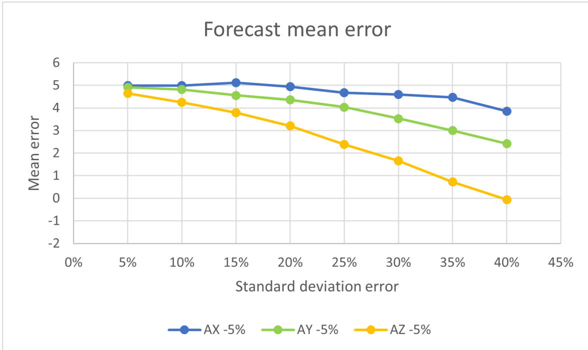
Figure 4.7: Forecast accuracy and bias

As discussed above, the forecasts cannot be negative. This results in a deviation between the generated and realized mean of the forecast error. The chance that the forecast is lower than zero increases with the volatility of the items and the forecast error standard deviation. The forecast error parameters and the actual bias are shown in the figures below in Figure 4.8. The lines indicate an item group and the corresponding mean forecast error used for the forecast generation. The X-axis shows the forecast standard deviation as a percentage of the mean, which is also an input parameter for the forecast generation. The actual mean error is shown on the Y-axis, a reminder that the mean for the forecast generation is the bias metric.

The assumption that the forecasts cannot be negative has a small impact on the X items. Only with a high uncertainty, significant deviations are shown. The deviations for the Y and Z items are higher, again increasing with the standard deviation of the forecast error. In the most extreme case, a Z item with high forecast uncertainty even realizes a mean of zero with a 5% generated bias. It is important that the deviation of the input and realized mean of the forecast error are kept in mind, as the lines in the plots indicate the generated bias and not the realized one.



(a) AX generated mean error of 10%



(b) AX generated mean error of 5%

Figure 4.8: Generated vs actual mean error

Forecast improvements

To determine the financial benefits of an improved forecast, the difference between the costs and accuracies are compared. The percentage cost difference is calculated with the following formula:

$$\Delta = \frac{New - Base}{Base} * 100\% \tag{4.3}$$

The cost difference is determined with this equation and used in the rest of this section. The worst case is used as the base scenario. The other cases with higher accuracies are the new values. The percentage differences for the total costs and the absolute accuracies differences are compared for different cases.

In Figure 4.9 are the cost and accuracy differences for an AX item compared. As seen before, the costs of a negative bias increase when the forecast accuracy increases. The cost difference for a negative five percent bias with an accuracy increase of 38.38% and 32.86% results in approximately the same costs difference. The reason that the 38.38% deviates from the other points is that the high forecast accuracy requires no safety stock and therefore, differs from other points with safety stock. The relation between the total cost difference and accuracy difference for a positive or no bias is approximately linear. The costs decrease when the forecast accuracy increases.

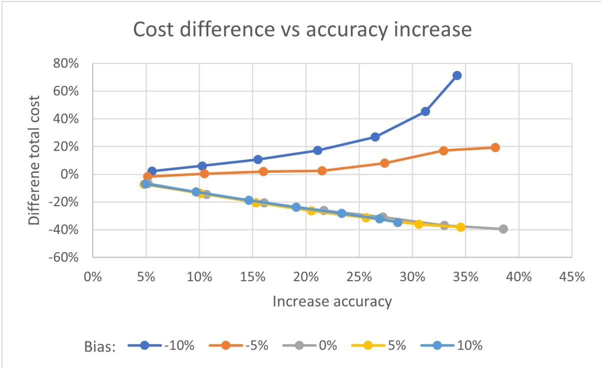
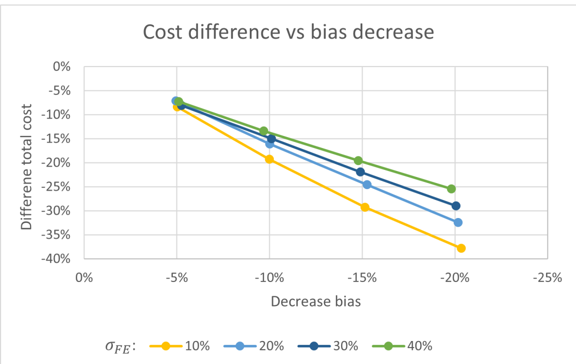


Figure 4.9: Cost difference vs accuracy difference for AX item

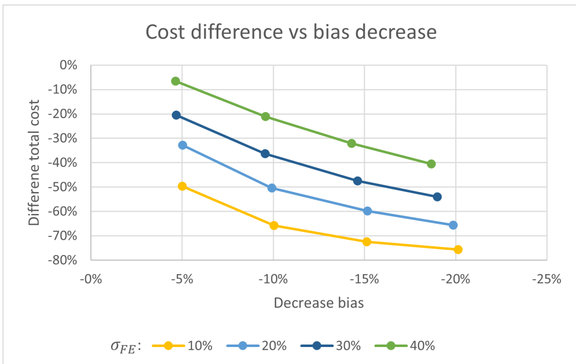
The XYZ items have the same trend for the total cost differences. However, to decrease the same amount of total cost, a slightly different accuracy decrease has to be realized. The same absolute forecast error has more impact on the accuracy for the more volatile items. Resulting in slightly different spread between the forecast accuracies for approximately the same cost decrease. The ABC items also show the same trend for the different biases, but there is less difference in total costs. The same ordering cost and review period are used for all the items. The impact of the holding and backorder costs decrease in comparison to the ordering costs for A, B and C, respectively. The ordering costs, which do not change for the different items groups, become the dominant cost factor, reducing the impact of the forecast accuracy and bias. The cost decrease for no bias and a forecast accuracy decrease of approximately 30% goes from 23.2% to 4.5% and 1.0% for AX, BX and CX, respectively. The impact for C items is almost totally diminished.

Forecast bias

The same is done for the forecast bias. The decrease in cost for reducing the bias to zero is shown below in Figure 4.10. The cost difference of decreasing the percentage bias with 5%, 10%, 15% and 20% is shown. Decreasing the bias is different for a negative bias than for a positive bias. Therefore, are the two separated with the results for a positive bias in Figure 4.10a and a negative bias in Figure 4.10b. The lines indicate different forecast error standard deviations, which determine the forecast accuracy.



(a) Positive bias cost difference



(b) Negative bias cost difference

Figure 4.10: Cost difference vs bias difference for AX item

The results show that decreasing the bias depends on the standard deviation of the forecast error. This is explained earlier, as the safety stock calculations assume no bias. A high forecast accuracy with a high bias has the highest potential for decreasing the costs. Also, the actual bias is lower than the generated bias for forecasts with a higher uncertainty. The ratio between the forecast accuracy and bias determines the impact of the bias. When the forecast errors are mainly dependent on the bias, the highest cost reduction of decreasing the bias can be realized. The negative bias has a higher potential for improvement than the positive bias, as seen before. The overall impact of the bias is higher than the forecast accuracy. The importance of the forecast bias is shown, and having unbiased forecasts is crucial for the inventory control performance. The impact of the bias also decreases with the A, B, C item groups, respectively, as seen with the forecast accuracy.

Lead time and review period

The impact of the lead time and review are explored, as these two inventory parameters have an impact on the reorder level and safety stock. Changing these parameters will, therefore, also change the impact of the forecast accuracy and bias. Different combinations of L and R are shown in Figure 4.11 for an AX item with no bias. The cost differences versus accuracy differences of improving the worst forecast are shown.

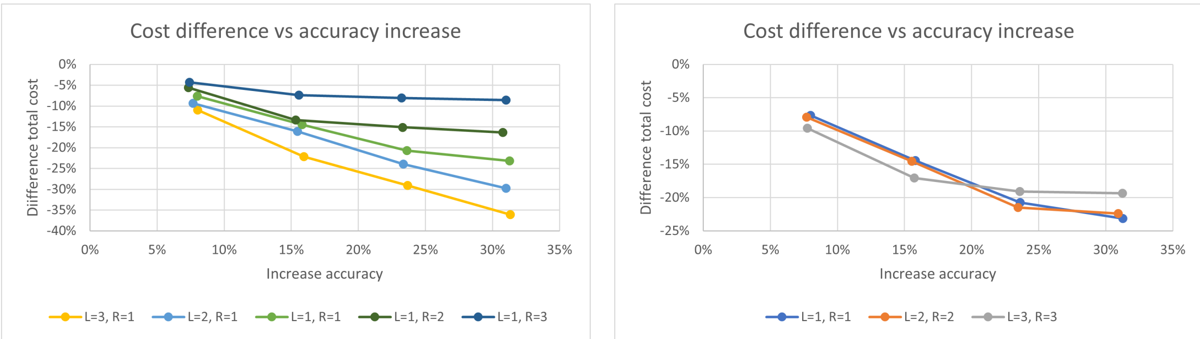


Figure 4.11: Impact lead time and review period for AX item

The lead time and review period have a different impact on the cost differences. The lead time and review period are used to determine the safety stock and reorder level. Longer lead times increase the importance of the forecast accuracy. Figure 4.11 shows that the decrease in costs for the same forecast accuracy increases with the lead time. This can be explained by the safety stock calculations. The safety stock is determined for the forecast uncertainty during L + R. Increasing the lead time increases the protection interval, resulting in a higher impact on the forecast accuracy. The review period shows the opposite effect. The impact on the forecast accuracy decreases with the review period. This is caused by the larger order quantity, resulting in more cycle stock. A larger order quantity requires less safety stock for the same forecast accuracy. The larger order quantity results in more cycle stock and hence more demand fulfilled from stock without needing any safety stock. The impact of the bias also decreases with the increase of the review period. This results in a new trend for a negative bias. The costs decrease with a decrease in forecast accuracy instead of decreasing with an increase in forecast accuracy. Having a review period of 2 results in this new trend for a -5 percent bias and for a review period of 3, this new trend is also seen for a -10 percent bias. Increasing the review period and lead time results in a trade-off between more safety stock and larger order quantity.

Service level

The service level is another parameter that has an impact on the cost differences. A higher service level results in a higher safety factor and triggers more safety stock for the same forecast accuracy. This results in more impact on the forecast accuracy. As a reminder, the backorder costs are determined with the target fill rate. The new fill rate also results in new backorder costs. The increase in backorder costs has very little impact on the forecasts without bias or with a positive bias. The cost difference of improving the forecast accuracy for an AX item with target fill rates of 95%, 97.5% and 99% are shown below in Figure 4.12. Reminder Equation 4.3 is used to determine the cost differences.

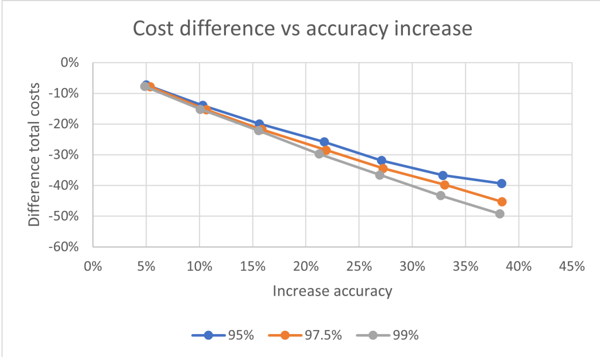


Figure 4.12: Impact service level for AX item

The increase in service level for forecasts without bias results in more financial benefits of an improved forecast. The main cause is the extra safety stock which is triggered with a higher service level. The same holds for the forecasts with a positive bias. A negative bias results in a trade-off between higher safety stocks, higher backorder costs and fewer backorders allowed. Keeping the backorder costs the same results in lower costs for the negatively biased forecasts because more safety stock can be used.

Cost factors

The last variables that influence the impact of the accuracy and bias are the cost factors. As explained in Section 3.4, the holding costs are determined with the item price and the backorder costs with the holding costs and the target fill rate. The third component is the order costs, which is a fixed amount. The impact of the cost factors is investigated by changing the item price. The item prices 1, 10, 100 and 1000 are compared. The results for an AX item with no bias is shown below in Figure 4.13.

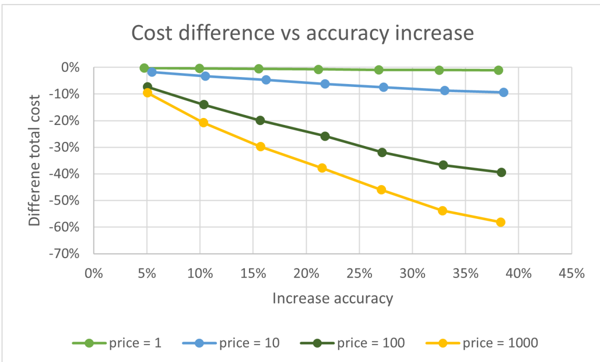


Figure 4.13: Impact price for AX item

The results show that the impact on the forecast accuracy increases with the item price. The same holds for a negative and positive bias. This is caused by the increase in holding and backorder costs while the ordering costs stay the same. The forecast accuracy and bias have an impact on the holding and backorder costs and not on the ordering costs. Increasing the holding and backorder costs decreases the impact of the ordering costs. Shifting the dominant cost factor from ordering costs to holding and backorder costs. This will then increase the impact of the accuracy and bias. The ratio between the item price and order costs is another important factor for determining the impact of the forecast accuracy and bias.

Relation between variables
The analysis of different input variables and item groups showed that the total costs depend on multiple factors. The demand standard deviation and seasonality factor often have no significant impact on the total costs. The safety stocks and reorder levels are based on the forecasts and its errors and not the standard deviation and seasonality. Therefore, are the total costs the same if the same forecast accuracy and bias are achieved. The forecast accuracy is, however, dependent on the standard deviation of the demand. The sMAPE uses the actual demand to determine the relative error. The actual demand, especially when there are periods with low demand, has an impact on the sMAPE. The mean demand does not have an impact on the sMAPE but on the total costs, as more inventory is needed.

The holding and backorders costs depend on the mean demand. The items with more demand have higher holding and backorders costs, resulting in a different ratio with the ordering costs. Hence, the impact of the forecast accuracy decreases for B and C items because the ordering costs become the dominant cost factor, which is independent of the forecast accuracy. The impact of the cost factors causes the same effect. The impact of the forecast accuracy increases with the price/ordering costs ratio.

The lead time has the same effect on all the item groups. A longer lead time requires more safety stock. Therefore, the impact of the forecast accuracy increases with the lead time. The impact of the forecast accuracy decreases with the review period. A longer review period results in a larger order quantity and a longer protection interval. The increase in order quantity decreases the amount of safety stock needed, and the increase of the protection interval increases the amount of safety stock needed. The results show that the increase in order quantity outweighs the increase in the protection interval. Resulting in a decrease in the impact of the forecast accuracy. This is expected because the order quantity increases linearly with R, while the forecast uncertainty of the protection interval increase with the square root of R.

Lastly, the impact of the service level is explored. The higher service level results in a higher safety factor, which is multiplied by the RMSE. Therefore, the impact of the forecast accuracy increases with the service level for the forecast without or with a positive bias. The impact of a negatively biased forecast was a trade-off between higher safety stocks, higher backorder costs and fewer backorders allowed.

4.4.2 Analysis (s, Q) policy

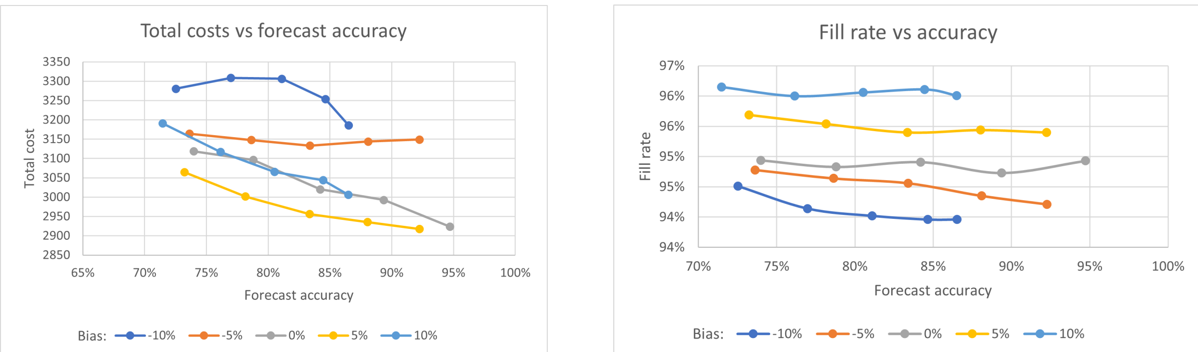
The second inventory control policy used in this experiment is the (s, Q) policy. The (s, Q) policy is a continuous review policy with a reorder level and a fixed order quantity. The forecast-based (s, Q) policy becomes the (s_t, Q_t) policy with a dynamic reorder level and order quantity. The forecast accuracy and bias have an impact on both the inventory control parameters. However, the assumptions of the (s, Q) policy make it more challenging to determine the right reorder levels and safety stocks. The inventory position has to be exactly equal to the reorder level when an order is triggered. The first option for the (s, Q) policy is, assuming that the demand is equally distributed over a day. The demand is then observed with order quantities of size one, solving the problem of the undershoot. However, this causes a problem. The forecasts are often done on a daily, weekly, or monthly basis and updated every period. The new forecasts result in a new reorder level which has to be updated. However, with continuous review and demand equally divided over a day, replenishments can be triggered every moment. When an order is triggered halfway through the day, the wrong forecast is used. With daily forecasts, the forecast is last updated on time t, using the protection interval t+L, but the actual order is then triggered at t+0.5, requiring the protection interval of periods t+0.5+L. The difference between the used protection interval and the actual interval results in lower service levels than targeted. This does not occur when forecasts are flat, but this is not the case now and often not in practice.

Getting the right protection interval can be solved by introducing a review period. The (s, Q) policy becomes an (R, s, Q) policy then. The inventory position will then not be equal to the reorder level when an order is triggered, resulting in undershoot, which must be taken into account. There are several methods for determining the undershoot for stationary demand. Multiple methods for an (R, s, Q) policy are explained in Janssen et al. (1996). However, these methods assume a fixed reorder level and order quantity, which is not the case in the dynamic policy. The dynamic policy also causes another problem. The static policy has undershoot when there is demand. The dynamic policy can also have undershoot when the reorder levels are raised due to an expected increase in future demand. The reorder level can then be raised above the inventory position, also causing undershoot. Lastly, the undershoot is also static and determined with historical data. The forecast-based inventory control policy has then a static part that does not depend on the forecasts. Making the policy less fit for seasonality or other non-stationary demand patterns. The (R, s, Q) is hard to solve, and the identified literature gives no solutions for the above-mentioned problems.

The (s_t, Q_t) is, therefore, a difficult policy in practice. Getting the right service levels with a small deviation from the target is challenging. The identified policy in the literature also results in a deviation between the target and actual fill rates. The deviations make it more difficult to compare the costs of different forecast accuracies and biases.

Undershoot method

The (s_t, Q_t) is used with a review period of one period. The resulting $(1, s_t, Q_t)$ inventory control policy is used. The undershoot method explained in Section 3.3 is used. The mean and standard deviation of the undershoot is determined and added to the forecast and forecast uncertainty to determine the safety stock and reorder level. The order of events is the same as for the (R, S) policy. The reorder level and order quantity are updated at the start of each period. Afterward, the inventory levels are checked, and an order is released when the IP_t is below s_t. Lastly, the demand is deducted from the inventory levels. The results for an AX item with base parameters are shown below in Figure 4.14a.



(a) (R, s, Q) Total costs vs accuracy

(b) (R, s, Q) Fill rate vs accuracy

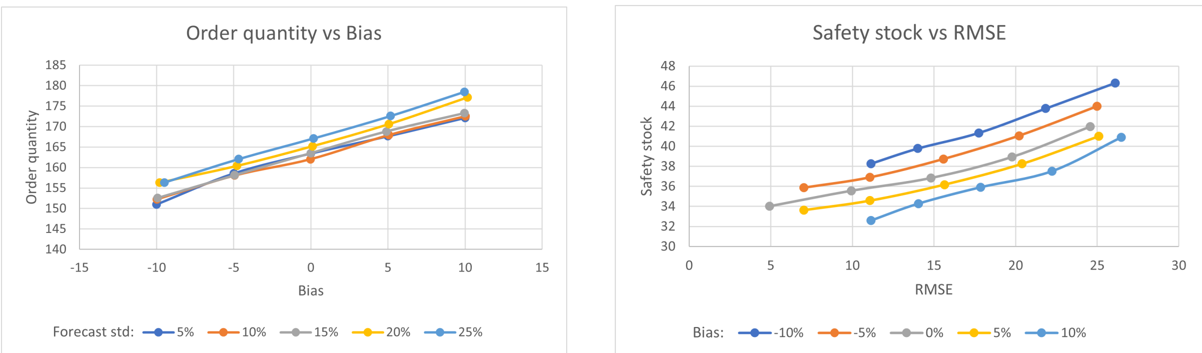
Figure 4.14: Results (R, s, Q) policy

The (R, s, Q) policy shows a decrease in the total costs with an unbiased or positive biased forecast. The negatively biased forecasts show a different behavior, as seen for the (R, S) policy. The costs for the negatively biased forecasts can be explained by the achieved service levels. The differences between the different forecast accuracies and biases are minimal. Most of the differences are not significantly different. The service levels also show smaller differences for the different biases than for the (R, S) policy. The fill rate for a forecast without bias is slightly below the target. The behavior of the policy can be explained by the undershoot, which is a complex variable that mostly determines the safety stock. The impact of the forecast accuracy is, therefore, much less than for the (R, S) policy. The main reason for the 5% bias having the lowest costs is the minimal difference in safety stock, and the forecasts without bias have backorder costs because the service level is slightly below target. The small amount of backorder costs outweighs the minimal difference in holding costs.

The (R, s, Q) policy is a difficult policy and less suited for integrating forecasts. The undershoot is a complex variable that can be estimated for stationary demand. This, however, does not hold for non-stationary demand. The (R, s, Q) policy is, therefore, not well suited for integrating forecasts. The policy results in differences between the target and actual fill rates, even when there is no bias. The same holds for the method used by Babaï and Dallery (2006).

Safety stock
The safety stock is used as a countermeasure for the forecast uncertainty. In this experiment, a target fill rate was used to determine the safety stocks. The safety stock depends on the service level, order quantity, forecast accuracy and bias. The impact of the bias and accuracy is different for an (R, s_t, Q_t) than for an (R, S_t) policy. The bias with an (R, s_t, Q_t) policy also impacts the order quantity and therefore, the safety stock. The relationships between the safety stock and the variables are explained to understand the results better. The first variable is the order quantity. The safety stock increases when the order quantity decreases. The fill rate is the percentage of demand which can be met from stock. A larger order quantity automatically increases the cycle stock and hence, the demand fulfilled from stock. Therefore, the impact of the forecast accuracy on the safety stock is dependent on the order quantity. A large order quantity may not require any safety stock, and the forecast accuracy is then irrelevant. When the order quantity is not too large, and safety stock is needed to reach the target fill rate, the amount of safety stock required increases with the forecast uncertainty.

The impact of the forecast accuracy on the order quantity and reorder level for the (R, s_t, Q_t) policy is shown below in Figure 4.15. The order quantity for different biases and accuracy are shown in Figure 4.15a. The five cases that are plotted have a different bias. The safety stock is shown in Figure 4.15b. The RMSE and safety stock are plotted for five different biases. The dynamic order quantity Q_t is used for the safety calculations.



(a) Order quantity vs mean error

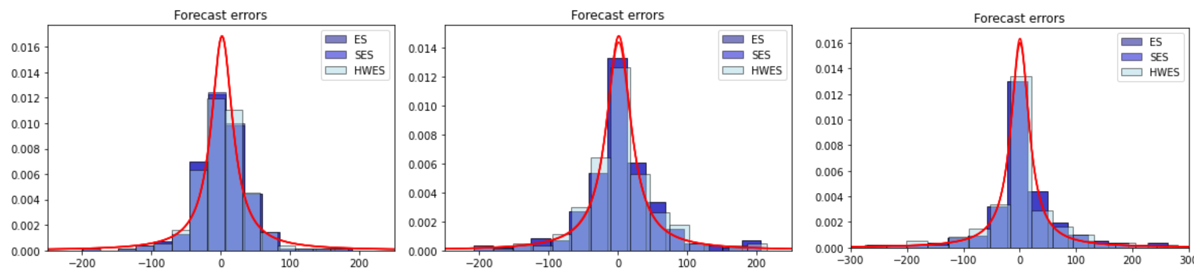
(b) Safety stock vs RMSE

Figure 4.15: Order quantity and safety stock

The results show that the bias has a clear impact on the order quantity. The order quantity is higher with a positive bias and lower with a negative bias. The forecast uncertainty has a small impact on the order quantity because the realized bias is different. The same realized bias for different forecast uncertainties will result in the same order quantities. Knowing that the order quantity increases with a positive bias, which is a negative mean error, less safety stock is needed for the same target fill rate. This is also what the results show, the same forecast uncertainty but with a different bias results in different safety stocks. The safety stock can also be determined by using the expected order quantity by using the mean demand. The safety stock is then independent of the bias, and the same safety stock is used for a negative or positive bias. When the forecasts are used to determine the order quantity, this has to be taken into account.

4.5 Sensitivity analysis

A sensitivity analysis for the (R, S) policy is performed to determine the impact of the forecast error distribution. The Cauchy distribution has been identified as a reasonable fit for the more volatile items. The results of the forecasts errors and the Cauchy distribution can be seen below in Figure 4.16. The Cauchy distribution has heavier tails than the normal distribution and fits, therefore, better for the more volatile items. The red line indicates the PDF of the Cauchy distribution, which is fitted on the forecast errors.



(a) X item (b) Y item (c) Z item

Figure 4.16: Forecast errors with Cauchy distribution

The mean and variance of the Cauchy distribution are not defined. Therefore, are the data transformed to change the mean and standard deviation. The X represents the standard Cauchy distributed data, which has a mean of zero. The mean is changed by adding the constant A to the generated data. The variable B is also a constant and is multiplied with the data to change the standard deviation. So, the demand is generated by using the following equation:

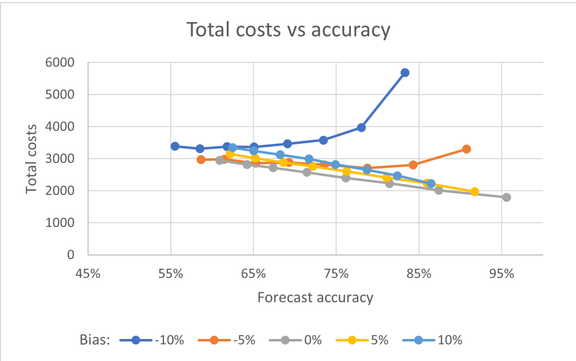
$$y = A + B * X \tag{4.4}$$

The variable A is used to shift the demand distribution and the variable B to increase the standard deviation. The variables A and B are used to get approximately the same accuracies and biases as for the normally distributed errors by using trial and error. The impact of the more heavily tailed forecast errors is determined by repeating the experiments in Section 4.4.1.

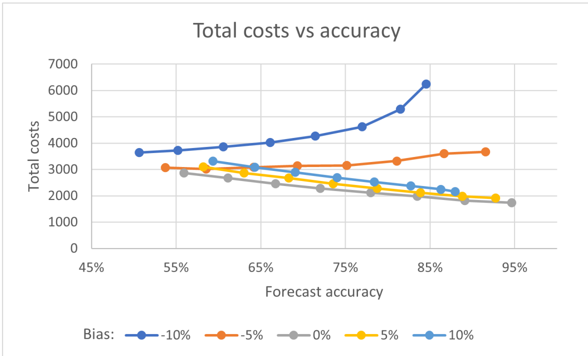
Results

The results of the simulations with Cauchy distributed forecast errors are used to determine the impact of the assumed forecast error distribution. As explained above, the mean and standard deviation of the Cauchy distribution are undefined. Therefore, it is impossible to get exactly the same forecast error parameters. This causes small differences between the normal and Cauchy distributed forecast errors. The results for an AX item are shown in Figure 4.17.

The results on the lefts side in Figure 4.17a show for the items without a bias or with a positive bias the same trend and only small differences in costs. The deviations can be explained by slight differences in the accuracy and bias, the distribution being more centered around the mean and its heavier tails. The costs for a negative bias differ the most. This is caused by the heavy tails of the Cauchy distribution. The heavy tails result in more extreme values of the forecast errors. This causes more often the violation of the assumption that the forecast cannot be negative, resulting in a lower actual negative bias. The results show that the costs of the negative bias forecasts are slightly lower than for the normally distributed forecast errors. This is logical because the lower negative bias results in fewer penalty costs, which is the dominant cost factor when a negative bias exists. So, the generated forecasts with a negative bias result in a lower actual bias and have, therefore, lower costs. The impact of the Chauchy distribution on the results is limited. The same overall trend is seen and the costs are often very close to those of the normal distribution.



(a) Total cost vs accuracy Cauchy



(b) Total cost vs accuracy Normal

Figure 4.17: Cauchy vs normal distributed forecast errors

4.6 Conclusion

In this chapter, an experimental study has been used to explore the financial benefits of an improved forecast. The impact of the forecast accuracy, bias and other factors on the inventory control performance was determined by simulating different scenarios. Three sub-questions were developed to answer Research Question 3.

3a. *What are the financial benefits of integrating forecasts into the inventory control policies?*

3b. *How does the forecast-based inventory control policy perform given a forecast accuracy and bias?*

3c. *Which inventory control parameters are important for determining the impact of the forecast accuracy and bias?*

The results of the (R, S) showed that the integration of forecasts could significantly decrease the costs in most cases. The (R, S) policy is well suited for integrating forecasts, and especially when demand is non-stationary, huge opportunities for integrating forecasts exist. The (s, Q) policy, however, is a difficult policy for integrating forecasts. The assumption of continuous review and periodical forecast updates caused misalignments, resulting in deviations between the target and realized fill rate. There was no method identified that could solve this problem, especially for non-stationary demand. The results of integrating forecasts into the inventory control policy answer Research Question 3a.

The impact of the forecast accuracy and bias have been extensively investigated in the experimental study. The bias has a large impact on the inventory control policy. In particular, the negative bias results in a large increase in costs. The impact of the forecast accuracy depends on the bias. Improving the forecast accuracy only reduces the costs when the forecast is unbiased or positively biased. The best inventory control performance is always realized with a high forecast accuracy and no bias. Research Question 3b is answered with the different experiments of the forecast accuracy and bias.

At last, Research Question 3c is answered. The inventory control parameters that influence the impact of the forecast accuracy and bias are identified. The important factors that influence the financial benefits of an improved forecast are the demand characteristics, lead time, review period, service level and cost factors. The relation between the identified factors and the forecast accuracy and bias answers Research Question 3c.

Chapter 5

Prediction model

To reach the research goal, a model has to be developed that can quantify the financial benefits of an improved forecast for a case. The simulation models cannot be used for this because of the computation time. So, a new prediction model has to be developed that can be used for a case study. The insights and results of the experimental study are used to develop the prediction model. This chapter is dedicated to the development of the prediction model and answers the following research question:

4. How can a prediction model for quantifying the financial benefits of an improved forecast be developed?

The following sections are used to answer the research question. Section 5.1 explains the approach and why the simulation models cannot be used for a case study. In Section 5.2 are machine learning models presented that can be used as prediction models. Section 5.3 presents the results and the final prediction model. The conclusion of this chapter is given in Section 5.4.

5.1 Approach

The experimental study in Chapter 4 showed that the impact of the forecast accuracy and bias depends on multiple variables. The forecasts with different accuracy and bias were generated using the forecast errors. However, the experimental study showed that the realized forecast accuracy and bias depend on the demand characteristics and forecast error parameters. Therefore, it is hard to use the simulation model to get the same forecast accuracy and bias as achieved on a case. The prediction model has to be able to use a given forecast accuracy and bias as input for quantifying the financial benefits of an improved forecast. The simulation model would have to run many trials to get the same forecast accuracy and bias given as input. The computation time for such a model would be too large to be used on a case. The number of combinations of input variables is also too large to create a table with different scenarios and use a look-up to get the corresponding financial benefits of two forecast accuracies and biases. A new model has to be developed that is able to predict the financial benefits of an improved forecast given the forecast accuracy, bias and other identified factors as input.

The simulation model is used to generate a large number of data points that can be used by a model to learn the dependency between the input and output variables. Machine learning models can be used for this type of predictions. The machine learning models can learn the dependencies between the total costs and forecast accuracy, bias and other identified factors. The financial benefits can then be quantified by taking the difference of the total costs of the old and new, improved forecast. Only the (R, S) policy is used because the (s, Q) policy could not integrate forecasts correctly. This policy is widely applicable and also an appropriate policy for the case study.

5.2 Machine learning

Several machine learning models are used to determine the best model. The models tested are: Multi-layer Perceptron (MLP), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), eXtreme Gradient Boosting (XGB), Light Gradient Boosting Machine (LGBM), CatBoost (CB), Natural Gradient Boosting (NGB). A detailed explanation of the models can be found in Makridakis et al. (2018b), Chen and Guestrin (2016), Ke et al. (2017), Hancock and Khoshgoftaar (2020), Duan et al. (2020). The models need to be capable of handling a large amount of data. The results of the different machine learning methods are compared to determine the best model. The accuracy and bias are used to determine the performance of the prediction models.

The models are trained on a data set, which is a large number of simulation scenarios. The data set consists of 80,000 observations with different demand, inventory and forecasting characteristics. The parameters that are used for the simulations can be found in Appendix C. The same parameters are used as input for the prediction model, except for the forecast error standard deviation, mean error and seasonality. The forecast accuracy and bias metrics are used instead of the forecast error parameters, and the seasonality is included in the standard deviation. The sMAPE and PB are used as forecast accuracy and bias metrics. The same metrics are used for the forecasting models for the case study. So, the prediction models use the accuracy, bias, price, review period, lead time, target fill rate, mean demand, and demand standard deviation as input variables. These variables have been identified as important for determining the financial benefits of an improved forecast in Chapter 4. The prediction models use the input variables to predict the output variable, which is the total costs.

The first step is to split the data into a training and test set. The training is used to train the prediction model and the test set to determine the prediction model's accuracy. The train-test split is set at 80%-20% and is randomly sampled. So, the prediction models are first trained on 80% of the data. Next, the model predicts the total costs for the remaining 20% of the data. The prediction model accuracy is determined by comparing the predictions with the actual costs. Note that the prediction model accuracy is now determined. This has nothing to do with the forecast accuracy. The sMAPE is used to determine the prediction model accuracy and the MPE for determining the bias. The MPE is preferred over the PB because the bias per item is important. The model should have a small bias on all the items. In this case, the PB looks to the overall bias for all predictions, which puts a heavier weight on the cases with a high total cost.

Secondly, the input data are normalized such that the input range is between 0 and 1. Normalizing the data can improve the accuracy of the used model (Singh and Singh, 2020), and is important for supervised machine learning models (Kotsiantis et al., 2006). The min-max normalization is used in this research. The min-max normalization is done with the following formula:

$$x'_i = \frac{x_i - min(x)}{max(x) - min(x)} \tag{5.1}$$

The normalized input is used to train the model and make predictions. The min-max normalization uses the train data set to determine the minimum and maximum values. The test set is not used for this to get a realistic estimate of the prediction model accuracy.

The hyperparameters optimization of the machine learning models is done with the Optuna package (Akiba et al., 2019). Optuna uses a combination of efficient searching and pruning algorithms to improve the hyperparameter optimization effectiveness significantly. The Optuna packages support the pruning of non-promising hyperparameters for several models, saving computation time. The results of the hyperparameter optimization for the best model are discussed in the next section.

5.3 Model results

The models with the corresponding best hyperparameters are used to make predictions for the test set. The predictions are compared with the actual values to determine the accuracy and bias of the prediction models. The accuracy is determined with the sMAPE, which is given in Equation 2.7. Also, the bias is measured for the prediction model. The MPE is used to measure the bias, the formula is given in Equation 2.11. The results of the different models are compared to determine which model is the best suited for quantifying the financial benefits. The results of the models are shown in Table 5.1.

The XGB, LGBM, CB and NGB are the best performing models. All these models use gradient boosting. This is one of the most powerful machine learning techniques for developing prediction models. The MLP, KNN, SVM and RF have a lower accuracy and a higher bias. The prediction is often significantly overestimated. The high bias also results in a lower sMAPE and hence, higher accuracy. These models are less suited as prediction models for this problem.

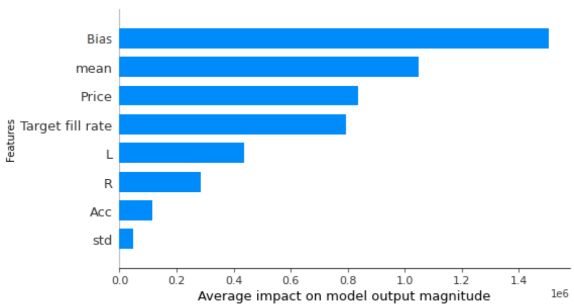
The Catboost model has the highest accuracy and only a small bias. The Catboost is chosen over the LGBM because of the higher accuracy. The accuracy was used as objective and for the hyperparameter optimization. Therefore, is the accuracy more important than the bias. So, the CatBoost model is used for the case study to quantify the financial benefits of an improved forecast. The results of the parameter optimization for the CatBoost model can be found in Appendix D. None of the hyperparameters reached the optimization bounds, and increasing the number of trials did not improve the accuracy anymore.

Model	MLP	KNN	SVM	RF	XGB	LGBM	CB	NGB
Accuracy	72.85%	65.65%	65.67%	72.71%	83.27%	88.01%	90.06%	88.17%
MPE	-9.32%	-49.56%	-32.34%	-12.75%	-4.36%	0.74%	-2.52%	-2.50%

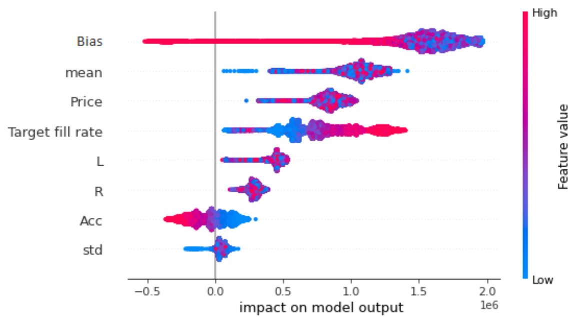
Table 5.1: Accuracy prediction models

The results of the CatBoost model, feature importance and impact on the output are further investigated to get an understanding of the model's behavior. The output is, in this case, the total costs. The feature importance of the CatBoost model is shown in Figure 5.1a. The average impact of the input features on the total costs is used to rank the input features. Figure 5.1b shows the feature values and the impact on the total costs.

The bias has by far the highest impact on the total costs. A negative bias has more impact than a positive bias, as can be seen in the figure. This is in line with the results of the Chapter 4. Figure 5.1b shows that the impact of the positive bias can differ. The impact of the bias depends on other factors. The mean demand, target fill rate and price also have a relatively high impact on the total costs. The impact of the mean and price depend on each other. For example, a high mean with low price results in a low impact of the mean. However, a high mean with a high price results in a high impact of the mean. The same holds the other way around for the price. The target fill rate increases the total costs when the input value is higher, as can be seen in Figure 5.1b. The impact of the lead time and review period depends on other factors. The lead time and review period have an impact on the safety stock. For example, the impact can be low when a high accuracy is realized and no safety stock is required. The impact of the forecast accuracy shows a clear difference. The high accuracy has a negative impact on the total costs. On the other hand, a low accuracy results in a higher prediction of the total costs, as expected. The standard deviation has the smallest impact and shows no clear difference between high and low values. The target fill rate and accuracy are the only two variables that show a clear difference between high and low. These variables are directly related to the safety stock, resulting in different costs. The impact of other input variables depend on other factors and show non-linearity.



(a) Feature importance



(b) Feature impact

Figure 5.1: Features CatBoost

5.4 Conclusion

As discussed at the beginning of this chapter, the simulation model could not be used to predict the financial benefits of an improved forecast for a case. Another prediction model had to be developed to quantify the financial benefits of an improved forecast. The results of this chapter answer the three sub-questions of Research Question 4.

4a. What are appropriate prediction models for quantifying the financial benefits?

4b. Which prediction model is the best suited for quantifying the financial benefits?

4c. How accurate can the prediction model quantify the financial benefits?

Research Question 4a has been answered by identifying several machine learning models that can be used for predicting the financial benefits of an improved forecast. The simulation models could not be used as prediction models because of computation time. The machine learning models provide a good alternative and can be used for a case study.

The machine learning models have been trained on a large simulation output data set. The data set is based on different scenarios of the identified input variables. The data was split into a training and test set to determine the performance of the machine learning models. The CatBoost model was identified as the best performing model, answering Research Question 4b.

The results of the machine learning models showed that the CatBoost model could predict the financial benefits of an improved forecast with a 90.06% accuracy. The model has only a small bias of -2.52%. This answers Research Question 4c.

Chapter 6

Case study

The research goal is to develop a model that can quantify the financial benefits of an improved forecast, and apply this to a case. A prediction model has been developed in Chapter 5. This chapter is used to apply the prediction model to a case.

The chapter is organized as follows. Section 6.1 gives the case description. In Section 6.2 is the ABC-XYZ analysis performed to get insights into the items and their characteristics. Afterward, in Section 6.3, the pre-processing steps for forecasting are explained. In Section 6.4 are the results of the forecasting models presented. The achieved forecast accuracy and bias are used as input for the prediction model to quantify the financial benefits of an improved forecast. At last, Section 6.5 presents the results of the case study.

6.1 Case description

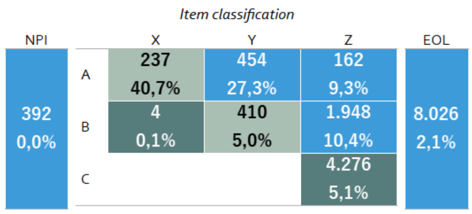
The case consists of 2 years of historical sales data of a company active in the process industry. The sales data of two countries is available. The data consist of daily demand data at the customer level. The forecasts are done on the country/weekly aggregation level. This results in 15.913 demand forecasting units. The items are first split into three groups using the life cycle: New Product Introduction (NPI), End Of Life (EOL) and Active. The NPI group consists of items that have up to three months of positive demand. Items that have three months of no demand after the last observed positive demand are EOL. All the other items are classified as Active, and are used for the ABC-XYZ classification. The NPI and EOL items are also excluded from the forecasting process. The lead time and review period are for the case equal to one week. The time lag for determining the forecast accuracy and bias is, therefore, equal to three periods. The mean demand of the item groups are plotted in histograms to get an idea of the volume of the items for the case. The histograms can be found in Appendix E. A large part of the items has a low volume. There are five items with a mean higher than 100, with the two highest volume items having a mean around 500. The average demand of the A, B and C item groups are respectively 12.83, 1.16 and 0.71. This is lower than the used volumes in the experimental study.

6.2 ABC-XYZ analysis

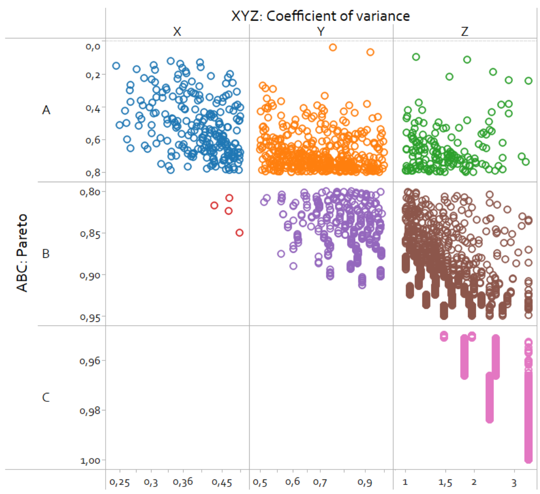
The ABC-XYZ analysis was used in Chapter 4 to experiment with different items and is now used to get an idea of the items and their characteristics. The ABC-XYZ analysis is based on the sales data of the last year with a weekly/country aggregation level. The ABC analysis is performed on the sales volume with the threshold between A and B on 80 percent and between B and C on 95 percent. So, the A items generate 80 percent of the sales, B items 15 percent and C items 5 percent. The XYZ analysis is performed on the coefficient of variation of items, with the threshold between X and Y on 0.5 and between Y and Z on 1. The results of the ABC-XYZ classification are shown in Figure 6.1.

The first number in Figure 6.1a for the item groups indicates the number of items in the group. The percentage below the number of items is used to indicate the percentage of total sales of that group. Items that are NPI or EOL receive no ABC-XYZ classification. The number of NPI and EOL items are shown on the left and right side of the ABC-XYZ classification. The ABC Pareto values and coefficient of variations are shown in Figure 6.1b. The distribution of the items into the item groups gives an overview of the items and their characteristics. Because the ABC classification is based on volume and has a weekly level aggregation level, it is possible that there are no CX and CY items. The low-volume items are irregular, resulting in a high coefficient of variations. This also causes the vertical lines in the CZ item group. The items have the same low sales value and hence the same coefficient of variation.

The ABC-XYZ item groups are also used for determining the inventory control strategy. The target fill rate is matched with the item groups, which have different priorities. The A items have the highest business value and therefore, the highest target fill rate. For this case, the target fill rates are for the A, B, C items equal to 98%, 97% and 95%, respectively.



(a) ABC-XYZ results



(b) ABC-XYZ distribution

Figure 6.1: ABC-XYZ analysis

6.3 Pre-processing

The data requires several pre-processing steps before the data are in the right format and ready to be used for forecasting. Besides putting the data in the right format, outliers have to be corrected. The aggregation and outlier correction steps are explained in this section.

Aggregation level

The daily historical data are available for forecasting. The data are aggregated to a lower time-frequency, also known as temporal aggregation. The new aggregation level is used to match the forecasts with the decision for inventory control. The aggregation of daily demand into weekly or monthly time buckets also decreases the probability of zero demand observations and generally reduces the uncertainty of demand (Rostami-Tabar et al., 2013). It is, therefore, preferable to aggregate to weekly or monthly time buckets than having a long forecasting horizon. As mentioned before, the aggregation level for the case is weekly.

Outliers

The statistical forecasting methods assume that historical sales is a good predictor for future sales. To improve the forecasting performance, data cleaning is used for historical sales. Outliers will be removed using the z-score method. Sigma is used to determine the upper and lower bounds for each item. The observations that are out of bound are marked as outliers and corrected to the average. The sigma for determining the bounds is set at 2.5.

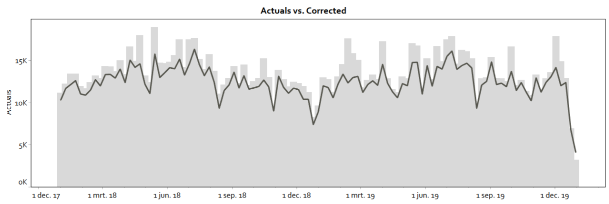


Figure 6.2: Overview outlier correction total demand

6.4 Forecast accuracy and bias

To determine the financial benefits of an improved forecast, a forecast is done using statistical forecasting models. The statistical forecasting models are used as baseline forecast. The achieved forecast accuracy and bias are used as input for the prediction model. The financial benefits of improving the reached forecast accuracy and bias are determined.

The forecast accuracy and bias are determined on SKU/country level. The sMAPE and PB are used as metrics for determining the accuracy and bias. Several forecasting models are tested. The best model and corresponding parameters are determined for each demand forecasting unit. The forecast models used are MA, SES, DES, HWES and Croston, as these are often used in practice, and also used for forecasting fast scans at EyeOn. The results of the total actual and forecasted demand are shown below in Figure 6.3.

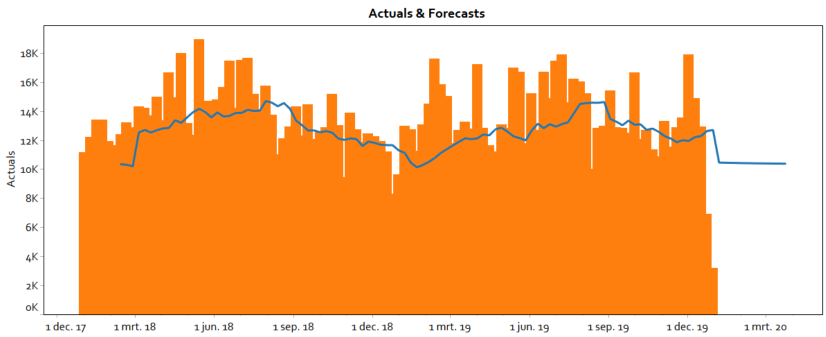


Figure 6.3: Total actual and forecasted demand

The last week was excluded for determining the forecast accuracy and bias because this week is incomplete. The week starts on Monday 30 December and only includes two days of sales data. The weighted average can be used to determine the accuracy and bias of item groups. The forecast accuracy and bias are shown in Figure 6.4 for the ABC-XYZ classification. The accuracy is shown on the left side and the bias on the right side. As seen before, there are no CX and CY items.

The results show that the forecast accuracy decrease with X, Y, Z, respectively. This is expected as the more volatile items are harder to forecast. The overall weighted forecast accuracy is equal to 57.2% and bias equal to -4.9%. The bias is for most item groups negative, except for the CZ items. The AZ item group has a relatively large negative bias. The forecast accuracy and bias on item level are used in the next section as input for the prediction model. It is important to note that the bias shown here is a weighted average. The bias on item level can be much larger for some items.

	Forecast accuracy		
	X	Y	Z
A	72,8%	58,9%	34,9%
B	55,3%	51,9%	40,5%
C			20,5%

	Forecast bias		
	X	Y	Z
A	-1,4%	-6,2%	-17,4%
B	-8,0%	-1,7%	-3,7%
C			0,5%

Figure 6.4: Forecast accuracy and bias

6.5 Results case study

The forecast accuracy, bias, demand characteristics and inventory parameters for the case are used as input for the prediction model. The model is used to predict the total costs for two given forecasts. The total costs of the forecast accuracy and bias reached by the statistical forecasting models are used as a baseline. The total costs of reaching a higher forecast accuracy or lower bias are compared with the costs corresponding to the statistical forecasting models. The costs of the baseline and improved forecast are compared to determine the financial benefits of an improved forecast.

The inventory control parameters are one of the input variables. The lead time and review period are one week and the same for all the items. The item price is estimated between 100 and 500 for the different items. Because the price is unknown, the assumption is made that the item price is discrete uniform distributed between 100 and 500. The impact of the price uncertainty due to the distribution is minimal. Nevertheless, the prediction is repeated ten times to get a good estimate of the results. The A, B, C items have a target fill rate of 98%, 97% and 95%, respectively. The sMAPE, PB, mean demand and standard deviation of the demand are determined for each item and also used as input. Only items with a mean higher than 0.5 are included in the estimation of the financial benefits. The items with a mean lower than 0.5 are excluded because they are very hard to forecast, and with a short lead time and review period, the added value of improving the forecast for these items is assumed to be zero.

The forecast accuracy and bias are plotted in a histogram. The results are shown below in Figure 6.5. The forecast accuracy is shown on the left and the forecast bias on the right. The histogram of the bias shows that more items have a negative bias than a positive bias. The histograms of the accuracy, bias and demand for the ABC-XYZ item groups can be found in Appendix E. The results show that the accuracy decreases for the X, Y, Z item groups, respectively. On the other hand, the bias increases for the X, Y, Z item groups, respectively. The same is seen for the ABC item groups but to a lesser extent. This is logical because the B item group has only a few X items and the C item group has only Z items.

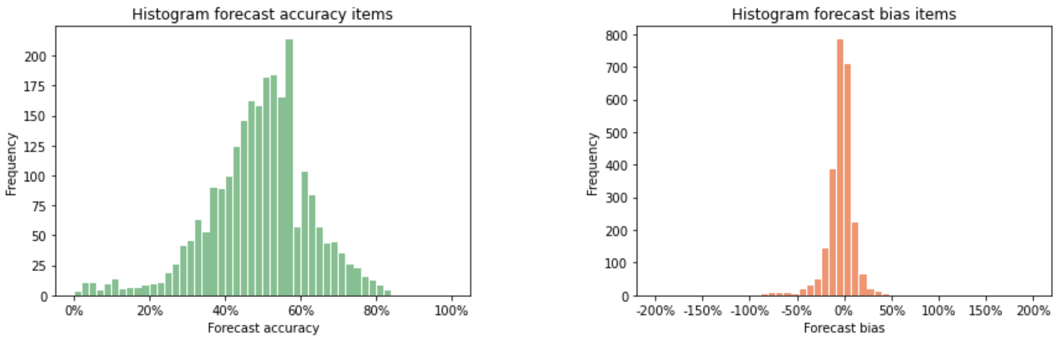


Figure 6.5: Forecast accuracy and bias histograms items

The prediction model developed in Chapter 5 is used to estimate the costs of each item. The total costs of all items are compared with the new total costs of a improved forecast to determine the percentage cost difference. The forecast accuracy is increased with steps of 5% and the upper bound on item-level is set at 100%. Reducing the bias is a bit more difficult. The bias is decreased with steps of 10%. If the bias of the item is smaller than the percentage decrease, the bias is set to zero. Improving the bias with 100% is reducing the bias for every item to zero. The results of the model for increasing the accuracy and decreasing the bias are shown below in Figure 6.6.

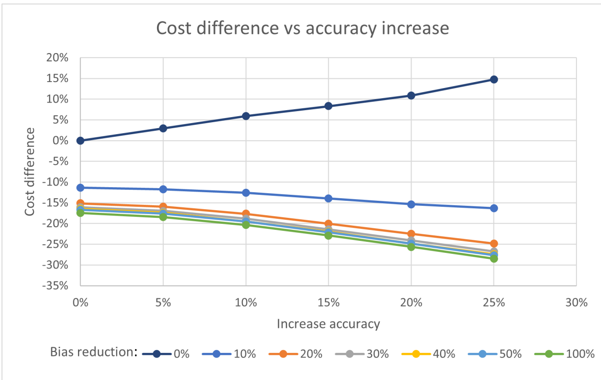


Figure 6.6: Cost reduction vs forecast improvement

The results show that increasing the forecast accuracy increases the total costs with the current bias. The experimental study showed that increasing the accuracy with a negative bias resulted in higher costs. The same is seen for the case, as the overall bias is -4.9%. Reducing the bias by 10% changes this. Increasing the forecast accuracy then results in lower costs. The impact of further reducing the bias with 30%, 40%, 50% and 100% is small, as only a few items have a bias this large.

The overall results show that the bias is the most important factor for this case and should be reduced as much as possible. Besides the costs benefits of reducing the bias, the impact of improving the forecast accuracy also increases. The total costs can be reduced by approximately 17.5% if an unbiased forecast is realized. The costs can be further reduced to 20.31% and 25.64% if the forecast accuracy is increased by 10% and 20%.

The results of the case study show the importance of the bias. The assumption of inventory control policies that forecasts are unbiased does not hold in practice. Especially, the negative bias can be devastating for the inventory performance. The forecast accuracy can also significantly reduce the costs but only when the forecast bias has been reduced.

Chapter 7

Conclusion and discussion

In this chapter are the conclusions drawn, recommendations given and is reflected on the research. Several research questions were used to systematically achieve the research goal and answer the main research question. In Section 7.1 are the research questions answered based on the results of this research. Next, in Section 7.2 are recommendations given. Section 7.3 reflects on the scientific contribution of this research. In Section 7.4, the main limitations of the research are discussed. Lastly, in Section 7.5 are options for future research provided.

7.1 Research questions

In this thesis is the interaction between forecasting and inventory control studied to identify the financial benefits of an improved forecast. The challenges of EyeOn and the absence of literature were addressed in this research. The answers to the research questions are presented in this section.

1. *Which forecasting models can be used for inventory control, and how can their performance be measured?*

A literature review on demand forecasting was performed to identify two different forecasting methods. The first forecasting method consists of several statistical forecasting models. The forecast models MA, SES, DES, HWES and Croston are often used in practice and also used in the case study to determine the forecast accuracy and bias. The second method used the forecast error and demand data to create forecasts of different qualities. The forecast error distribution and corresponding parameters were used to change the forecast accuracy and bias. This method was used in the experimental study to explore the impact of the forecast accuracy and bias independently.

To get a good estimate of the forecast accuracy and bias, several forecasting metrics were identified and used throughout this research. The sMAPE and PB have been selected as metrics for determining the forecast accuracy and bias. These metrics were preferred over the MAPE and MPE. The MAPE and MPE are undefined when the actual values contain zero values and can take extreme values when the actual demand is very low. The RMSE has been used to estimate the forecast error standard deviation. The RMSE was preferred over the MAD because it is more widely applicable.

2. *What are appropriate inventory control policies and how can forecasts be integrated?*

The literature on inventory control was used to identify applicable inventory control policies. The existing literature on the interaction between forecasting and inventory control is, however, limited compared to the research on the distinct fields. The (R, S) and (s, Q) policy are often used in practice and could both integrate forecasts. The forecast-based inventory control policies use a dynamic order-up-to-level or reorder level to better anticipate changing demand patterns. The decision variables are determined based on the forecasts and its errors. The inventory control policies assume unbiased forecasts as input. So, the safety stock is only determined with the accuracy and not the bias.

3. *How does the performance of the inventory control policies depend on the forecast accuracy, bias and other factors?*

An experimental study was used to explore the relationship between the forecast quality and inventory control performance. The forecast-based (s, Q) policy had a significant deviation between the actual and target fill rate. The assumption of continuous review and that the reorder level is exactly equal to the IP when a replenishment is triggered caused misalignments between the forecast updates and reorder levels. No method has been identified that solves this problem, especially for non-stationary demand. The (R, S) policy was well suited for integrating forecasts. The integration of forecasts resulted in lower costs in every case, except for stationary demand with a high negative bias.

Next, the impact of the forecast accuracy, bias, demand characteristics and inventory control parameters on the forecast-based inventory control policy was determined. The results showed that the bias had more impact on the inventory control performance than the forecast accuracy, and that the lowest costs were always achieved with an unbiased forecast. The impact of the forecast accuracy, on the other hand, depended on the magnitude of the bias. The results showed that the inventory control performance could decrease with an increase in accuracy when the forecasts had a negative bias. Furthermore, the results showed that the impact of the accuracy and bias increased with the demand volume, lead time, target fill rate and item price. The impact of the accuracy and bias generally decreased with the review period because of the larger order quantity, needing less safety stock to reach the target fill rate.

4. *How can a prediction model for quantifying the financial benefits of an improved forecast be developed?*

The results of Chapter 4 were used to develop a prediction model that can quantify the financial benefits of an improved forecast for a case. The simulation models could not be used because of computation time. Machine learning models were a good alternative and were used as prediction models. Several machine learning models were tested to find the best model. The machine learning models were trained on a large simulation output data set to learn the relationship between the identified input variables and total costs. The accuracy and bias were determined for each prediction model, and the CatBoost model performed the best. The CatBoost model had the highest accuracy and could estimate the financial benefits with a 90.06% accuracy and had only a bias of -2.52%.

Main research question and research goal

The goal was to develop a model that could quantify the financial benefits of an improved forecast, and apply it to a case. The goal resulted in the main research question, which is answered in this thesis. The goal and main research question were stated as follows:

> *Develop a model to quantify the financial benefits of an improved forecast for a forecast-based inventory policy given a service level target, and apply this to a case.*

This research goal resulted in the following main research question:

> *What are the financial benefits of an improved forecast for a forecast-based inventory control policy given a service level target?*

A case study was performed to estimate the financial benefits of improving statistical forecasting models using the prediction model. The forecasting models had an overall negative bias, which has a high impact on the inventory control performance. The estimated total cost reduction is approximately 17.5% if an unbiased forecast is realized. The costs can be further reduced to 20.31% and 25.64% if the forecast accuracy is increased by 10% and 20%.

Taking the all the research questions together, a general conclusion can be drawn. Based on the findings of this research, a large opportunity for integrating forecasts into inventory control exists. The performance of the inventory control policies depends greatly on the forecast accuracy, bias and other identified factors. The bias has the highest impact on the inventory control performance. The inventory control performance can be significantly improved by reducing the bias, and the lowest costs are always realized with an unbiased forecast. The impact of accuracy improvements depends on the magnitude of the bias. The inventory control performance is not always improved with a higher forecast accuracy because unbiased forecasts are assumed. The prediction model can quantify the financial benefits of an improved forecast and show the actual value of forecast improvements.

7.2 Recommendations

The implications of the results of this research results in recommendations for EyeOn. The following recommendations are given:

- The prediction model should be integrated with an inventory or forecast assessment. The financial benefits of improving the forecast accuracy and bias can be quantified by the prediction model and show the actual value of improving the forecast.
- It is recommended to use the prediction model for other cases to further explore the financial benefits of an improved forecast. The financial benefits for other industries and companies can be determined.
- The model should be validated, which can be done in several ways. Business experts, customer surveys or the computationally expensive simulation model can be used to validate the estimated cost savings of improved forecasts.
- The importance of the bias has been one of the main findings of this research. The forecast-based inventory control policies assume unbiased forecasts. This is a common assumption in inventory control that is violated in practice. The inventory control policies should include the forecast bias and compensate for over or under-stocking. It is recommended to further investigate the role of the forecast bias on inventory control. This is also recommended for future research.

7.3 Scientific contribution

In this thesis, is the interaction between demand forecasting and inventory control investigated. The existing research on forecasting and inventory control has mainly focused on the distinct fields and not on the interaction between them (Gardner, 1990; Syntetos et al., 2009; Petropoulos et al., 2019). This research used two different inventory control policies to investigate the integration of forecasts into inventory control and the financial benefits of an improved forecast. The main goal of the thesis was to quantify the financial benefits of improving the accuracy or reducing the bias. This research differs from the existing literature because it investigated the impact of the accuracy and bias in a general way. The forecast errors and their distribution are used to determine the impact of forecast accuracy and bias independently. The existing literature focused on the performance of forecasting models and their impact on inventory control.

This thesis went beyond the theoretical insights by applying the results to a case study. The insights gained in this thesis are used to develop a prediction model which can quantify the financial benefits of an improved forecast. The prediction model is able to estimate the inventory costs given the identified input variables. The financial benefits of improving the forecast for a case are quantified and discussed.

To the best of our knowledge, has the impact of the forecast accuracy and bias on inventory control not been studied with the same methodology. Therefore, the results are a contribution to the scarce literature on the interaction between forecasting and inventory control. Providing new insights into the forecast accuracy and bias by quantifying the potential benefits of improving forecasts.

7.4 Limitations of the research

This research contains some limitations, which provide areas for improvement and could be used for future research.

The first limitation of this research is the assumption of the independent and identical distributed forecast errors. This assumption is often made in the literature and used in this research to investigate the impact of the forecast accuracy and bias. The resulting forecasts may be too well behaved because of this assumption. The forecast errors of items in practice may violate the assumptions made for inventory control.

Secondly, the limitation of using the prediction model for one case study has to be mentioned. The prediction model is developed for a given range of input parameters. The input parameters of other cases may be outside the used bounds or be concentrated on a small range of parameters. More cases would strengthen the applicability of the prediction model.

Thirdly, the experimental study showed the difficulty of the assumption of continuous review for inventory control. The (s, Q) policy is less suited for integrating forecasts, and the applicability is limited. The further investigation of the (s, Q) policy was left out of scope. This problem is an interesting area for future research.

Lastly, the limitation of keeping trend items out of the analysis is important to mention. The trend items are left out of scope because they require another approach. The assumption that the magnitude of forecast errors is equal over time would not be valid. Seasonality patterns are returning cycles, assumed to result in the same forecast errors over time. Trend items would have an increasing or decreasing demand pattern, changing the magnitude of the forecast errors.

7.5 Future research

The limitations and insights of this research provide several options for future research. The options for future research are given below:

This research investigated the impact of the forecast accuracy and bias by using the forecast errors. The distribution of the forecast errors and possible correlations between forecast errors should be further investigated. Investigating the forecast errors in practice and checking whether the assumptions hold would be of value. In this research, two forecast error distributions have been used. Investigating more forecast error distributions would also be interesting.

This research showed the impact of the bias on the inventory control performance. The inventory control policies assume unbiased forecasts, which is violated in practice. An interesting topic for future research would be to develop a method that can correct biased forecasts. The bias should be included in the safety stock calculations to optimize the inventory control performance.

As mentioned before, further investigating the integration of forecast into the (s, Q) policy would be interesting. This research was limit in investigating the integration of forecasts into this policy. However, several important factors, which have to be taken into account, are identified. Further researching the policy and the integration of forecast would be an interesting option for future research.

The metrics used in this research to determine the forecast accuracy and bias are often used for forecasting. However, new forecast metrics may give a better indication of the forecast quality for inventory control. For example, the shape or distribution of the forecast errors may also be an important KPI to include in the validation of the forecast quality, as this is important for the inventory control models. Further research is needed to explore the impact of different forecast metrics.

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Appendix A

Approximation safety stock normal distribution

The safety stock for a target fill rate with the normal distribution can be approximated. The study of Waissi and Rossin (1996) provided a very accuracy approximation which can speed up the simulation significantly. The following formula can be used to meet the target fill rate:

$$Gu(k) = \frac{Q}{\sigma_L} * (1 - P_2) \tag{A.1}$$

Where P_2 is the target fill rate, σ_L the standard deviation during lead time and Q the order quantity. The Gu(k) is the loss function and is the expected number of shortage per order cycle. The mathematical definition of Gu(k) is:

$$Gu(k) = f_u(k) - k * p_{u\geq}(k) \tag{A.2}$$

The standard normal probability density function (pdf) is $f_u(k)$ and the standard normal cumulative density function (cdf) is $F_u(k)$. Gu(k) can be solved by computing the following equation:

$$Gu(k) = f_u(k) - (1 - F_u(k)) * k \tag{A.3}$$

The equation above can be used to determine the service level of a given safety stock. The expected shortages per replenishment cycle (ESPRC) can be determined with the following equations.

$$\begin{aligned} &k = ss/\sigma \\ &ESPRC = f_u(k) - (1 - F_u(k)) * \sigma \\ &fill\ rate = 1 - ESPRC/Q \end{aligned} \tag{A.4}$$

An optimization function for the safety stock (ss) can be used such that the target fill rate is reached. However repeating this procedure a large number of time reduces the speed of the simulation. The approximation is therefore used to determine the safety stock. The formula provide in Silver et al. (1998) is the following:

$$z = \frac{a_o + a_1 k + a_2 k^2 + a_3 k^3}{b_o + b_1 k + b_2 k^2 + b_3 k^3 + b_4 k^4} \tag{A.5}$$

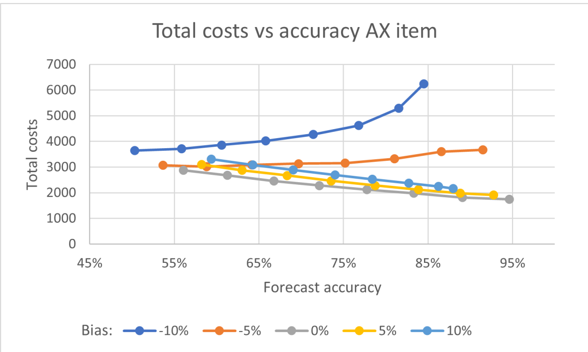
Where:

$$
\begin{aligned}
k &= \sqrt{\ln\left(\frac{25}{Gu(k)}\right)} \\
a_o &= -5.3925569 \\
a_1 &= 5.6211054 \\
a_2 &= -3.8836830 \\
a_3 &= 1.0897299 \\
b_o &= 1 \\
b_1 &= -7.2496485 * 10^{-1} \\
b_2 &= 5.073266225 * 10^{-1} \\
b_3 &= 6.69136868 * 10^{-2} \\
b_4 &= -3.29129114 * 10^{-3}
\end{aligned}
\tag{A.6}
$$

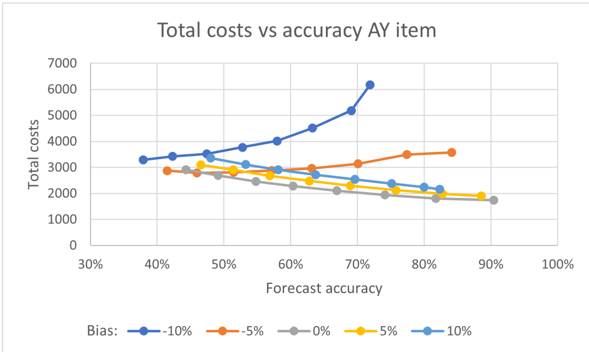
Using Equation A.1, the parameters above and Equation A.5 gives z. This safety factor can then be used to determine the safety stock.

Appendix B

Total costs vs forecast accuracy item groups

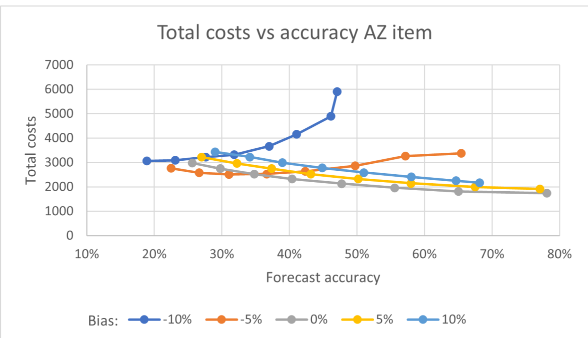


(a) Total costs vs forecast accuracy AX

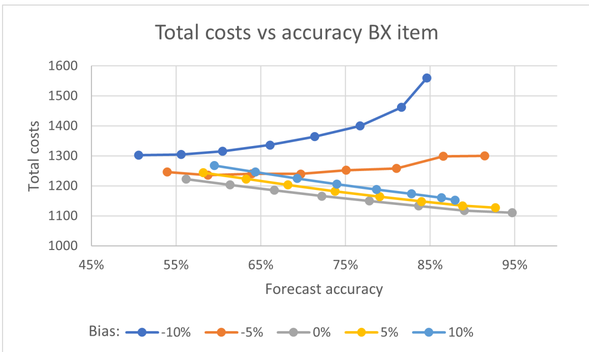


(b) Total costs vs forecast accuracy AY

Figure B.1: Total costs vs accuracy AX and AY

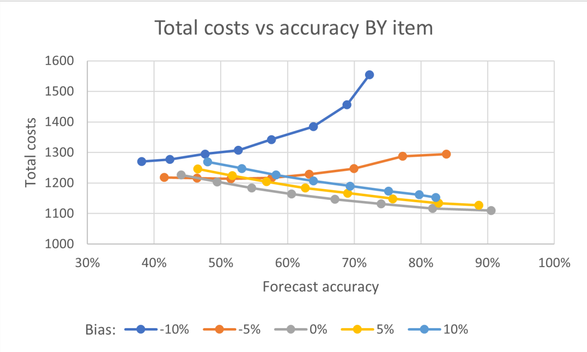


(a) Total costs vs forecast accuracy AZ

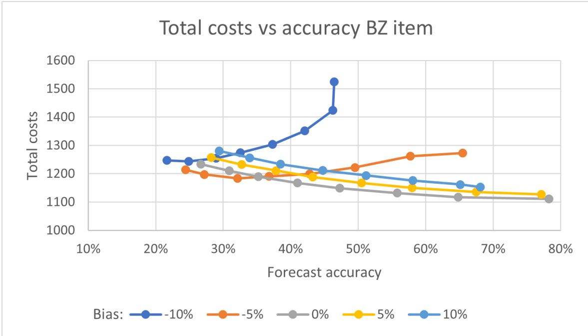


(b) Total costs vs forecast accuracy BX

Figure B.2: Total costs vs accuracy AZ and BX

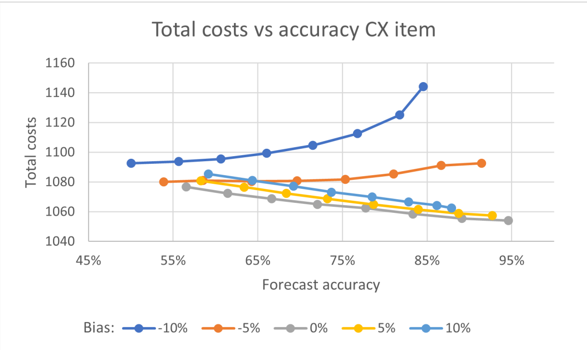


(a) Total costs vs forecast accuracy BY

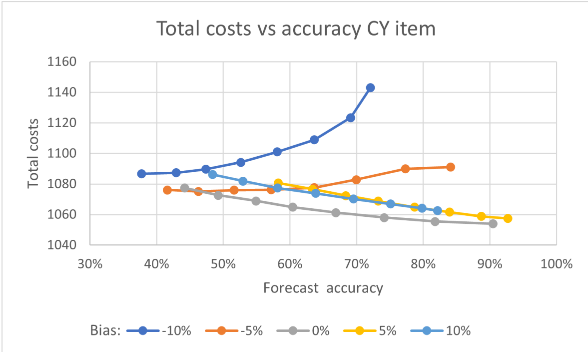


(b) Total costs vs forecast accuracy BZ

Figure B.3: Total costs vs accuracy BY and BZ



(a) Total costs vs forecast accuracy CX



(b) Total costs vs forecast accuracy CY

Figure B.4: Total costs vs accuracy CX and CY

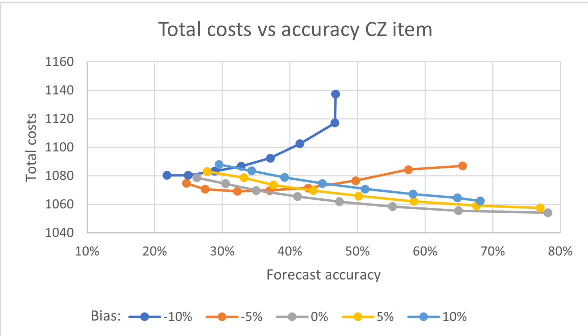


Figure B.5: Total costs vs accuracy CZ

Appendix C

Parameters simulations

The parameters of the simulations are shown below. The standard deviation of the demand, seasonality index, standard deviation error and mean error are percentages of the mean demand.

Parameters	min	max
Fill rate	80%	99.50%
Lead time	1	8
Review period	1	8
Price	10	1000
Mean demand	0.5	1000
Standard deviation demand	10.00%	200%
Seasonality index	0	80%
Standard deviation forecast error	5%	90%
Mean forecast error	-60%	60%

Table C.1: Parameters simulation

Appendix D

Parameter optimization

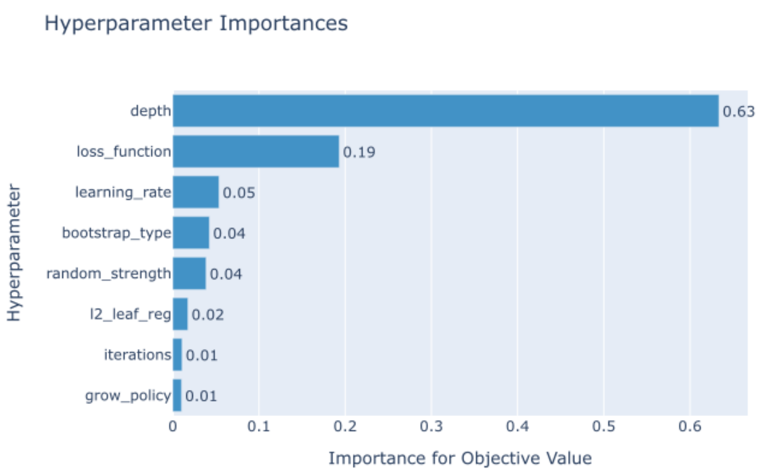


Figure D.1: Catboost parameter importance

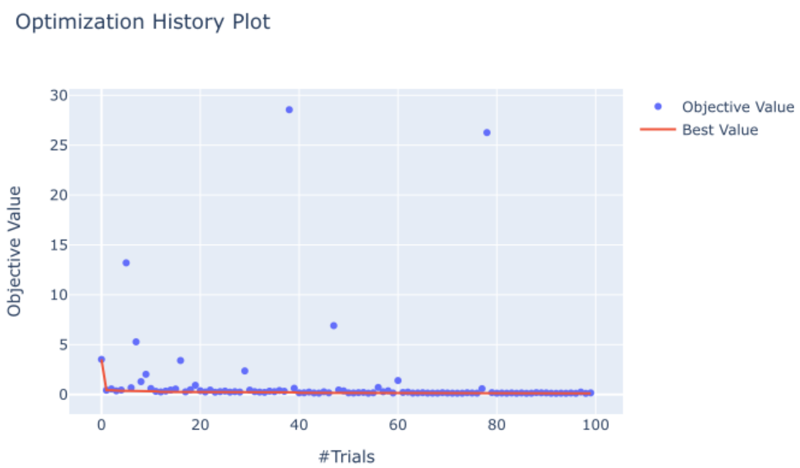
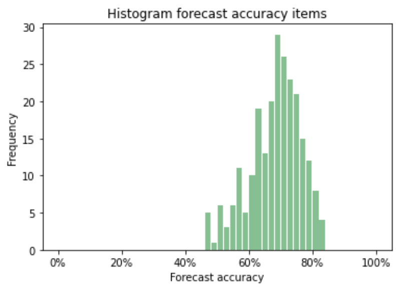


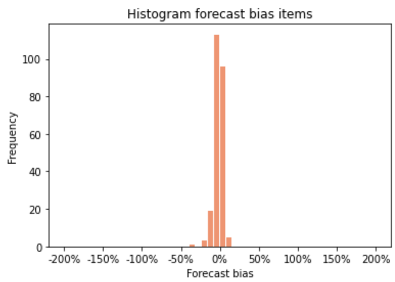
Figure D.2: Catboost optimization history

Appendix E

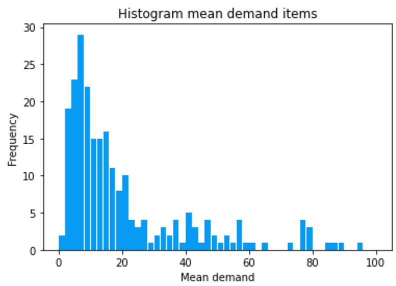
Histograms ABC-XYZ items case study



(a) A item histogram accuracy

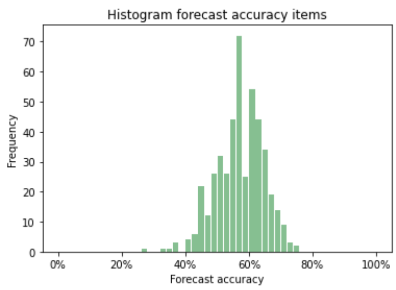


(b) A item histogram bias

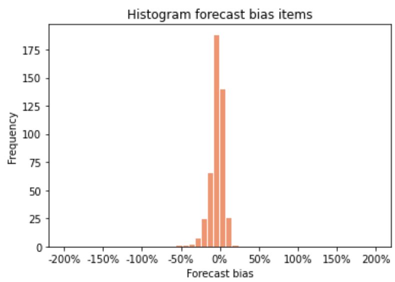


(c) A item histogram demand

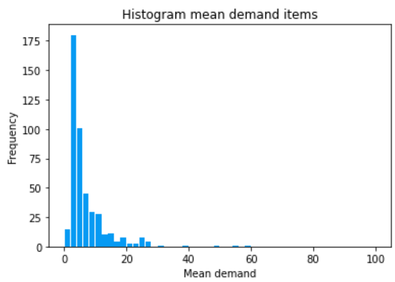
Figure E.1: Histograms AX item



(a) AY item histogram accuracy

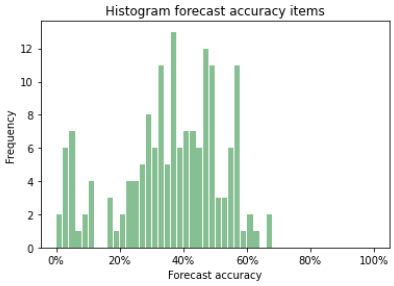


(b) AY item histogram bias

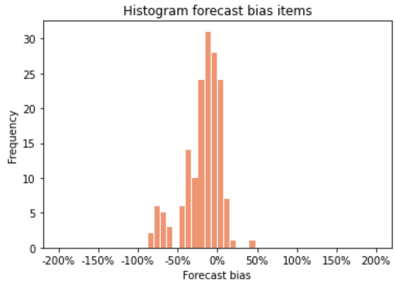


(c) AY item histogram demand

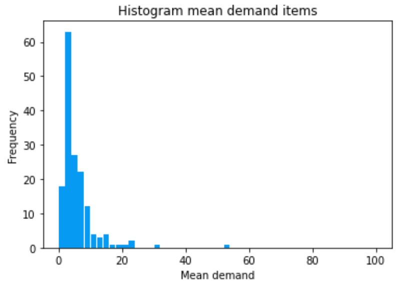
Figure E.2: Histograms AY item



(a) AZ item histogram accuracy

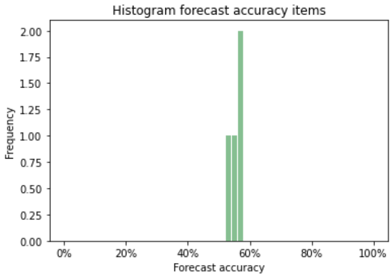


(b) AZ item histogram bias

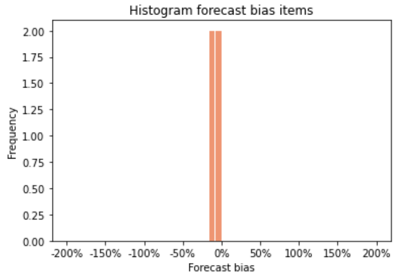


(c) AZ item histogram demand

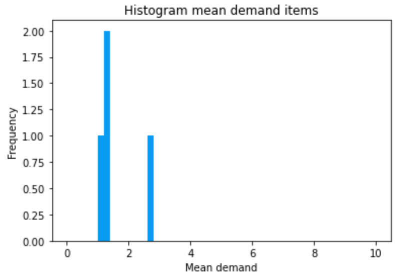
Figure E.3: Histograms AZ item



(a) BX item histogram accuracy

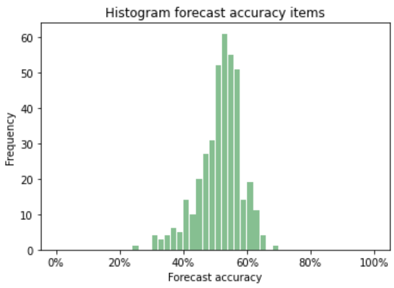


(b) BX item histogram bias

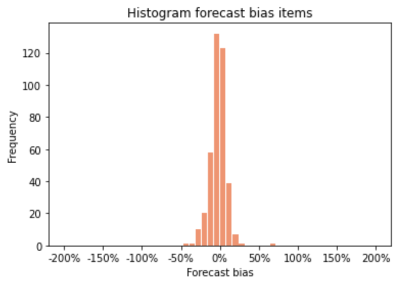


(c) BX item histogram demand

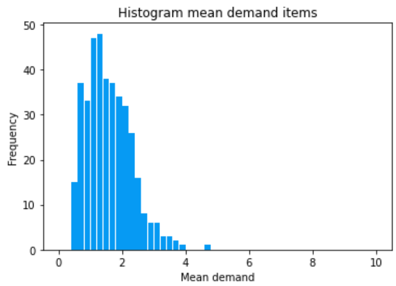
Figure E.4: Histograms BX item



(a) BY item histogram accuracy

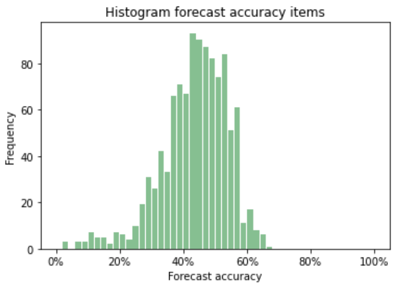


(b) BY item histogram bias

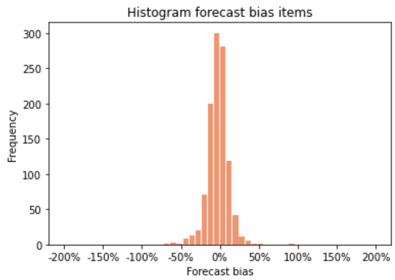


(c) BY item histogram demand

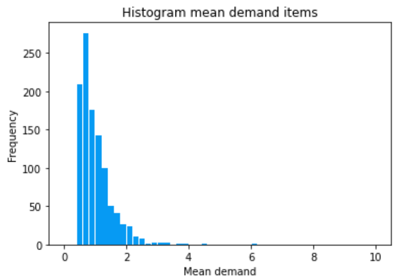
Figure E.5: Histograms BY item



(a) BZ item histogram accuracy

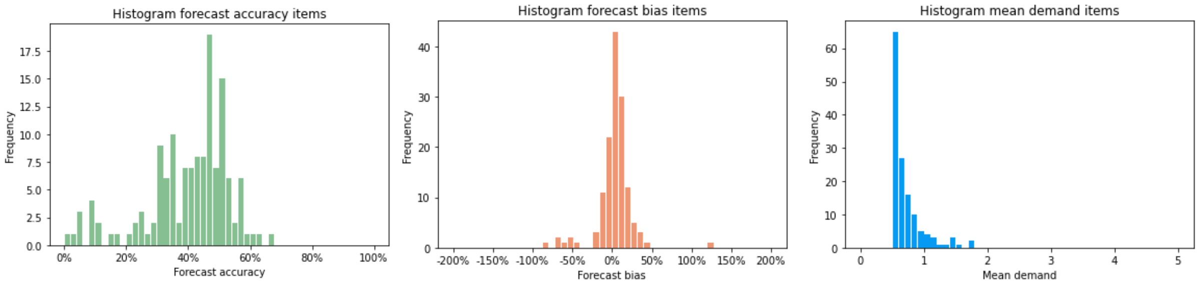


(b) BZ item histogram bias



(c) BZ item histogram demand

Figure E.6: Histograms BZ item



(a) CZ item histogram accuracy (b) CZ item histogram bias (c) CZ item histogram demand

Figure E.7: Histograms CZ item