Bachelor Thesis

“Optimising the ordering policy for overseas-transported products by quantitatively forecasting demand.”

Bart Beermann

S2073137

University of Twente

April 2021

Industrial Engineering and Management Science

Faculty of Behavioural and Management Sciences

“It is tough to make predictions, especially about the future. One may be tempted to treat demand forecasting as magic or art and leave everything to chance. (Chopra & Meindl, 2016)”

Proposal Report Bachelor Assignment

Title:	Optimising the ordering policy of overseas-transported products by quantitatively forecasting demand.
Date of publication:	5 April 2021
Location:	Enschede
Author:	Bart Beermann
Student number:	S2073137
Study:	BSc Industrial Engineering & Management

Author
Bart Beermann

Industrial Engineering and Management

University of Twente

University of Twente
Drienerlolaan 5

7522 NB, Enschede

The Netherlands

Haco C.I.V.
Leehove 70

2678 MC, De Lier

The Netherlands

Supervisors

First supervisor University of Twente:	Dr. D.R.J. Prak (Dennis)
Second Supervisor University of Twente:	Dr. E. Topan (Engin)
First supervisor Haco:	J. Lancée (Jan)
Second supervisor Haco:	W. Olde Weghuis (Wouter)

Preface

Dear reader,

In front of you lies my bachelor thesis 'Optimising the ordering policy for overseas-transported products by quantitatively forecasting demand'. Within this research, an open-minded and theoretically focused look is taken on the supply chain of Haco, by which it is tried to improve performance. To conduct this research, I worked at Haco from October 2020 until February 2021.

Hereby, I want to thank all people who supported me in the past few months. I primarily want to thank Dennis Prak, my first supervisor from the UT, for all his time and effort to supervise this research. I adored the profound discussions and exchanges of thoughts we had during our meetings and the critical, but constructive feedback given on all developments. Secondly, I want to thank Haco C.I.V., and everyone related, for their time and interest. Jan Lancée and Wouter Olde Weghuis have been a good support and a stable providence of necessary knowledge and data. Furthermore, I want to thank Jan Lancée for giving me the opportunity to apply my theoretically visioned mindset and theoretical knowledge to the artisanal practices of Haco.

I sincerely hope that you enjoy reading this thesis, and it generates new insights into the possibilities of applying theoretical insights into traditional practices.

Kind regards,

Bart Beermann

Enschede, April 2021

Management Summary

Haco C.V. (Haco) is a Dutch furniture company, located in Netherlands and Spain. Haco imports its products from all over the world, including domestic transportations and overseas shipments, using containers.

The problem that Haco is currently facing is in its international logistics strategy. This strategy creates a prosperous price position by reduced product costs and soaring profit margins but makes Haco carry the logistical risks and responsibilities themselves.

Currently, no clear purchasing policy is set up to regulate the moment and amount of ordering. Purchases are partially based on a brief look at primitive data but mostly on intuition and experience. This absence of policy triggers unwanted volatilities in purchasing amounts, caused by reactive handling on the regularly occurring stockouts, which result in mal performance on the optimal cycle service level (as shown in Table 11). In turn, stockouts cause volatilities in the number of product sales per week (Figure A.2), completely disorientating the warehouse and its personnel and indirectly in higher warehousing- and logistics costs; three of the five observed problems from the problem cluster.

Following Heerkens (2012) method and the four rules of thumb (Heerkens & Van Winden, 2017), the following core problem is found: ‘Not having a stable and predominantly data-driven purchasing policy for overseas-transported products’. To create a solution design for overcoming the core problem, the following research question is formulated:

How can Haco reduce inventory costs and improve service levels by optimising the purchasing policy and inventory stability for overseas-transported products by forecasting demand?

The research started by analysing the current inventory situation, clearly allocating the company’s current purchasing decisions and policy. The current ordering policy of Haco, used for overseas-transported goods, is the (R, s, Q)-policy. For this policy, the current parameters of reorder levels and reorder quantities are found in their ERP-system and differ per product type; review period R is assumed to be two weeks.

The currently handled reorder level is an addition of the handled safety stock and the number of sales during lead time, as calculated with the SMA method. This safety stock contains five weeks of average sales, determined by the SMA of thirty-day sales.

After stating Haco’s current situation was clear, literature was studied about inventory control and forecasting. It was found that the currently achieved cycle service levels are below the optimal values, which are approaches from the Newsboy model. To improve these cycle service levels and achieve them efficiently, a model has been developed to optimize the reorder levels' determination and reorder quantities. This model uses the self-optimising SES method to forecast demand and the formula of Prak et al. (2017) to include parameter uncertainties in safety stock. From this model, it was found that the approach for the most cost-efficient cycle service level, cycle service levels had to rise with an average of 17.9%. In comparison, safety stock rises by 11.9% on average.

With this model, the core problem of not having a stable and predominantly data-driven purchasing policy for overseas-transported products will be solved. Furthermore, the problem cluster's starting problems (Appendix B) will be solved within this thesis. With the model, higher cycle service levels are achieved, resulting in fewer stockouts and more consistency in inventories. Furthermore, the held safety stocks consider volatilities in demand as well as the forecasting errors. Lastly, it is advised to include the developed model in Haco’s ERP system. This inclusion will automize the ordering decisions, structurally improving the efficiency of the ordering process.

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Readers guide

Chapter 1 – Introduction and Research explanation

In this chapter, the introduction to the research is given. It tells more about the company and its problem, and why this specific problem is relevant. The Problem-Solving Approach is discussed, using the mentioned research questions and models, in the form of deliverables. This chapter explains why and how the research is done.

Chapter 2 – Literature Review

This chapter discusses the relevant literature used later in designing the model. It includes three main themes: (i) inventory management theory, necessary for understanding influencing concepts of inventory management, (ii) forecasting techniques, (iii) and inventory control policies.

Chapter 3 – Current Situation Analysis

Here, the current situation, or reality of Haco as it is titled in chapter 1.3, is analysed. Their purchasing policy, relevant purchasing strategy decisions and current inventory situation will be analysed. Furthermore, the currently used formulas for ordering and inventory decisions will be discussed and measured, just as their performances on KPIs relevant to the ordering process.

Chapter 4 – The Model

This chapter analyses and explains the recommended improvements and adjustments, which are coming from the developed model. Primarily, the use of the formulas is explained, after which its most significant changes are sophisticated.

Chapter 5 – Results

This chapter addresses the theoretical- and statistical results from the model's adjustments. The results are discussed and compared with the old situation. Furthermore, the influence on different factors is compared, showing their importance and

Chapter 6 – Conclusion and Recommendations

In this chapter, the conclusions and recommendations of the research will be presented. Besides, a discussion will be made about the addition and limitations of the research. The conclusion will result in answering the main research question

Abbreviations and Variable Representations Table

SS	Safety Stock
CSL$^{(*)}$	(Optimal) Cycle Service Level
D	Demand
L	Lead Time
Q	Ordering Quantity
s	Reorder Level
MPSM	Managerial Problem-Solving Method
(S)ES	(Single) Exponential Smoothing
(S)MA	(Simple) Moving Average
MAD	Mean Absolute Deviation
ERP	Enterprise Resource Planning
L.P.	Limited Partnership
Ltd.	Private Limited Company
LTU	Lead Time Uncertainty
PMU	Parameter Uncertainty
MDL	Model (referring to the model developed in the research)
SF	Skewness Factor

1. Introduction

This chapter introduces the research. More is told about the company and why this research is done. Hereafter, the problems which Haco is struggling with are identified and will be elaborated, resulting in an all-encompassing core problem. Allocating this core problem is done with research questions and a problem-solving approach, which elaborates on the method used to answer the research questions. Lastly, the factors impacting the research and behaviour towards data are discussed.

Contents:

1.1. Company Description

Haco C.V. (Haco) is a Dutch furniture company, purchasing and selling a fulfilling portfolio of individual furniture items and a diverse offer of furnishing packages in 33 shops throughout the Netherlands and Spain. Its headquarters is located in De Lier (South-Holland). For over fifty years, Haco has been trading in high-end furniture, categorised by inventory furniture and personalised furniture.

Haco distinguishes themselves by their high service level, short delivery times, and competitive prices caused by mass-purchases. The company is still growing every year and invests in new warehousing facilities (either rented or constructed) and improved logistic capacities to keep fulfilling demand.

Haco imports its products from all over the world, including domestic transportations and overseas shipments, using containers. The sold products are distributed to the shops nationally and internationally by cargo trucks, for which the company created an intelligent logistics construction for its shops. The shops (separate Ltd.'s) order at the logistics centre (L.P.), also known as the central purchasing association.

1.2. Research Motivation

The problem that Haco is currently facing is in its international logistics strategy. This international logistics strategy means that they leave out wholesalers within the supply chain and order their products overseas and in containers from low-cost countries. This strategy creates a prosperous price position by reduced product costs and soaring profit margins but lets Haco carry the logistical risks and responsibilities themselves.

Moreover, no clear purchasing policy is set up to regulate the moment and amount of ordering. Purchases are partially based on a brief look at primitive data but mostly on intuition and experience. This insufficiency of policy triggers unwanted volatilities in purchasing amounts, caused by reactive handling on regularly occurring stockouts. In turn, stockouts cause volatilities in the number of product sales per week (Figure A.2), which causes disorientation of the warehouse and its personnel.

Nevertheless, this situation has more detrimental consequences; the company is missing out on profit by not having a demanded product in stock and causing deterrent waiting times. This phenomenon is tried to be tackled by ordering more products, yet without the desired success. This unattainance is caused by a lack of structure in the purchasing policy, which does not use data-driven demand anticipation. Besides, extra (decentral) warehouses must be rented to cover the inventory peaks; resulting in the higher warehouse- and logistic costs because of the rent of - and necessary transportation between - warehouses. Above all, the current working conditions cause the personnel's rising stress levels because of the demanding workload.

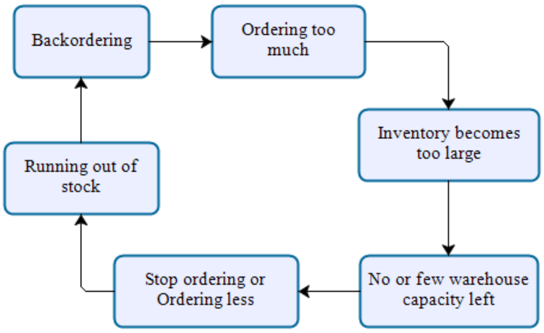

Figure 1.1: Circular Problem Statement

Furthermore, by looking at the statistics of product purchases overseas, it is found that each year overseas-transported products play a more critical role within Haco (see Appendix A). This growing impact means that behaviour towards overseas-transported products would have a more impact every year, intensifying the inventory situation and aggravating the effects stated in Appendix B.

1.3. Core problem

The core problem is defined by using the problem-solving method of Heerkens & van Winden (2012), as thoroughly elaborated in Appendix B, which resulted in the following core problem:

Not having a stable and predominantly data-driven purchasing policy for overseas-transported products.

A particularly intuition- and experience-based purchasing policy is currently handled for overseas-transported products, not being automated or entirely formula-based. Moreover, no demand forecasting is considered in this process, and no (cycle) service level (chapter 2.1.4) is calculated. All in all, the current purchasing policy leads to inconsistent inventory levels, especially for container-transported goods and an overpacked warehouse. When looking at Figure 1.2, the current situation would enable reaching level 3. Yet, purchasers' improper use of the ERP system limits this to level 2; the purchasers are not aware of all data-delivering functions included in the wide-ranging ERP system and often corrupt the indicated purchasing advice. Many statistics which can be extracted from the system are not considered in purchasing processes or checked from time to time.

The norm in this process would be a data-driven and quantitative forecast-considering purchasing policy. This policy comes with a recommended and data-based optimal safety stock, leading to more consistent inventory levels anticipated on demand. Furthermore, data about cycle service levels, product demand and shortage- and holding costs must be measured within the norm-fulfilling system, influencing purchasing amounts and held safety stocks.

Moreover, these improvements would enable Haco to be more responsive to their customers by accomplishing higher cycle service levels. Higher cycle service levels are attained by reducing stockouts, lowering the current shortage costs. Furthermore, unnecessary holding costs and risks of obsolescence are reduced by the demand-based purchasing anticipation. The achieved cycle service level calculates the norm within this research after applying the model. However, measuring the level of professionalism in inventory management is more critical, as shown in Figure 1.2 from (Beerens & Kusters, 2015).

The adjusted structure on inventory management would create an opportunity to realise the, in Figure 1.2 mentioned symptoms of level 4 professionalism. However, this level can only be achieved when the adjustments are diligently implemented and used structurally.

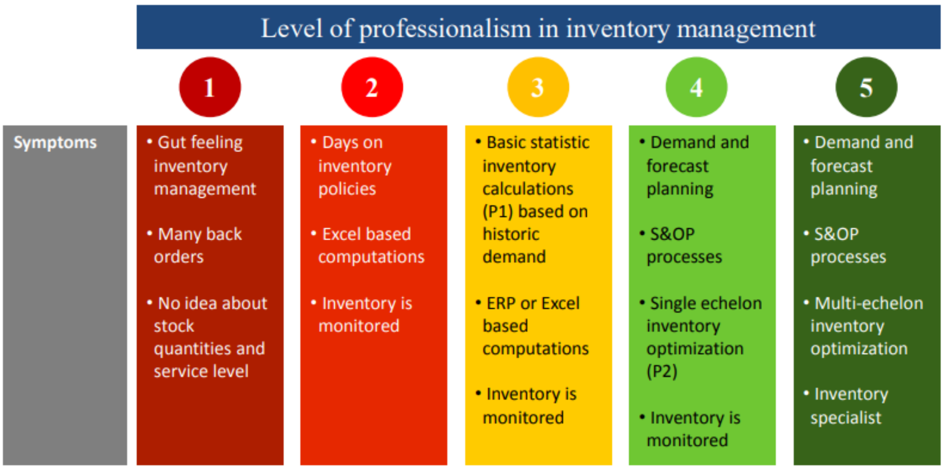

Figure 1.2: Professionalism Classifications in Inventory Management

This research aims to improve professionalism up to level 4 by applying literature (chapter 2) on the current situation. After all, the current purchasing policy would be improved by applying the developed model inventory management, explained in chapter 4.

1.4. Research Questions

Several research questions have been formulated to fulfil the research problem structured and thoroughly. The main research question will be the backbone of the research, on which the essence of the research is based.

1.4.1. Main Research Question

How can Haco reduce inventory costs and improve service levels by optimising the purchasing policy and inventory stability for overseas-transported products by forecasting demand?

The main research question determines the research target but cannot be answered instantly. Its complexity and confluence of different aspects require sub-research questions to be set up to divide the main question. These sub-research questions will be answered throughout the chapters. The chapter which most thoroughly answers the sub research question is mentioned behind the question.

1.4.2. Sub Research Questions

1. What does the current purchasing policy at Haco look like for overseas-transported products? *(chapter 3.1)*
    a. Which factors affect this purchasing policy? (*Chapter 3.1)*
    b. What limitations does the purchasing policy face? *(Chapter 3.1)*
    c. Which Cycle Service Levels are currently achieved? *(Chapter 3.1.2, Table 1)*
    d. How can these limitations be overcome to improve the purchasing policy? *(Chapter 4)*
2. What are the characteristics of the demand for overseas-transported products, and how can they be measured? *(Chapter 3.5)*
    a. How volatile is that demand? *(Chapter 3.5, Table 3)*
    b. Is the demand for overseas-transported products normally distributed? *(Chapter 3.5.2, Table 3)*
    c. What other probability distributions are applicable to this demand? *(Chapter* 3.5, *Table 4)*
3. How can demand for overseas-transported products accurately be forecasted? *(Chapter 2.2)*
    a. What factors affect demand forecasts? *(Chapter 2.2)*
    b. Which forecasting techniques can be applied? *(Chapter 2.2 & chapter 4.1)*
    c. What is the performance of this forecast? *(Chapter 5.1)*
4. Which information is needed as input to the inventory model? *(Chapter 4.1 & chapter 4.2)*
    a. Upon which parameters need to be decided? *(Chapter 4.4)*
    b. Which KPIs are relevant to the company? *(Chapter 4.4)*
5. What is the optimal ordering policy for overseas transported products? *(Chapter 4 & chapter 5)*
    a. What are the optimal cycle service levels? *(Chapter 5.2, Table 10)*
    b. What are the resulting reorder levels and safety stocks? *(Chapter 5.2, Table 10)*

1.5. Theoretical Perspective

The way of handling literature within the research is based on the theoretical perspective. This perspective is mainly operations-focused, influenced by the subjects: Demand & Supply Planning and Inventory Management, and Operations Research. The latter is a scientific approach to decision-making that seeks to best design and operates a system, usually under conditions requiring allocation of scarce resources (Winston, 2004).

Within the research, purchasing policies play a significant role. These policies determine how much is ordered and when. This decision is based on the current inventory and ordered inventory, minus the backorders. The resulting concept is better known as the cycle inventory. To control this inventory systematically, inventory control policies have been developed. These policies can be divided into continuously monitored policies and periodically monitored policies.

For periodical inventory control policies, parameter R determines the interval on which ordering decisions are made. The other variables on which a purchasing policy can distinguish itself are its reorder-point (s), order up-to level (S), and lot size (Q).

Haco uses the (R, s, Q)-model for container-transported products which cannot jointly be ordered (chapter 3.2). This periodic policy is a combination of the (s, Q)- and (R, S)-policy and orders a lot size Q or a multiple n of the lot size (resulting in nQ), when the current inventory level is below the reorder point. These order-determining measurements are done after every review period R.

The research aims to lower costs on logistics and inventory management and optimise service levels by improving coordination. However, as stated in the book of Supply Chain Management from Chopra and Meindl, this requires information including demand patterns, cost of carrying inventory, costs of stocking out, and ordering costs.

This information on demand patterns is gathered by making validated forecasts. Demand forecasts form the basis of all supply chain planning (Chopra & Meindl, 2016) and often increase (cycle) service levels (CSL) without having extra costs. This CSL percentile measures the probability that no stockouts will occur during an order cycle. When forecasting, the CSL is mainly influenced by lead time volatility and forecast errors. Researchers rightly suggest that if there is more variance that should be taken into account, then ignoring it will lead to an underestimation of the safety stocks needed to sustain a certain service level performance (Prak et al., 2017).

Forecasting is essential to reach a fulfilling CSL; by getting to know more about the existing demand parameters and anticipating the parameters, higher CSLs can be reached. However, inventory levels still rise exponentially when increasing cycle service levels; an increase from 87% to 89% requires eight times less inventory than increasing it from 97% to 99% (Schalit & Vermorel, 2014).

With quantitative forecasting, historical data is used to forecast. However, forecasting models can be made as elaborated and complex as desired. A commonly used but well-performing quantitative forecasting method is the single exponential smoothing (SES) method. It forms the basis of time-series forecasting and can easily be expanded by taking into account a trend (which is a prevailing direction of the pattern within the development of the forecast), and a seasonality which includes a seasonal factor on the forecast. This seasonality is determined by a predictable cyclic variation depending on a specific time within the year (Sankaran et al., 2019)). These elaborations could improve forecasting accuracy. Nevertheless, seasonality factors are not always relevant to product demand.

1.6. Deliverables

Apart from answering the research questions from chapter 1.5, the following deliverables are presented to the company to reach the research target:

- A worksheet containing (graphical) data analyses on the current inventory situation for overseas-transported products; giving more insight into possible improvements with a theoretical viewpoint.
- A forecasting method, giving more insight into future demand and including a concise elaboration on the inclusion of trend and seasonality within the forecast done on selected overseas-transported products.
- A safety stock model, calculating the optimal safety stock for different products.
- An analysis and advice on current purchasing policy, considering the optimal safety stock and demand forecast on a product.
    - Eventual implementation will not be part of the deliverables, as this is not doable in the given timeframe. Therefore, advice on future implementation will be made.

2. Literature Review

In this chapter, the theory relevant to the research and applied for the advice on Haco's current situation will be discussed. Primarily, it focuses on inventory management theory, necessary for understanding influencing concepts of inventory management within the research. Secondly, the used theory about quantitative forecasting and the used times-series analysis techniques are discussed. Finally, the theory about the considered inventory control policies and supply chain optimisation is studied, which will be used to implement the model, explained in chapter 4.

Contents:

2.1. Inventory Management Theory

Inventory are the items stored in the warehouse. The products kept in storage are meant to cover the disruption of communication between suppliers and consumers, and volatility between supply and demand. These uncertainties are often inevitable, for example, when having to deal with minimum order quantities (MOQs). Furthermore, unknown and unexpected external factors can have unexplainable effects on demand. Safety stock is meant to overcome this risk of not meeting this demand, increasing the probability of not having a stockout within a given replenishment cycle, known as the cycle service level (chapter 2.1.4).

At Haco, the net inventory consists of the unsold inventory physically present in the warehouse and the inventory on its way to the warehouse. From the moment a product is sold to a customer - even though it is still present in the warehouse - it is no longer part of the net inventory.

The way of dealing with inventory could either be the backbone or a backlash for companies. It determines the company's strategy and represents either its responsiveness or its budget-focused strategy. Responsive strategies, coming along with high inventory levels, get along with higher holding cost and higher risks of value depreciation caused by either losing popularity or usefulness. Nevertheless, higher inventory could eventually lead to more sold goods. In general, managers should aim to reduce inventory in ways that do not increase costs or reduce responsiveness (Chopra & Meindl, 2016)

2.1.1. Cycle Stock and Safety Stock

When looking at the inventory of Haco, there are two different types of stock: cycle stock, safety stock. The first type to be discussed is cycle stock; this is the type of inventory that is worked with when trying to cover demand and the part of the inventory expected to be sold before receiving a new order.

Many factors influence this cycle stock; the ordering quantities directly influence the average cycle stock, and ordering time determines how often the cycle stock is filled upon a certain level.

Safety stock is inventory carried to satisfy the demand that exceeds the forecasted demand. Safety stock is required because demand is uncertain, and costly shortages occur if actual demand exceeds the forecast demand (Chopra & Meindl, 2016).

Therefore, supply chains cannot operate without safety stock (Gonçalves, Sameiro Carvalho, and Cortez, 2020). Within the calculation of safety stocks, the volatility of demand is often considered. Furthermore, volatilities in lead times, forecasts or parameters can all (independently) be considered. When volatilities are higher or more types of volatilities are considered, safety stocks levels rise. In the short-term, safety stocks can be used to cover positive trends in demand in the short-term, but in the long-term, ordering quantities need to be reconsidered when wanting to meet rising demand.

When demand is forecasted, demand uncertainty is lowered as much as possible, meaning that safety stocks can be reduced. However, not all uncertainties can be taken away by trying to predict the future. Therefore, even when forecasting, a safety stocks is held; but only if the costs of understocking are higher than costs of overstocking. To determine this safety stock, it must be known how uncertain the forecast is, in other words, how large the forecast errors tend to be (Axsäter, 2006).

2.1.2. Lead Times and Lead Time Volatilities

When sourcing from low-cost countries, in-transit inventory becomes a more significant part of total inventory. In-transit inventory is the type of inventory owned by the company but not physically present in the warehouse and thus not usable for selling. Because of higher lead times, many products must be in-transit to maintain a constant inflow of goods. Furthermore, products with higher lead times sooner experience high lead time volatilities.

The extended lead time inherent in international logistics means that products run the risk of becoming obsolete during their time in transit (Harrison et al., 2019). Furthermore, products could face shipment risks (water damage or difficulties with ships, harbours, or containers). They are less flexible because they come in larger amounts simultaneously, often in whole containers. Lastly, minor external influences may have great effects on the lead times, and therefore inventory flows. To counter the higher lead time volatilities and higher risks present in a globalised supply chain environment, higher use of safety stocks is observed (Absi & Kedad-Sidhoum, 2009).

2.1.3. Shortage Costs and Holding Costs

Volatilities and uncertainties in demand and lead times can cause difficult situations for companies. Product delivery delays or unexpected growth in demand bring on higher probabilities of stockouts. These stockouts increase customers' waiting times and decrease customer satisfaction, which are possible motives for a no-buy decision.

Until now, methods on measuring how stockouts affect both current and future demand (and calculating the coming along shortage costs) have been a bottleneck for implementing inventory policies (Andersen et al., 2006). Calculating how much earnings are missed because of a stockout is nearly impossible because of the many uncertain factors. The unsolvability of calculating these has been a real brain teaser for researchers. Questions like: 'Does the customer agree on the accessory lead time or will it take a look at a competitor?', 'Will the customer buy another product from the same category, substituting his primer wish?', 'Will the customer stay loyal to the shop after it could not be served in the past?' and, 'Will this product be from the same price category?', need to be answered before being able to indicate the cost of a stockout.

Nevertheless, one formula is occasionally used in production businesses. This formula, created by Oral et al. in 1972, is based on a case study at a manufacturing company and was first in combining probabilities and costs in different stages. The case study resulted in a regression-based formula, generated by analysing the cost results. Because Haco is not a manufacturing company, and the scenario in the case study deviates too much from Haco their current situation, this formula could not doubtfully be used in the research. Therefore, only the added gross profit per product was considered as shortage costs per product. These costs are just like the holding costs per product (chapter 3.3) used for calculating the optimal CSL (chapter 2.5). Yet, shortage costs will not be a part of the research's results, but only indicate the importance of improving CSL.

2.1.4. Cycle Service Level

To indicate the probability of not having a stockout during a replenishment cycle, CSLs are used. This CSL improves when safety stock levels rise or inventory is better anticipated on demand.

To be able to measure service levels for Haco, the CSL is used. It is one of the most important indicators, making it a Key Performance Indicator (KPI). It gives insight into the company's strategy: if it is responsive or budget focused. For more responsive companies, CSLs tend to be higher, trying to achieve higher customer satisfaction levels. To reach high CSLs more efficiently, inventory is anticipated on demand by demand forecasting, elaborated on in chapter 2.2.

When safety stock is known, CSL can be calculated by filling in safety stock formulas considering CSL as a variable or given parameter. These formulas can only be used when the demand for a product is normally distributed. More about these formulas is told in chapter 2.5.

The performance of measurements on the CSL is often compared to the measurement performances of the fill rate (FR). Where a CSL calculates the chance of not having a stock- out, the FR calculates the percentage of demand which can be fulfilled from available inventory (Chopra & Meindl, 2016). Although, in practice, the FRs gives a better overview of how much demand is fulfilled, calculating the FR can only be done when orders and ordering quantities from customers are known at any time. The orders may not be influenced by the availability or lead time of a product (Andersen et al., 2006). This condition cannot be fulfilled at Haco, and therefore measuring the FR is not doable.

The hardest part about cycle service levels is finding the optimum. For an optimal cycle service level (CSL^*), every change lower or higher would be less cost-efficient; reducing inventory would increase shortage costs more than it would cost to hold one more product in inventory, increasing inventory would cause more holding costs than it would decrease shortage costs. Determining this optimum is elaborated on in chapter 2.5.

2.2. Forecasting Methods: Time-series Analysis Techniques

Forecasting gives more insight into the future by analysing the past. Forecasting can be done with many techniques, applicable to different situations and varying in complexity and intensity. There are essentially two basic types of forecasting: qualitative, which is non-data driven and reliance on critical factors; and quantitative, consisting of time-series and causal methods. Quantitative methods are (and should be) steeped in science, whereas there is a heavy dose of social science involved in qualitative methods (Sankaran et al., 2019). However, choosing the correct forecasting technique is essential for proper functioning. This selection is based on (i) the context of the forecast, (ii) the relevance and availability of historical data, (iii) the degree of accuracy desirable, (iv) the period to be forecasted, (v) the benefit (or value) of the forecast to the company, (vi) and the time available for making the analysis (Chambers, Mullick & Smith, 1971).

As mentioned, forecasting can be done in countless ways. The relevant and used techniques are discussed in this chapter. An elaboration is done on their possible additions and applicability.

Time series analysis is a qualitative forecasting technique applied to sequent values over time, solely using historical data. This technique functions best when valid and reliable data from several years is available. The data is processed with mathematical techniques, developing projections of future data.

2.2.1. Simple Moving Average Method

The simple moving average (SMA) method, as the name implies, adjusts the calculated average on the newly available data. The SMA procedure creates a new average as each new observation (or actual demand) is available. The calculation is done by dropping the oldest substantial demand period and including the newest actual demand period.

The method flattens volatilities and thus, slowly adjusts to changing trends and cannot efficiently consider seasonality. For this reason, the method is meant for long-term trend analyses. Nevertheless, the method can predict only one period with any degree of accuracy. Predictions tend to fall apart after two or more periods into the future (Chase, 2013).

This quantitative method is used regularly, but exponential smoothing methods are generally superior to moving averaging methods. Finally, if there is a sudden shift in demand, the SMA method cannot catch up to the change in a reasonable amount of time (Chase, 2013). This relatively inaccurate method is mainly used for low-volume items and therefore not appropriate for largely batched container shipments. However, the method is straightforward, relatively easy to implement, and therefore accessible for all businesses. It can be an uncomplicated manner to start getting a few insights into data.

2.2.2. Single Exponential Smoothing

The Single Exponential Smoothing (SES) method is a time-series analysis technique that consists of a mathematical model, optimising itself with every input of data by partially adjusting to the realised value. This phenomenon is meant to decrease errors throughout the data and is commonly valued for its accuracy.

When performing SES, one period ahead is forecasted. This forecast is dependent on a fixed smoothing variable α, which regulates the fractal influence of the latest data on the forecast. The smoothing factor causes more recent data to have a higher impact on the forecast. The total weights for all past periods sum to one, with impact decreasing exponentially over time (Chase, 2013).

A higher smoothing factor lets the latest data have a more significant influence than smaller factors; although this smoothing factor α can reach between 0 and 1, its value is mainly taken between 0.1 and 0.3 to maintain its smoothing function. To calculate the most-fitting value of α, a comparison was made on the MAD (chapter 2.1.1).

To forecast values in periods in the further future, historical periods can be taken together to forecast a more extensive period ahead. Unfortunately, for all forecasting methods, accuracy falls as more extended periods are forecasted.

The SES method is often performed for production and inventory control. Because the method lowers peaks and raises drops, turning points are hard to identify. These turning points can be seen from adjusting trends but, depending on the chosen smoothing-parameter α, take an amount of time to get included in the forecast (Brown, 1959). However, for products with a relatively short demand history (6-12 months), SES is most likely the best quantitative method to deploy (Chase, 2013).

2.2.3. The Croston Method

The Croston method is developed by Croston (1972) to forecast when dealing with intermittent demand. Intermittent demand appears with many periods having no demand in between (Sankaran et al., 2019). This intermittent demand is observed for one of the products (chapter 3) and is therefore considered in the research.

With the Croston method, the forecasted values will be updated with exponential smoothing, only when demand occurs, with a ratio depending on the given smoothing factor α. With this method, the time between two demand occurrences, and the demand level when demand occurs are forecasted.

2.2.4. The TSB-Method

This method, developed by Teunter, Syntetos & Babai (2011), is a probability-including customisation on the Croston method and thus used when having intermittent demand. The Croston method solely adjusts its forecast when demand occurs. However, when this demand does not occur, this is not taken into consideration. In many situations, this projects improper outcomes and is seen as a shortcoming of the forecast. When demand does not occur, an alteration was included, lowering the outcoming probability on a demand occurrence, with a ratio, dependent on smoothing factor α. This method is more accurate when dealing with time-series with constantly low, but very intermittent demand (Babai et al., 2019).

2.2.5. Holt-Winters' (Seasonal) Method

Holt-Winter's method is an extension of the SES method, developed by Holt (1957) and Winters (1960). In several cases, SES comes short when dealing with turning points in data. To overcome this error-expanding shortcoming, Holt & Winters developed a model where both trend and seasonality can be considered. As always with exponential smoothing methods, a smoothing constant is used. In this case, independent smoothing parameters are used for trend, seasonality, and level.

To calculate and apply seasonality within this method, at least two years of data needs to be available. The lack of this condition made the method inapplicable on the dataset used in the research. Here, only 48 weeks of data are converted to a usable format. Nevertheless, Holt-Winter's method would be a proper inclusion within further research on inventory management within Haco.

2.3. Measuring Forecast Errors and Volatilities

A forecast error can be measured by calculating the Mean Absolute Deviation (MAD). This MAD is the expected value of the absolute deviation from the mean (Axsäter, 2006). When forecasting, it can be calculated with the following formula:

$$MAD = \frac{1}{n}\sum |Realized\ value - Forecasted\ value| \quad (1)$$

Where, n = number of data inputs

Another method statisticians find attractive is the Mean Squared Error (MSE). However, it is advised not to use this (Root) Mean Squared Error to measure forecast errors because of its lower accuracy (Armstrong, 2001).

When forecasting demand, the optimal safety stock's determination is heavily influenced by the forecast error, which is advised to be measured by the MAD (chapter 2.1.1). In most cases, MAD and σ give a very similar representation of deviations around the mean. They can even be linked when assuming the data is normally distributed. Formula (2) approximates this link:

$$\sigma = (\sqrt{\pi/2})MAD \approx 1.25\ MAD \quad (2)$$

The link is often used in forecasting calculations, even when it is less natural to assume that the forecast errors are normally distributed (Axsäter, 2006).

To put forecast errors and volatilities more into perspective, the MAD is measured as a percentage of the actual value. This outcoming percentage is called the Mean Absolute Percentage Error (MAPE) and works best when there are no zeros or extremes in the data. When applied in forecasting situations, the MAPE can be calculated with the following formula:

$$MAPE = \frac{1}{n}\sum \frac{|Realized\ value - Forecasted\ value|}{Realized\ value} * 100\% \quad (3)$$

Where, n = number of data inputs

2.4. Inventory Control Policies

To be able to create consistency in inventory, a stable and clear purchasing policy is crucial. These policies are created to keep control of inventory and are, therefore, also known as inventory control policies. An inventory control policy determines when and how much should be ordered, stated by the predetermined parameters (chapter 1.6). The determination of when and how much to order should be based on the inventory position, the anticipated demand, and the lead time (Axsäter, 2006). For inventory models within the research, the remaining warehouse capacity is not considered.

2.4.1. Continuous Review Policies

Unlike the other policies, continuous review policies do not contain a review period but are continuously reviewed. The (s, Q)-policy is a continuous review policy, which orders a lot size Q when inventory position reaches below the reorder point. This policy is a relatively simple, widely used method. It is used for predictable production requirements and not meant for large orders. Because of its simplicity, the chance of errors is slight, and the production requirements for the supplier are predictable (Silver et al., 2017). Often, the optimal lot size (Q*) is equal to the Economic Order Quantity. However, in this research, it is determined by adding forecasted demand during the lead time and the recommended safety stock, which are elaborated on in chapter 4.

2.4.2. Periodic Review Policies

Periodic policies require higher inventories because review periods cause extra uncertainty and, thus, higher safety stocks. This uncertainty can be the volatility of demand, but also the forecasted demand during the review period must be considered. These effects combined are called the undershoot problem and become more influential for more extensive review periods. Still, in practice, periodic review policies are preferred over continuous systems because of their ease of coordination.

Periodically ordering containers, which bring along lot sizes, are best done with the (R, s, Q)-policy. The (R, s, Q)-policy is the periodic form of the (s, Q)-policy, adding a review period. It is commonly used and well-performing for container-shipped goods. Compared to the (R, s, S)-policy, the (R, s, Q)-policy is easily implementable. In the (R, s, S)-policy, after every R, an order is done up to maximum S when inventory is below the reorder point. Calculating and deciding upon reorder level is complex and sensitive to errors. Moreover, a fixed reorder quantity must be handled when ordering in containers or dealing with a fixed MOQ. Therefore, the (R, s, Q)-policy is used in this research. The exact determination of the parameters of the policy is elaborated on in chapter 4.2, for which the resulting levels are shown in chapter 5.2, Table 11.

2.5. Calculating Reorder Levels

Reorder levels (s) can be calculated in many ways and are directly linked to the calculation of safety stocks. Minimising safety stocks by letting out variances and errors does not always minimise inventory costs. However, the relationship between holding and shortage costs and the availability achieved at the most economical solution does still hold. This leads to an important insight: costs should be used to design the system, because focusing on minimising inventory variance, or safety stocks can lead to an incorrectly specified system (Disney et al., 2016).

The simplest formula for calculating reorder level comes to the order point by adding the average demand- or number of sales during the lead time and the safety stock. This formula is currently used at Haco and does not consider any volatility of factors when calculating safety stock. When used on periodic review policies, the average demand during R must also be considered. This formula can also be adjusted to forecasting situations by replacing the average demand during the lead time and forecasted demand during lead time.

When considering volatilities on demand and lead time, within the calculation, safety stock levels (and thus reorder level levels) rise. When using the normal approximation, reducing lead times decreases reorder level, whereas reducing lead time volatility not necessarily decreases reorder level (Chopra et al., 2004).

For calculating an optimal reorder level when demand is forecasted, a formula is developed by Prak et al. (2017). This formula is developed for continuously reviewed (s, Q)-policies, calculates a safety stock with demand volatility during the lead time, and a forecast error. During the lead time and review period, the safety stock and forecasted demand result in the final reorder level. To come to the optimal safety stock, CSL^* is calculated. This is the most cost-efficient CSL and can be approximated with the Newsboy Problem, using the cost of overstocking and understocking per product to approximate the optimal level.

The formula initially does not consider the review period R, which is part of the purchasing policy used within this research. However, it can still be made applicable for the relevant (R, s, Q)-model, adding the review period to the lead time, which on their turn adds the forecasted demand during the review period to the reorder level.

When calculating CSLs coming from the simplest formula, the results can be seen as an upper-bound, compared to CSLs of formulas considering volatilities. They can only be equal when the considered volatilities tend to zero and thus not influence calculations.

Lastly, formulas considering lead time volatility can be used, for example from the paper of Eppen & Martin (1988), considering the volatility on lead times. When these formulas are used for overseas-transported products, related to high lead times, this method of calculating sizably rises safety stocks. However, safety stocks resulting from lead time volatilities often do not represent the necessary safety stocks. In many businesses, estimations of lead times are given by the supplier when ordering a product. If this lead times deviates from historical lead times, the difference is theoretically seen as volatility, while in practice, the order may arrive precisely on time.

3. Current Situation Analysis

In this chapter, the current situation, or reality of Haco as it is titled in chapter 1.3, is analysed. Their purchasing policy, relevant purchasing strategy decisions and current inventory situation will be elaborated on. Furthermore, the currently used formulas for ordering and inventory decisions will be discussed and measured, just as their performances on KPIs relevant to the ordering process.

Contents:

Because of the research's limited timeframe, the focus will be on products from one overseas-transporting supplier; seats from supplier Maxfurn and box springs from the domestic-transporting supplier OrangeHome. This variation is chosen to make comparisons and create a representative supplier selection. Nevertheless, the focus will be kept on overseas-transported products.

3.1. Current Ordering Policy of Haco

The current ordering policy of Haco, used for overseas-transported products, is the (R, s, Q)-policy. Haco makes use of its ERP system, keeping track of the incoming, available, and sold products. The system shows the number of products sold in the past month, quartile, and year. Moreover, it predicts the amount of time that inventory for the product covers demand, based on the SMA of sales in the last thirty days. This average tells the systems how many days of stock are left before stocking out. However, the recommendations coming from this SMA-based system are often ignored; the reordering advice is even commonly corrupted to keep track of all inventory positions in the scheme of products advised to order.

Because Haco offers a large variety of products, purchasing still requires human action and attention, not all overseas-transported products can be covered within their prearranged timespan for purchasing. For this reason, R is assumed to be two weeks, although purchases are made weekly. This variety of products create the need to make trade-offs on purchasing amounts: risks on obsolescence need to be minimised, the warehouse with its employees need to be able to process deliveries, but demand still needs to be covered from inventory. Furthermore, overseas transportations are done in containers, creating a minimum order quantity (MOQ) and fixed lot size (Q) or for each product.

3.1.1. Current Review Period (R)

As stated above, the current review period R amounts to two weeks (R = 2). This lengthy review period can be explained by the purchasing process being the one-of-many tasks for the management team. The higher review period lowers control on this part of the inventory and increases the probabilities of stocking out, caused by the undershoot problem (chapter 2.4.2).

3.1.2. Current Reorder Levels (s)

The currently handled reorder level is an addition of the handled safety stock and the number of sales during lead time, as calculated with the ERP system's SMA method. In this system, the future deliveries are considered as well, creating formula (4).

The ERP system advices to make an order for product i when:

$$\left(I_i + I_{i_{Fut}}\right) < (D_i * L_i + SS_i) \quad (4)$$

Where the following variables are relevant:

D_i = Average weekly sales on product i during the last thirty days
L_i = Lead time in weeks of product i
I_i = Physical Inventory of product i
I_{iFut} = Product deliveries for product i during lead time
SS_i = Determined safety stock on product i

Haco assumes in their policy that demand is equal to the number of sales. However, demand and sales are not always equal (e.g., sales are less than the actual demand when stockouts occur) (Tong et al., 2018). When a product is requested but out of stock and can therefore not be sold, it is by Haco wrongfully not considered demand.

The safety stock levels included in the formula are set by the purchasing manager and two general managers. This determination is predominantly based on their experiences and intuition. Haco handles a safety stock of five weeks of average sales, determined by the SMA of thirty-day sales. The safety stock for a product i can be represented by formula (5):

$$SS = 5 * D_i \quad (5)$$

This number of five weeks is a third of the latest total lead time of 105 days and half of the transporting duration of Maxfurn. This value is relatively low when looking at the high lead times (chapter 3.4) and the even more impactful deviations from average, which define volatilities. The volatilities do currently not influence the size of safety stock and consist of a lead time volatility of numerous weeks and volatility in sales of double-digit percentages (chapter 3.5). As seen in formula (5), the current safety stock does not take these into account, making it no surprise that safety stock a commonly used part of the inventory. This situation is not and must not be intended. Furthermore, the unrehearsed impact of the volatility factors causes the regularly appearing stockouts. This results in malperformance on the optimal service level (as shown in Table 11) and indirectly in higher warehousing- and logistics costs; three of the five observed problems from the problem cluster.

$$s = (L + 5) * D_i \quad (6)$$

$$s = (L + R) * D_i + \phi^{-1}\left(\gamma^*\right) * \sqrt{(L * \sigma)^2 + (D_{L+R} * \sigma_L)^2} \quad (7)$$

$$s = (L) * D_i + \phi^{-1}\left(\gamma^*\right) * \sqrt{(L * \sigma)^2} \quad (8)$$

Where the following variables are relevant:

$D_{L(+R)}$ = average weekly demand during the lead time (and review period)
$\phi^{-1}\left(\gamma^*\right)$ = cycle service level
L = average lead time in weeks
σ_L = standard deviation of lead time
$\sigma_{D_{L+R}}$ = standard deviation of demand during lead time and review period

The in Table 1 calculated expected and achieved CSLs are calculated by formula (7), which considers volatilities in demand and lead time. This formula more accurately represents reality and can even represent unnecessarily high volatilities in lead time (chapter 3.4). The outcoming CSLs can therefore be seen as the lower-bound of real CSLs.

Meanwhile the expected CSL represents the currently used formula. This formula does not take into account volatilities, and thus represents the upper-bound of the achieved CSL. The outcoming values in this column are only realised if there are no influencing volatilities in demand or lead times, which hardly occurs in practice.

The achieved CSL is calculated by filling in the used reorder level (6) and safety stock (5) in formula (7), leaving the CSL as the only unknown variable. The expected CSL is calculated by filling in formula (8), which only considers demand uncertainty during lead time. This formula approximates the handled safety stock of five weeks of demand, which does not depend on uncertainties.

Products	SS	s	Expected CSL	Achieved CSL
Stoel Army (2 stuks)	138	349	99.9%	82.3%
Stoel Barossa (2 stuks)	118	530	99.9%	79.2%
Stoel Bentley (Per stuk)	111	337	99.9%	79.10%
Stoel Chip (2 stuks)	46	239	99.9%	67.7%
Stoel Dahlia (2 stuks)	8	143	84.7%	53.2%
Stoel Diamond (2 stuks)	127	605	99.9%	84.0%
Stoel Exotic (2 stuks)	75	255	99.9%	6.0%
Stoel Flame (2 stuks)	44	173	99.9%	77.7%
Stoel Index (2 stuks)	62	268	99.9%	75.5%
Stoel Issue (2 stuks)	15	90	99.9%	73.5%
Stoel Jackson (2 stuks)	203	665	99.9%	60.9%
Stoel Riga (2 stuks)	139	524	99.9%	89.5%
Stoel Roady (2 stuks)	410	1583	99.9%	86.7%
Stoel Rock (2 stuks)	149	535	99.9%	95.6%
Stoel Scott (2 stuks)	43	210	99.9%	88.5%
Stoel Station (2 stuks)	61	195	99.9%	71.8%
Stoel Transfer/Grace (2 stuks)	306	1172	99.9%	78.2%
Stoel Utopia (2 stuks)	79	206	99.9%	89.6%
Stoel Watson (2 stuks)	181	603	99.9%	80.9%
Bonn Boxspring	1	4	99.4%	89.3%
Boxspringset Bonn.	20	71	99.9%	54.0%

Table 1: Current Results on ordering KPIs

When sourcing domestically, the currently used formula (6) could be considered because of the higher flexibility in lead ordering quantities lead times. However, when sourcing globally and in containers, inventory planners must account for uncertainties in both demand and lead time (Warburton & Stratton, 2002).

3.1.3. Behaviour Towards Ordering Quantities (Q)

As said before, the overseas-transported goods are shipped in containers. Container space is (and is becoming more and more) costly and thus should not be wasted. Containers must be filled completely, creating a prescribed number of cubic metres (often 66.7m^3, yet dependent on the type of container) that need to be filled. When shipping average-sized seats, this would take approximately five hundred pieces. This means that Haco orders approximately 500 seats of the same model, varying in colour or material.

These large ordering amounts cause higher average inventory positions, coming from a soared cycle stock. When the stated reorder quantity or MOQ does not match the optimal reorder level, the ordering amounts need to be rounded up to the stated reorder quantity or MOQ to cover these values. This rounding up increases cycle stock and thus average inventory positions.

3.1.4. Current Joint Ordering Situation

Not all overseas-transporting suppliers only deliver one product per container; this allows joint ordering. At this moment, one of the suppliers enables joint ordering but still handles a MOQ. There are three approaches to decide on the optimal lot-size (Chopra & Meindl, 2016); (i) each product is ordered independently, (ii) every product is jointly ordered in each lot or (iii) products are ordered jointly, but not every order contains every product; each order contains a selected subset of the products.

The resulting aggregation allows Haco to lower lot sizes for individual products because fixed ordering and transportation costs are spread across multiple products (Chopra & Meindl, 2016).

The application of joint ordering techniques on container-shipped products is not standard procedure because suppliers from low-cost countries produce their products in different factories spread across the country. Domestic-transported products are more often produced in one central factory, making joint ordering more common.

This research focuses on overseas-transported products, making this extensive subject limited in applicability and achievable results. Therefore, the joint ordering techniques, theorem, and their effects will not be elaborated on; joint ordering is decided to be out of the research scope.

3.2. Lead Times on Selected Products

When sourcing from low-cost countries, high lead times are inevitable. The products are transported by cargo ships and come from South- and South-East Asia. This transportation of the ship itself has an average duration of four up to seven weeks and, therefore, a significant effect on total lead times (Figure 3.1). Moreover, handlings related to container-shipping (blue) take more time than the handlings related to truck transport (orange). In the development of the model, the average lead times on the latest quartile are used on reorder levels and safety stock. Therefore, as shown in Figure 3.1, these average lead times are a constantly updating forecast used to forecast the subsequent order its achieved lead time.

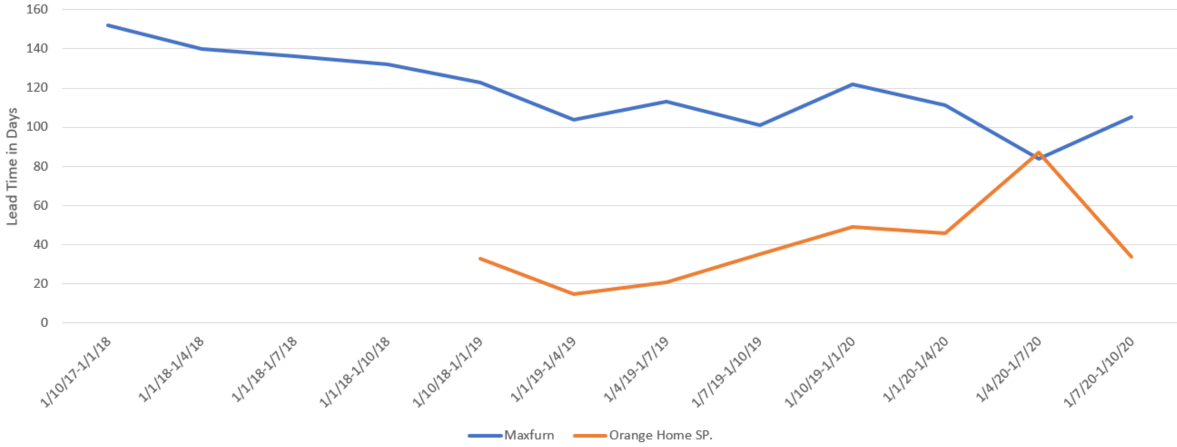

Figure 3.1: Average Lead Times in Days per Supplier

Furthermore, the MAD of the lead times (Figure 3.2) are, compared to the level of the mean, equal or lower than the MAPE of domestic products (Figure 3.3). However, they are more impactful when looking at realised numbers. Having a lead time deviation of one week, on a total lead time of twelve weeks, looks small when comparing fractal differences but have way more effect on inventory.

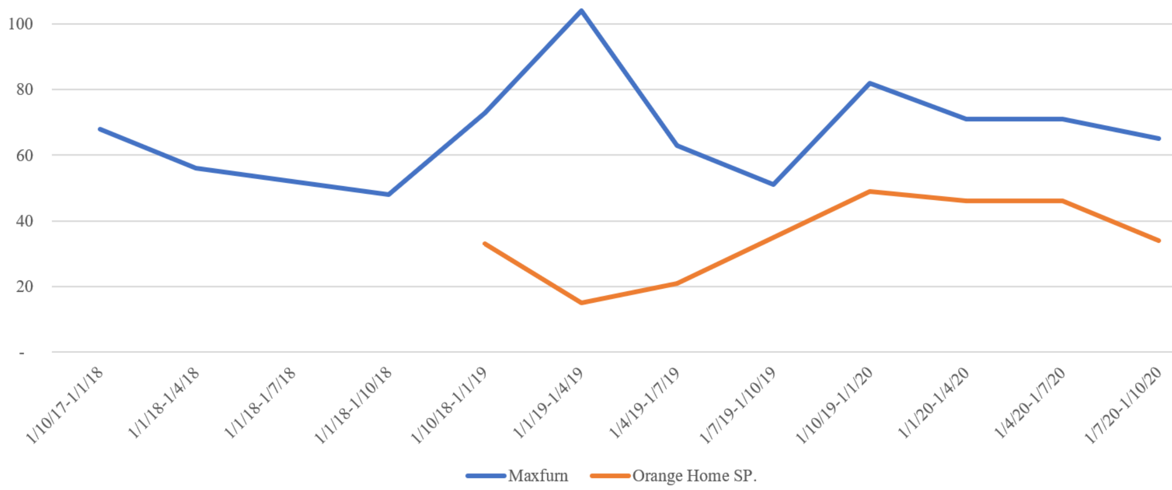

Figure 3.2: MAD in Days on Lead Time per Supplier

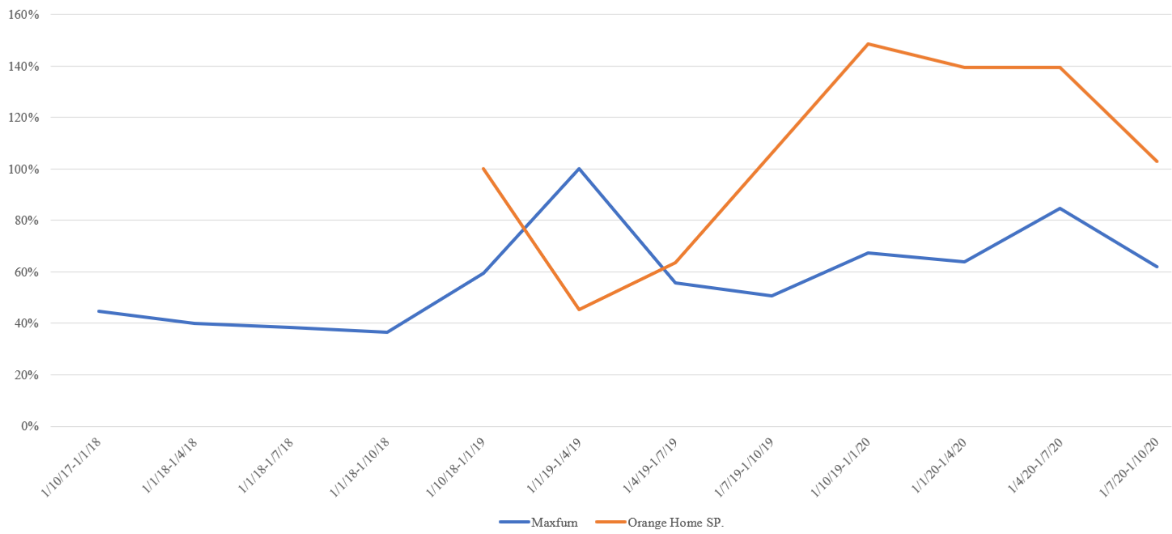

Figure 3.3: MAPE of Lead Times

As stated in chapter 3.4, deviations from historical lead times do not represent deviations from the scheduled arrival date as communicated by the supplier. Within Haco, the scheduled arrival dates are known but are not known within the research. Therefore, considering these lead time volatilities based only on historical data would cause unnecessarily high safety stocks and is not recommended. Performances on reorder levels and safety stock are tested in chapter 5.

3.3. Analysis on Current Demand

The core principle for successful businesses is persistent demand. Without demand, a business cannot operate. Although this is the case at Haco, a fraction of the potential sales is lost caused by stockouts and high lead times. From which we can conclude that a part of the total demand is missed.

At Haco, demand occurs in different types and patterns. Several product types enjoy continuous and stable demand patterns, on which forecasts can be done more facilely. Yet, other product types stick to more volatile or even intermittent demand, complicating fluent inventory control and demand forecasting.

Within Table 4, the mean and standard deviation on demand per product are shown. Furthermore, a normality test is done, and the number of weeks without sales are counted. These weeks without sales indicate whether a product could have intermittent demand, while higher standard deviations increase the uncertainty for a demand pattern.

Products	Average D per product	Sample Standard Deviation on D	Test on Normality (0.05)	Weeks without sales
Stoel Army (2 stuks)	17.3	13.50	Normal	0
Stoel Barossa (2 stuks)	30.4	13.69	Not-Normal	0
Stoel Bentley (Per stuk)	17.4	11.01	Not-Normal	2
Stoel Chip (2 stuks)	17.9	8.78	Normal	0
Stoel Dahlia (2 stuks)	12.0	8.93	Not-Normal	1
Stoel Diamond (2 stuks)	27.4	10.53	Not-Normal	0
Stoel Exotic (2 stuks)	14.0	6.67	Normal	1
Stoel Flame (2 stuks)	10.6	5.23	Normal	1
Stoel Index (2 stuks)	11.9	7.77	Normal	0
Stoel Issue (2 stuks)	3.4	3.25	Not-Normal	13
Stoel Jackson (2 stuks)	32.9	11.44	Normal	0
Stoel Riga (2 stuks)	17.8	10.25	Not-Normal	0
Stoel Roady (2 stuks)	82.0	16.91	Normal	0
Stoel Rock (2 stuks)	24.1	9.41	Normal	0
Stoel Scott (2 stuks)	12.0	4.89	Normal	0
Stoel Station (2 stuks)	10.7	5.49	Normal	0
Stoel Transfer/Grace (2 stuks)	57.3	16.47	Normal	0
Stoel Utopia (2 stuks)	9.6	6.51	Normal	0
Stoel Watson (2 stuks)	31.6	11.18	Normal	0
Bonn Boxspring	0.1	0.00	Not-Normal	41
Boxspringset Bonn.	3.8	1.82	Normal	1
Cumulative	415.2	90.00	13 of 21 Normal-Distr.	60
Average	22.2	9.60	Avg. P-Value: 0.157	2.86

Table 2: Characteristics of Sales per Product Type in 2020

3.3.1. Demand Distributions

As stated above, the data on sales of Haco follows different patterns. With the help of demand distributions, it is simplified to analyse and process the data. Currently, demand distributions are not classified or considered when ordering; products with intermittent demand are analysed similarly as products with a consequent demand. Testing the applicability of demand distributions can give more insight into the demand patterns and sales distribution.

3.3.2. The Normal Distribution

The normal distribution is the most used demand distribution and is often assumed to simplify calculations. Normality even assumed if the data does not entirely fulfil the requirements by the test on normality, which can be the Shapiro-Wilk test. This test is found to be the most reliable test on normality, followed by the Anderson-Darling test (Mohd Razali & Bee Wah, 2011).

Within the done Shapiro-Wilk test, outliers were excluded. This choice is based on irregular demand peaks and -drops caused by the COVID-19 pandemic. Besides, before going into shops at full capacity, products are tested on popularity. Outliers coming along with these popularity tests would disrupt the normality test's validity, degrading the probability of a normal distribution for a product. As seen in Table 4, for 13 of the 21 tested product types, a normal distribution could be assumed with a 5% significance level. For the other eight products, a second thought is recommended on behaviour towards the outcomes of the developed model. One of the product types experienced 41 weeks without demand and deviated too much from the normal distribution. The normality test resulted in a p-value of 0.00, on which is decided to not take this product further into consideration with the regular forecasting method. The other non-normal products are tested on other probability distributions but are still considered in the regular forecasting method.

3.3.3. Testing Non-Normal Products

On the non-normal products, the Weibull-, Log-Normal-, Gamma- and Exponential distribution are tested. These distributions come closest to the normal distribution, looking at skewness- and tail shapes. The distributions are tested with the Anderson-Darling test, which can be applied on distributions other than the normal distribution, and as stated above, is still very reliable.

The Weibull-distribution could most often be assumed (2 of 8 cases), along with the Gamma-distribution. Where exponential followed (1 of 8 cases, outliers excluded) and Lognormal could never be assumed. The product 'Bonn Boxspring', having intermittent demand, was not tested for this Anderson-Darling test because it would not fit any of the other tested distributions because these distributions are, unlike the demand pattern, continuous.

Product	Anderson-Darling Test on Weibull Distribution	Weibull Distribution assumed? (AD < 0.43)	Other distribution?
Barossa	0.57	No	Gamma (AD = 0.29)
Bentley	0.32	Yes	Exponential (AD = 0.32)
Dahlila	0.49	No	No
Daimond	0.65	No	No
Issue	0.54	No	No
Riga	0.40	Yes	Gamma (AD = 0.33)
Watson	0.50	No	No

Table 3: Anderson-Darling Test on Weibull Distribution for Non-Normal Products

Applying formulas and methods assuming normality can be done with more security for the products assumed to have a Weibull distribution; the normality distribution follows a Weibull distribution, applied with specific parameters. For the products assumed to have a Gamma distribution, future research can be done on the application of inventory models (chapter 6.4).

1.1.1. Shortage Costs per Product

Because Haco acts in a very transparent sector with slightly homogeneous products, it is assumed that when a stockout appears and a product cannot be directly delivered from inventory, it is not sold. Losing this sale brings so-called unrealised costs: costs that cannot be observed in income and expenditure but still negatively influence profitability.

The costs of understocking are influenced by the lost profit from both the shops and the logistics centre. This because the logistics centre managers also manage several shops, and the shops' profitability directly determines the continued existence of the logistics centre. The logistics centre's profit is determined by a fixed percentage on the purchasing price (9%), while the profit margin of the shops fluctuate as a percentage of the selling price. The shortage costs per product (C_u) for both parties can be calculated as follows:

$$C_u = Purchasing\ Price * 0.09 + Profit\ Margin\ for\ Shops * Product\ Selling\ Price$$
(9)

This formula results in the shortage costs per product, as shown in Table 6.

Products	Gross Profit (%)	Purchasing Price	Gross Profit Margin	% of Profit Margin	Profit Margin shops	Selling Price	C_u shops	Total C_u
Stoel Army (2 pcs.)	9%	€85	€7.65	49%	2.8%	€238	€6.66	€14.31
Stoel Barossa (2 stuks)	9%	€62	€5.58	49%	2.2%	€138	€3.08	€8.66
Stoel Bentley (Per stuk)	9%	€72	€6.48	49%	2.5%	€179	€4.46	€10.94
Stoel Chip (2 stuks)	9%	€72	€6.48	49%	1.9%	€138	€2.65	€9.13
Stoel Dahlia (2 stuks)	9%	€58	€5.22	49%	2.4%	€138	€3.28	€8.50
Stoel Diamond (2 stuks)	9%	€82	€7.38	49%	2.4%	€198	€4.77	€12.15
Stoel Exotic (2 stuks)	9%	€95	€8.55	49%	2.5%	€238	€5.97	€14.52
Stoel Flame (2 stuks)	9%	€86	€7.74	49%	1.8%	€158	€2.91	€10.65
Stoel Index (2 stuks)	9%	€75	€6.75	49%	2.6%	€198	€5.23	€11.98
Stoel Issue (2 stuks)	9%	€75	€6.75	49%	2.6%	€198	€5.23	€11.98
Stoel Jackson (2 stuks)	9%	€90	€8.10	49%	2.2%	€198	€4.36	€12.46
Stoel Riga (2 stuks)	9%	€98	€8.82	49%	2.6%	€258	€6.79	€15.61
Stoel Roady (2 stuks)	9%	€69	€6.21	49%	2.9%	€198	€5.68	€11.89
Stoel Rock (2 stuks)	9%	€78	€7.02	49%	2.5%	€198	€5.03	€12.05
Stoel Scott (2 stuks)	9%	€71	€6.39	49%	2.5%	€178	€4.47	€10.86
Stoel Station (2 stuks)	9%	€83	€7.47	49%	2.4%	€198	€4.73	€12.20
Stoel Transfer/Grace (2 stuks)	9%	€74	€6.66	49%	2.4%	€178	€4.29	€10.95
Stoel Utopia (2 stuks)	9%	€66	€5.94	49%	2.7%	€178	€4.81	€10.75
Stoel Watson (2 stuks)	9%	€89	€8.01	49%	2.2%	€198	€4.40	€12.41
Bonn Boxspring	9%	€180	€16.20	49%	2.5%	€449	€11.18	€27.38
Boxspringset Bonn.	9%	€180	€16.20	49%	2.8%	€499	€13.82	€30.02

Table 4: Calculations on Shortage Costs per Product

Because both product selling prices and profit margins for shops differ for each product type, C_u is not a fixed cost for every inventory product, as is the case for holding costs (Appendix C). Furthermore, the total costs of understocking cannot be calculated. This because the service measurer CSL, used in this research, calculates the chances that stock-outs do not occur, which is unequal to the part of the demand that can be covered directly from inventory (chapter 2.1.4). Because of this and the reasons stated in chapter 2.1.3, calculating the shortage costs on the total lost sales cannot be done within this research. Nevertheless, this is not a limitation for answering the main research question, nor achieving the intended norm, as stated in chapter 1.3.

2. Solution Design: The Model

This chapter will analyse and explain the recommended improvements on the current problems, explained in chapter 3. Furthermore, it discusses adjustments coming from applying and combining the mentioned formulas. These applications and combination will be called the 'developed model' or 'the model'. Primarily, the way of using the formulas is explained, after which its most significant changes are sophisticated.

Contents:

2.1. Demand Forecasting Methods

Within the development of the model, many formulas have been used to come to optimization. Where forecasting formulas fill the upper tone, they are used together with safety stock-, CSL- and reorder level calculations. A suiting forecasting technique for Haco would develop an approximation on future data and develop more consciousness on the effect of handled strategies on the KPIs (chapter 4.4)

2.1.1. Single Exponential Smoothing

An essential part of the model is the forecast of weekly demand with the help of the SES method. This forecast improves insight into future demand and enables Haco to better anticipate on upcoming demand. This method forecasts one period of demand, which in this research indicates one week ahead. This forecasted period can be denoted as period t+1. The calculation goes by the following formula:

$$f_{t+1} = (1 - \alpha)f_t + \alpha * X_t \qquad (10)$$

Where, apart from the smoothing factor α ($0 < \alpha < 1$), the following variables are relevant:

F_{t+1} = the forecasted demand for the period t + 1
F_t = the forecasted demand for period t
X = the actual demand observed in period t

As seen in the formula, the previous forecast is considered in this formula, which is updated after every review period R. Although this smoothing factor α can reach between 0 and 1, its value is mainly taken between 0.1 and 0.3 to maintain its smoothing function (chapter 2.2.2). To calculate the most-fitting value of α, a comparison was made on the MAD. For each α ($0.1 < \alpha < 0.3$), the MAD was calculated on the performed forecasts for each of the selected products (formula (1)). This is done over the time they are included in the product range at full capacity. The time a product is small-scale tested on its popularity is not considered because this gives a distorted view on its forecast and MAD.

Hereafter, the average MAD per value of α is calculated. With results of 7.714, 7.763 and 7.693, for α-values of 0.1, 0.2 and 0.3 respectively (Table 8). The value of 0.3 for α was proven to be the most accurate while still achieving its smoothing purpose. Moreover, the value of 0.3 was best- or equally achieving for most products independently when comparing MAD-values with MAD-values for other values of α.

2.1.2. TSB-Method

Not all products have a constant demand. For the 21 tested products, one product was dealing with intermittent demand. This intermittent demand made the SES an invalid and unreliable method because SES relies on forecast optimization by consistency and volatility flattening. Furthermore, the distribution of the intermittent demand product deviated too much from a normal distribution, so that the inventory control policy development for the SES method could not doubtfully be applied.

Therefore, an exponential smoothing method was used, which is developed to forecast intermittent demand. When demand occurred, only one product was sold. This made the also applicable Croston-method forecast too optimistic compared to realised demand. This method does not adjust to zero-demand occurrences, which made the probability-considering TSB-method the best-fitting method.

The TSB-method uses the following formulas to fill in formula (11):

$$a_{t+1} = \alpha * f_t + (1 - \alpha) * a_t$$

$$p_{t+1} = \alpha + (1 - \alpha) * p_t$$

$$f_{t+1} = a_{t+1} * p_{t+1} \qquad (11)$$

Where, apart from the smoothing factor α ($0 < \alpha < 1$), the following variables are relevant:

$a_{t(+1)}$ = Demand level in period t(+1)
$p_{t(+1)}$ = Probability of demand occurring in period t(+1)
$f_{t(+1)}$ = Forecasted demand in period t(+1)

This TSB-method, just like all exponential smoothing methods, uses a smoothing factor α ($0 < \alpha < 1$). Furthermore, its forecasts per week may result in values below one, from which the expected number of weeks until demand can be calculated (a forecast of 0.25 means four weeks on average until demand). When choosing a smoothing factor between 0.1 and 0.3, the value of 0.3 still had the slightest forecast error of 13.81, compared to 14.65 and 17.65 for the values of 0.2 and 0.1, respectively.

2.2. Determining Reorder Levels With CSL^*

Given the mean and standard deviation, the most common approach for developments of inventory control policies is to assume that the lead time demand is normally distributed (Axsäter, 2006).

This normal distribution enables the determination of reorder level and needed CSL^* by using the Newsboy Problem. This Newsboy Problem goes with the following formula:

$$CSL^* = \frac{C_u + C_o}{C_u} \qquad (12)$$

Where the following variables are relevant:

C_u = costs of understocking per product per month
C_o = Costs of overstocking per product per month

Costs of overstocking are calculated in chapter 3.3 and total €0.51 per product/month, while costs of understocking differ for each product type and are explained in chapter 3.5.4.

The optimal s, from the (R, s, Q)-model when demand is forecasted, is calculated by the following formula (Prak et al., 2017):

$$s = r^* = (R + L)\hat{Y}_N + \phi^{-1}(\gamma^*)\sqrt{(R + L)\sigma^2 + (R + L)^2 Var(\hat{Y}_N)} \quad (13)$$

Where the following variables are relevant:

$s = r^*$ = Optimal reorder level

$\sigma^2 = Variance\ of\ demand$

$(R + L)\hat{Y}_N = Forecasted\ demand\ during\ lead\ time\ and\ review\ period$

$\phi^{-1}(\gamma^*)$ = Phi-value of CSL* from normal distribution

$L\sigma^2 = Variance\ of\ demand\ from\ true\ mean\ during\ lead\ time\ and\ review\ period$

$L^2 Var(\hat{Y}_N) = Variance\ of\ forecast\ error\ during\ lead\ time\ and\ review\ period$

For which, $Var(\hat{Y}_N) = \sigma^2\alpha/(2 - \alpha)$, as a given formula for smoothing factor α ($0 < \alpha < 1$)

As can be seen, this formula needs the forecasted demand during lead time and review period as a pre-determined parameter. This forecasting is done with periods of one week and performed with the SES method, elaborated on in chapter 4.1.1. The naïve method, assuming future values will remain the same as the latest demand forecast, is used. This value is multiplied by the lead time and review period.

When calculating the safety stock, the forecast error and demand variance during lead time and review period are considered. The forecast error depends on the smoothing factor α, which, as stated in chapter 4.1.1, is chosen to be 0.3. The safety stock is calculated by the second part of the formula and can easily be adjusted to a different CSL by taking the corresponding phi-value.

When having reached this reorder level, as calculated by the formula above, a certain amount must be ordered. This ordering amount is to the utmost extent determined by the MOQ stated by the supplier but is derived from the reorder level, as calculated with formula (13).

The volatility of the lead time itself is not considered for the calculation of reorder level in this research, which is explained in chapter 3.4. When Lead Time volatility would be considered when forecasting, the following formula could be used:

$$\text{Var(L)} = \square(\text{L})^2 = (\sqrt{(\pi)}/2) * \text{MAD(L)})^2 \quad (14)$$

For which: σ_L^2 = the variance of the lead time

MAD_L = MAD of the lead time

2.3. Influencing and Resulting KPIs

KPIs are essential within the model. They determine the outcoming results and are the most important outcomes of the model. The most influencing (relationships between) KPIs are discussed.

2.3.1. Shortage Costs and Holding Costs

Shortage costs and holding costs are assumed to be directly connected. When service levels are lower, shortage costs soar and holding costs plunge; if service levels rise, the opposite happens. However, this correlation does only hold if the same level of demand allocation is handled. Furthermore, with the calculation of shortage costs per product, it is assumed that all goods are sold at their full price.

It is assumed that the same efficiency level is handled for holding costs, as was done on 01/12/2020. The calculation of holding costs per product per month is dependent on both the total costs of warehousing and the number of sales during that month. As a result, holding cost per product per month can vary each month.

This shortage- and holding costs are used to calculate the optimal CSL (CSL^*), hence this KPI is necessary for calculating the optimal reorder level (s^*).

2.3.2. Cycle Service Levels

As stated above, CSL and CSL^*, which is the most cost-efficient level for this indicator, significantly influence other KPIs. This probability and complementary ϕ-value greatly influence the safety stock and thus the reorder point. For these calculations, CSL is the achieved value, while CSL^* is the desired value.

2.3.3. Effects and Relevant KPIs

Because implementation of the model is out of the timeframe of the research, it is hard to say what its effects are in practice. Technically seen, an automatic ordering system can be developed from this model, replacing multiple employees or enlightening their workload. Their disappearing tasks could be replaced by optimizing the model by researching the influencing trade-offs and resulting behaviour.

Furthermore, the resulting KPIs can be used to measure their performances on different business aspects:

- The CSL can be used to measure to which extent is Haco responsive.
- Holding costs per product/month measures how efficient is Haco with the use of warehouses.
- Volatilities in lead time indicate up to which extent the average lead time can undoubtfully be used as the forecasted lead time.

3. Results From Solution Design

In this chapter, the theoretical results from the adjustments of the model are discussed and compared with the old situation.

Contents:

3.1. Optimal Smoothing Factor and Demand Forecasts

The first developed section of the model is the forecasting component. With the help of the SES method, explained in chapter 4.1.1, demand is forecasted over 48 weeks. This forecasted demand deviates from the realised demand but also deviates for each smoothing factor. Before implementing the forecast in the model, the best smoothing factor is tested.

As seen in Table 7, for 12 out of 21 products, the smoothing factor of 0.3 is the most accurate. When 0.3 is not the most accurate factor, MADs (chapter 2.3) from the optimal factor are tiny. The total deviation of forecasts from factor 0.1 to optimal is 9.346, and summed deviations from factor 0.2 to optimal are 3.163; total added deviations from 0.3 to optimal are only 1.698.

The stated errors indicate that 0.3 is the most accurate smoothing factor for the selected products during the researched period, as explained in chapter 4.1.1 and shown in Table 8. Therefore, this factor is used within the demand forecasting calculations.

For the best-achieving smoothing factor of 0.3, it is tried to find a pattern on forecasting accuracy compared to the average- and volatility in demand and the MAPE, as shown in Table 8. Unfortunately, no direct correlation could be proven between these factors.

Nevertheless, when looking at accuracy and the time a product is included in the inventory, a relation can be found. The longer a product is included, the lower the most accurate smoothing factor is. All products for which smoothing factor 0.1 was optimal, were included in inventory in 2016 or earlier. While apart from some exceptions, products for which 0.3 is optimal are primarily included in 2018, 2019 or beyond.

It is expected that higher smoothing factors, for which the realised demand has more influence on the next forecast, have higher accuracy for products with a smaller timespan in inventory. This higher accuracy can be explained by higher volatilities and unfactored trends, which are inevitable at the start of a product inclusion. Higher smoothing factors can more easily follow the trend and cover these volatilities, which would take longer for lower smoothing factor levels.

However, on the long term, large values of smoothing constant α lead to too low s-levels and CSL (Prak et al., 2017). Here, Prak et al. (2017) state that products that are longer included in the inventory achieve service levels closer to the optimal CSL with lower smoothing factors.

		Smoothing Factors				
Suppliers	**Products**	**0.1**	**0.2**	**0.3**	**Mean D**	**Std Dev of Demand**
MAD per Product	Stoel Army (2 stuks)	12.85	11.29	10.49	16.00	13.4
	Stoel Barossa (2 stuks)	11.86	11.89	11.76	30.44	13.7
	Stoel Bentley (Per stuk)	9.60	9.64	9.56	17.42	11.0
	Stoel Chip (2 stuks)	8.54	8.00	7.84	17.88	11.8
	Stoel Dahlia (2 stuks)	7.51	6.87	6.88	12.04	10.0
	Stoel Diamond (2 stuks)	9.07	9.00	9.01	27.40	10.5
	Stoel Exotic (2 stuks)	5.44	5.51	5.46	13.96	6.7
	Stoel Flame (2 stuks)	6.39	5.25	5.11	10.58	6.7
	Stoel Index (2 stuks)	1.71	8.24	8.07	11.89	7.5
	Stoel Issue (2 stuks)	3.58	3.00	3.09	3.23	3.9
	Stoel Jackson (2 stuks)	9.39	9.64	9.98	32.94	11.4
	Stoel Riga + armleuning (2 stuks)	7.76	7.17	6.90	20.38	11.7
	Stoel Roady (2 stuks)	18.76	18.84	18.58	82.02	24.2
	Stoel Rock (2 stuks)	7.76	7.75	7.84	24.13	9.9
	Stoel Scott (2 stuks)	4.96	5.05	5.16	11.98	6.0
	Stoel Station (2 stuks)	4.76	4.89	4.98	10.71	5.5
	Stoel Transfer / Grace (2 stuks)	14.29	14.58	14.76	57.29	18.1
	Stoel Utopia (2 stuks)	6.34	5.11	4.84	3.65	6.4
	Stoel Watson (2 stuks)	9.40	9.36	9.32	31.60	11.2
	Bonn Boxspring	0.37	0.31	0.29	0.15	0.4
	Boxspringset Bonn.	1.66	1.63	1.62	3.77	1.8
	Deviation per product	9.35	3.16	1.70		

Table 5: MAD per Product for Different Smoothing Factors

Smoothing Factor Alpha	**0.1**	**0.2**	**0.3**
Average MAD per Product	7.71 4	7.76 3	7.69 3

Table 6: Total Forecasting Errors for Tested Smoothing Factors

The SES method, using formula (10) and explained in chapter 4.1.1, results in the values of Table 9. This table shows the forecasted demand in that week for the optimal smoothing factor and the realised demand during that period. These outcomes are an important part of the research, as forecasting is one of the most important additions from the model.

However, this table is not only meant to show these values but indicate the accuracy of the forecast in a more appealing way than showing the MAD values.

Products	Realised D in last period	Forecasted D for alpha = 0.3
Stoel Army (2 stuks)	41	28
Stoel Barossa (2 stuks)	14	22
Stoel Bentley (Per stuk)	25	22
Stoel Chip (2 stuks)	3	8
Stoel Dahlia (2 stuks)	3	2
Stoel Diamond (2 stuks)	17	25
Stoel Exotic (2 stuks)	32	17
Stoel Flame (2 stuks)	7	8
Stoel Index (2 stuks)	19	13
Stoel Issue (2 stuks)	0	2
Stoel Jackson (2 stuks)	52	38
Stoel Riga (2 stuks)	24	26
Stoel Roady (2 stuks)	96	84
Stoel Rock (2 stuks)	21	28
Stoel Scott (2 stuks)	10	9
Stoel Station (2 stuks)	11	12
Stoel Transfer/Grace (2 stuks)	52	60
Stoel Utopia (2 stuks)	20	15
Stoel Watson (2 stuks)	23	33
Boxspringset Bonn.	5	4

Table 7: Forecasted- and Realised Demand for the Optimal Smoothing Factor

As stated in chapter 3.5.2, the product which experienced intermittent demand was not considered in the regular forecasting method. For this product, the TSB-method (chapter 4.1.2) uses formula (11) to forecast demand probability and so demand level. The resulting values for each smoothing factor are shown in Table 10, just as their forecast errors (MAD). It is seen that also for this method, the smoothing factor of 0.3 is most accurate. ‘

Smoothing Factor	Forecasted Weekly D	MAD
0.3	0.256	0.288
0.2	0.243	0.305
0.1	0.213	0.368

Table 8: Forecasted Demand and Resulting MAD Using the TSB-method

However, this product's demand distribution deviated too much to be processable with the regular calculations on reorder level, safety stock, and CSL; therefore, the results are not further considered. Nevertheless, this table can give more insight into the demand for this product: when analysing the forecasted demand, the safety stock can be adjusted to this level.

3.2. Results on Parameters of (R, s, Q)-policy

The forecasts and formulas (12) and (13), discussed in chapter 4.2, most importantly create the new ordering policy for Haco. The values replace the currently handled values for reorder level (s) and reorder quantity (Q) with the recommended values, coming from the formulas. This ordering policy is mainly influenced by the handled review period, reorder level and safety stock, influenced by the CSL. The recommended review period of one week is fixed for all products, but reorder levels and reorder quantities vary per product. The results from calculating the current and recommended safety stocks, cycle stocks and reorder levels can be seen in Table 11 and result from the developed model.

The values for the recommended CSL come from the Newsboy-problem (formula (12)), while recommended safety stock, cycle stock, and reorder level come from formula (13) of Prak et al. (2017). Within these formulas, the recommended review period is handled, while within the current situation, the currently used review period is taken.

The reorder quantity (Q) is not shown within Table 11, as this value is heavily dependent on unknown lot sizes. Furthermore, they are influenced by the lead time, review period, and the number of products sold underneath the reorder level.

Products	Recom . SS	Recom . s	Recom . CSL	Curren t SS	Curren t s	Curren t CSL
Stoel Army (2 stuks)	188	645	96.6%	138	349	81.7%
Stoel Barossa (2 stuks)	185	536	94.4%	118	530	76.1%
Stoel Bentley (Per stuk)	160	508	95.5%	111	337	80.1%
Stoel Chip (2 stuks)	125	252	94.7%	46	239	63.0%
Stoel Dahlia (2 stuks)	107	143	94.3%	8	143	52.7%
Stoel Diamond (2 stuks)	155	559	96.0%	127	605	82.3%
Stoel Exotic (2 stuks)	98	373	96.6%	75	255	79.5%
Stoel Flame (2 stuks)	85	215	95.4%	44	173	69.5%
Stoel Index (2 stuks)	138	353	95.9%	62	268	74.4%
Stoel Issue (2 stuks)	53	88	95.9%	15	90	61.9%
Stoel Jackson (2 stuks)	173	792	96.1%	203	665	91.3%
Stoel Riga + armleuning (2 stuks)	126	542	96.8%	139	524	84.2%
Stoel Roady (2 stuks)	318	1670	95.9%	410	1583	92.3%
Stoel Rock (2 stuks)	135	593	95.9%	149	535	87.6%
Stoel Scott (2 stuks)	86	231	95.5%	43	210	69.8%
Stoel Station (2 stuks)	86	274	96.0%	61	195	78.6%
Stoel Transfer / Grace (2 stuks)	247	1223	95.5%	306	1172	91.6%
Stoel Utopia (2 stuks)	81	326	95.5%	79	206	83.1%
Stoel Watson (2 stuks)	161	693	96.1%	181	603	89.2%
Boxspringset Bonn.	15	39	98.2%	20	71	66.6%

Table 9: Comparison of Current- & Recommended Purchasing Decisions

Table 12 shows the adjustments recommended by the model and compares the two situations (current and recommended) from Table 11. The cells marked in red show parameters which could be lowered while having a more financially efficient CSL. This table aims to focus on the impact of the model by showing its adjustments yet put these adjustments into perspective by taking it as a percentage.

Products	Adjustment SS	Adjustment s	Adjustment CSL	% Change SS	% Change s
Stoel Army (2 stuks)	50	296	14.9%	36.3%	84.9%
Stoel Barossa (2 stuks)	67	6	18.4%	56.4%	1.1%
Stoel Bentley (Per stuk)	49	171	15.5%	44.3%	50.7%
Stoel Chip (2 stuks)	79	13	31.8%	171.6%	5.4%
Stoel Dahlia (2 stuks)	99	0	41.7%	1242.0%	0.1%
Stoel Diamond (2 stuks)	28	-46	13.7%	22.2%	-7.6%
Stoel Exotic (2 stuks)	23	118	17.1%	31.1%	46.3%
Stoel Flame (2 stuks)	41	42	26.0%	93.3%	24.4%
Stoel Index (2 stuks)	76	85	21.5%	123.3%	32.0%
Stoel Issue (2 stuks)	38	-2	34.1%	252.9%	-2.7%
Stoel Jackson (2 stuks)	-30	127	4.8%	-14.9%	19.0%
Stoel Riga (2 stuks)	-13	18	12.6%	-9.1%	3.5%
Stoel Roady (2 stuks)	-92	87	3.7%	-22.4%	5.5%
Stoel Rock (2 stuks)	-14	58	8.4%	-9.7%	10.9%
Stoel Scott (2 stuks)	43	21	25.7%	100.7%	10.0%
Stoel Station (2 stuks)	25	79	17.4%	40.7%	40.3%
Stoel Transfer/Grace (2 stuks)	-59	51	4.0%	-19.2%	4.3%
Stoel Utopia (2 stuks)	2	120	12.4%	2.1%	58.4%
Stoel Watson (2 stuks)	-20	90	6.8%	-10.9%	14.8%
Boxspringset Bonn.	-5	-32	31.8%	-25.6%	-45.4%
Average	19.4	65	17.9%	105.3%	17.8%

Table 10: Recommended Adjustments and Their Percentual Changes

As shown in Table 12, the average improvement on CSL, coming from the model's adjustments compared to the current situation, is 17.9%. This peerless increase of CSL goes along with an average increase in safety stock of 12 pieces (101.4%, which number is heavily affected by the Dahlia product), an average increase in reorder level of 319 pieces (11.9%) and an average increase of cycle stock of 20 pieces (3.0%). Each of the included percentages is individually lower than the increase of CSL. Therefore, it can be stated that the model is efficient in its improvement.

To compare the model's performances, KPI values from the model are compared to KPI levels of formula (7), considering lead time uncertainty (LTU). As seen in Table 13, the model (MDL) requires much lower inventory levels than the formula considering parameter uncertainty while still achieving the same optimal CSL, as calculated with the Newsboy problem. This efficiency can be explained by demand forecasting, which will be elaborated on in chapter 5.3, and a different ratio between the reorder and safety stock levels. This different ratio between reorder level and safety stock can be explained by unrepresentative volatilities in the lead time uncertainty (chapter 3.4) and the improper demand allocation.

Products	Current SS	Curren t s	Current SS - LTU SS	Current s - LTU s	LTU SS - MDL SS	LTU s - MDL s
Stoel Army (2 stuks)	138	349	-20	-86	29	167
Stoel Barossa (2 stuks)	118	530	-46	-121	10	-151
Stoel Bentley (Per stuk)	111	337	-32	-85	8	52
Stoel Chip (2 stuks)	46	239	-78	-171	-6	-174
Stoel Dahlia (2 stuks)	8	143	-98	-156	-5	-165
Stoel Diamond (2 stuks)	127	605	-39	0	-20	-84
Stoel Exotic (2 stuks)	75	255	-52	-96	-35	-3
Stoel Flame (2 stuks)	44	173	-54	-95	-18	-67
Stoel Index (2 stuks)	62	268	-52	-32	16	31
Stoel Issue (2 stuks)	15	90	-48	-29	-13	-37
Stoel Jackson (2 stuks)	203	665	11	-54	-29	19
Stoel Riga (2 stuks)	139	524	-13	86	-33	67
Stoel Roady (2 stuks)	410	1583	116	-24	5	-51
Stoel Rock (2 stuks)	149	535	-9	-9	-31	9
Stoel Scott (2 stuks)	43	210	-61	-86	-23	-80
Stoel Station (2 stuks)	61	195	-43	-81	-23	-21
Stoel Transfer/Grace (2 stuks)	306	1172	49	-2	-24	-35
Stoel Utopia (2 stuks)	79	206	-22	-49	-25	49
Stoel Watson (2 stuks)	181	603	-2	-86	-31	-44
Boxspringset Bonn.	20	71	-52	-62	-59	-100
Total Adjustment of KPI			-545	-1238	-308	-619

Table 11: Performance Comparison Between Different Formulas

When comparing Table 13 with Table 12, the average percentual rise of safety stock with 92.3% and an average rise of reorder level of 9.6% does not mean more items are held in the warehouse. What can be concluded is that safety stocks are more evenly spread, based on demand. This net decrease in inventory positions means that fewer holding costs must be made. However, this decrease in holding costs does not follow a linear pattern, a holding costs of €0.51 per product per month is saved (Appendix C). Assuming the decrease in holding costs is linear, this would mean the following decrease in holding cost for the selected products:

$$Savings\ on\ holding\ costs = €0.51 * (853 + \left(\frac{1856-853}{2}\right) = €690.80$$

3.3. Influence of Individual Factors and Sensitivity Analyses

In Table 14 the difference between CSLs when forecasting demand and without forecasting demand is shown. With this table it is shown that getting more insight in demand has a positive contribution to CSL.

For the results in Table 14, the current values and the values from the model are put into the in chapter 3.1.2 mentioned formula (7), considering LUT. As explained in chapter 3.4, considering this LUT is likely to result in lower CSL levels than achieved. When 'Using Demand Forecasts', the weekly forecasted demand calculated with the SES method is used, considering its MAD as demand uncertainty factor. The calculations for 'Without Demand Forecasts' use the mean and standard deviation within their formula, where the standard deviation indicates the demand uncertainty within the formula.

As can be seen, the reorder levels without demand forecasts deviate from the currently handled reorder levels. Compared to the current reorder levels, the levels without demand forecasts are

	Using Demand Forecasts			Without Demand Forecasts			
Products	**s**	**SS**	**CSL**	**s**	**SS**	**CSL**	**Change of CSL (%-Point)**
Stoel Army (2 stuks)	645	188	64%	349	138	69%	-5.0%
Stoel Barossa (2 stuks)	536	185	66%	530	118	60%	6.5%
Stoel Bentley (Per stuk)	508	160	65%	337	111	65%	-0.4%
Stoel Chip (2 stuks)	252	125	72%	239	46	56%	15.7%
Stoel Dahlia (2 stuks)	143	107	76%	143	8	52%	24.3%
Stoel Diamond (2 stuks)	559	155	63%	605	127	61%	1.7%
Stoel Exotic (2 stuks)	373	98	62%	255	75	63%	-0.8%
Stoel Flame (2 stuks)	215	85	69%	173	44	60%	8.5%
Stoel Index (2 stuks)	353	138	69%	268	62	63%	5.7%
Stoel Issue (2 stuks)	88	53	76%	90	15	60%	15.6%
Stoel Jackson (2 stuks)	792	173	60%	665	203	65%	-5.0%
Stoel Riga (2 stuks)	542	126	61%	524	139	68%	-7.7%
Stoel Roady (2 stuks)	1670	318	59%	1583	410	62%	-3.7%
Stoel Rock (2 stuks)	593	135	60%	535	149	65%	-4.6%
Stoel Scott (2 stuks)	231	86	68%	210	43	59%	8.8%
Stoel Station (2 stuks)	274	86	65%	195	61	64%	1.1%
Stoel Transfer/Grace (2 stuks)	1223	247	59%	1172	306	63%	-3.9%
Stoel Utopia (2 stuks)	326	81	61%	206	79	69%	-8.0%
Stoel Watson (2 stuks)	693	161	61%	603	181	64%	-3.2%
Boxspringset Bonn.	39	15	56%	71	20	59%	-3.6%
Average			65%			62%	2.1%

Table 12: Influence of Demand Forecasting on CSL

In the research, a repetitively discussed phenomenon is the inclusion of the review period. This problem occurs when not considering the review period R in the calculations on safety stock and reorder level, which is currently the case. For all calculations considering lead time L, the recommended review period (R = 1) was added to overcome this problem. In Table 15, the severe decline in CSL is shown when not considering this review period. This difference was calculated by leaving out the added R in formula (13) and filling in the same formula's resulting amount.

Products	s	s without R	CSL	CSL without R
Stoel Army (2 stuks)	645	521	93.3 %	73.0%
Stoel Barossa (2 stuks)	536	428	89.3 %	74.4%
Stoel Bentley (Per stuk)	508	409	91.4 %	74.0%
Stoel Chip (2 stuks)	252	186	89.9 %	77.6%
Stoel Dahlia (2 stuks)	143	91	89.2 %	79.2%
Stoel Diamond (2 stuks)	559	457	92.1 %	72.3%
Stoel Exotic (2 stuks)	373	306	93.4 %	71.5%
Stoel Flame (2 stuks)	215	166	91.0 %	75.9%
Stoel Index (2 stuks)	353	271	92.1 %	76.1%
Stoel Issue (2 stuks)	88	60	92.0 %	79.0%
Stoel Jackson (2 stuks)	792	667	92.4 %	68.7%
Stoel Riga (2 stuks)	542	451	93.8 %	69.9%
Stoel Roady (2 stuks)	1670	1429	92.0 %	66.0%
Stoel Rock (2 stuks)	593	498	92.1 %	69.5%
Stoel Scott (2 stuks)	231	182	91.3 %	75.4%
Stoel Station (2 stuks)	274	220	92.2 %	74.2%
Stoel Transfer/Grace (2 stuks)	1223	1042	91.4 %	67.5%
Stoel Utopia (2 stuks)	326	272	91.2 %	70.9%
Stoel Watson (2 stuks)	693	579	92.3 %	69.7%
Boxspringset Bonn.	39	23	96.6 %	42.1%

Table 13: The Effects of the Review Period on CSL

Because CSL indicates the probability of stocking out, instead of the part of demand covered from inventory (known as the fill rate), the inclusion of the review period problem violently influences this service indicator.

Within the developed model, the review period is lowered from two weeks to one week. It is tested what influence this adjustment has on reorder levels and safety stocks while handling the same CSL.

From Table 14, it can be seen that adjusting the review period has severe consequences on inventory levels. When returning the review period to two weeks, total reorder levels rise by 6.9% and safety stocks by 7.1%.

		R = 2		R = 1	
Products	**Optimal CSL**	**s**	**SS**	**s**	**SS**
Stoel Army (2 stuks)	96.6%	684	199	645	188
Stoel Barossa (2 stuks)	94.4%	569	196	536	185
Stoel Bentley (Per stuk)	95.5%	540	171	508	160
Stoel Chip (2 stuks)	94.7%	268	133	252	125
Stoel Dahlia (2 stuks)	94.3%	153	115	143	107
Stoel Diamond (2 stuks)	96.0%	594	165	559	155
Stoel Exotic (2 stuks)	96.6%	396	104	373	98
Stoel Flame (2 stuks)	95.4%	230	92	215	85
Stoel Index (2 stuks)	95.9%	374	146	353	138
Stoel Issue (2 stuks)	95.9%	94	58	88	53
Stoel Jackson (2 stuks)	96.1%	841	184	792	173
Stoel Riga (2 stuks)	96.8%	576	134	542	126
Stoel Roady (2 stuks)	95.9%	1771	335	1670	318
Stoel Rock (2 stuks)	95.9%	631	144	593	135
Stoel Scott (2 stuks)	95.5%	246	92	231	86
Stoel Station (2 stuks)	96.0%	291	92	274	86
Stoel Transfer/Grace (2 stuks)	95.5%	1299	263	1223	247
Stoel Utopia (2 stuks)	95.5%	347	87	326	81
Stoel Watson (2 stuks)	96.1%	735	171	693	161
Boxspringset Bonn.	98.3%	106	36	39	15
Total		10746	2917	10054	2723

Table 14: Consequences of Adjusting the Review Period

Apart from covering the volatilities coming with the review period, volatilities on demand are also considered with the calculation of safety stocks in the model, which is currently not the case. Table 16 shows the influence of demand volatilities on the probability of (not) stocking out. For most products, not considering the review period has a more significant influence on CSLs, but influences are still impactful.

Products	s considering σ2	s without σ2	CSL considering σ2	CSL without σ2
Stoel Army (2 stuks)	645	541	93.3%	78.9%
Stoel Barossa (2 stuks)	536	441	89.3%	77.9%
Stoel Bentley (Per stuk)	508	422	91.4%	78.4%
Stoel Chip (2 stuks)	252	187	89.9%	78.0%
Stoel Dahlia (2 stuks)	143	88	89.2%	77.9%
Stoel Diamond (2 stuks)	559	475	92.1%	78.6%
Stoel Exotic (2 stuks)	373	318	93.4%	78.9%
Stoel Flame (2 stuks)	215	171	91.0%	78.4%
Stoel Index (2 stuks)	353	278	92.1%	78.6%
Stoel Issue (2 stuks)	88	59	92.0%	78.6%
Stoel Jackson (2 stuks)	792	697	92.4%	78.7%
Stoel Riga (2 stuks)	542	471	93.8%	79.0%
Stoel Roady (2 stuks)	1670	1498	92.0%	78.6%
Stoel Rock (2 stuks)	593	520	92.1%	78.6%
Stoel Scott (2 stuks)	231	185	91.3%	78.4%
Stoel Station (2 stuks)	274	227	92.2%	78.6%
Stoel Transfer/Grace (2 stuks)	1223	1090	91.4%	78.4%
Stoel Utopia (2 stuks)	326	283	91.2%	78.4%
Stoel Watson (2 stuks)	693	605	92.3%	78.7%
Boxspringset Bonn.	39	26	96.6%	63.2%

Table 15: The Influence of Demand Volatilities on CSL

Because lead time volatility is the only volatility of the used factors which is not considered, a sensitivity analysis is done on this parameter. It is seen that a considerable part of the lead time can be covered with the recommended safety stock, from which it can be concluded that the parameter of lead time is not very sensible for volatilities.

This sensitivity analysis was performed by filling in the known parameters within the formula and calculating the unknown parameter var(LT). The result indicated up until what volatility it could be covered with safety stock.

Products	SS	Forecasted Weekly D	Var(LT) covered by SS (weeks)	Coverable Var(LT) as % of LT
Stoel Army (2 stuks)	188	28	6.6	41%
Stoel Barossa (2 stuks)	185	22	8.5	53%
Stoel Bentley (Per stuk)	160	22	7.4	46%
Stoel Chip (2 stuks)	125	8	14.9	98%
Stoel Dahlia (2 stuks)	107	2	48.4	300%
Stoel Diamond (2 stuks)	155	25	6.2	38%
Stoel Exotic (2 stuks)	98	17	5.8	36%
Stoel Flame (2 stuks)	85	8	10.5	65%
Stoel Index (2 stuks)	138	13	10.4	65%
Stoel Issue (2 stuks)	53	2	24.7	153%
Stoel Jackson (2 stuks)	172	38	4.5	28%
Stoel Riga (2 stuks)	126	26	4.9	30%
Stoel Roady (2 stuks)	318	84	3.8	24%
Stoel Rock (2 stuks)	134	28	4.7	29%
Stoel Scott (2 stuks)	86	9	9.6	60%
Stoel Station (2 stuks)	86	12	7.4	46%
Stoel Transfer/Grace (2 stuks)	247	60	4.1	255%
Stoel Utopia (2 stuks)	81	15	5.3	33%
Stoel Watson (2 stuks)	161	33	4.9	30%
Boxspringset Bonn.	15	4	3.7	62%

Table 16: Sensitivity Analysis on Lead Time Volatility

4. Conclusion & Recommendations

In this chapter, the conclusions and recommendations from the research will be presented. Its contributions to literature are mentioned, and possible subjects for further research are discussed. Lastly, a discussion will be made about the addition and limitations of the research.

Contents:

4.1. Conclusion

This thesis presents an improvement on the core problem. This core problem stated that Haco does not have a stable and predominantly data-driven purchasing policy for overseas-transported products. From this core problem, the following main research question was formulated:

How can Haco reduce inventory costs and improve service levels by optimizing the purchasing policy and inventory stability for overseas-transported products by forecasting demand?

To be able to answer this question, sub-research questions have been formulated. These sub-research questions have been the handholds for the research and the improvement on the core problem. Answering the main research question was done with the following approach:

1. The core problem was identified, and qualitative research was done on the current situation
2. Literature about the subject was studied to determine what inventory control policies could be applicable and what forecasting techniques would fit the situation, considering available data, timeframe, and research target.
3. A quantitative analysis is done on the current situation. The current demand distribution and purchasing policy are explicated, and the currently handled reorder level, safety stock and CSL values are calculated.
4. Weekly demand is forecasted with the forecasting technique, which was considered most applicable.
5. A quantitative analysis is done on the optimal purchasing policy, considering the mentioned KPIs and forecasted demand.

Currently, Haco does not apply demand forecasting and does not consider volatilities within its purchasing policy. This improper demand allocation causes (i) undesired stockouts and thus performances below the desired service level, (ii) higher inventory costs because of unnecessarily high safety stocks and (iii) lack of warehousing space because of improper demand allocation.

To improve on this current situation and remedy the causing factors, a model has been developed. This model uses the SES method to forecast demand and the formula of Prak et al. (2017) to include parameter uncertainties. When comparing the three formulas (no uncertainty, lead time uncertainty & parameter uncertainty), reality is most accurately approached with the formula considering parameter uncertainty. No inclusion of uncertainty represents too low safety stocks, while the consideration of lead time uncertainties led to unnecessarily high safety stocks. Therefore, it can be stated that the combination between forecasting and the use of the parameter uncertainty formula improves demand allocation and demand anticipation and, therefore, the ability to be more responsive by improving CSL. This improvement on CSL is based on calculating the optimal, which is done with the Newsboy problem. These calculations resulted in an average increase of CSL by 18.1%, while safety stock and reorder level only rose with 12.7% and 7.1%, respectively. In the long term, structurally reducing these inventory positions would enable Haco to save on holding costs by lowering the number of rented warehouses.

Nevertheless, the model's most important function is increasing service levels and reducing volatilities in the warehouse. The theoretical approach would undoubtedly improve service levels and reduce volatilities in the warehouse, however, it still needs to prove itself in practice.

All in all, the core problem of not having a stable and predominantly forecast-driven purchasing policy for overseas-transported products is solved. That means that the problem cluster's problems (Figure A.3) will be solved or firmly declined in impact. The company experienced too many backorders while warehouses were packed. As shown in Table 10, especially reorder levels need to rise; safety stock levels need to be better anticipated on demand but do not all have to rise. The higher reorder points bring higher CSLs with them, creating more stability in inventory. The main research question is therefore answered. Moreover, many more subjects are proposed and researched, which could be helpful for Haco.

4.2. Recommendations

Based on the experiences during the research and insights developed during the process, several recommendations can be made to the company.

The first recommendation includes instructing the IT partner to include the forecasting method using formula (10) and formula (13) to calculate reorder levels and safety stocks in the purchasing ERP for all overseas-transported products and suppliers. This inclusion would fully automate the calculations from the model, structurally decreasing the required time for ordering. When this purchasing system functions well in practice, products could be ordered automatically from the system's calculated reorder point, which would minimize R to zero, create an (s, Q)-policy and further decrease uncertainties.

Within the implementation of forecasting in the ERP, it is recommended to enlarge the dataset used for the SES method. When having a larger dataset, the method is even more accurate because it continuously optimizes itself.

The second recommendation would be to make strict arrangements with suppliers on lead times. Often, a supplier delivers either too late or too early, causing undesired chaos in the warehouse. When arrangements are made with suppliers about delivering dates, including rewards when delivering as scheduled or fines when not delivering as scheduled, this chaos can be reduced.

Furthermore, it would be helpful to improve data registration on KPIs. To improve the model's applicability, data on the used KPIs needs to be registered and handled more carefully. Currently, data is often overwritten or corrupted because it eases the administrational process. However, when applying the model, this can disrupt the ordering policy. Furthermore, this data is crucial to get more insight into business processes and products.

Besides, it would be recommended to make strict arrangements with suppliers on which products are delivered. For some suppliers, it is not even determined by Haco which products are shipped. The factory produces in a particular consecution, after which the finished products are shipped to Haco. This randomization considerably disorientates the warehouse control and complicates achieving the desired service levels.

Lastly, it would improve the current situation if the management team planned larger and constant ordering timeslots. Because ordering is one of many tasks for the management team, not all products can be handled during the reserved time slots. To reduce R from two to one, as desired in the new situation and applied in the model, larger timeslots need to be reserved for ordering. If this is not possible, it needs to be delegated to a trustworthy and qualified employee.

4.3. Contribution to Literature

This research its contribution to literature is primarily focused on the used formula of Prak et al. (2017); a review period R is considered within the existing formula and this theoretic formula is applied on a case study in practice.

Beyond these relatively small additions to literature, this research is a case study on the combination of quantitative forecasting and inventory management decisions. It studies the theoretical perspective beyond the formula of Prak et al. (2017), in practice and compares results. The results considering demand forecasting are compared with formulas not considering demand forecasting, with and without lead time uncertainty.

4.4. Further Research

4.4.1. Implementation on Domestic Goods

This research was the first time that an external party theoretically analysed the supply chain of Haco. Because the research had to be done with limitations, the findings in this thesis are just the tip of the iceberg. Many more subjects can be researched and optimized by analysing the current situation and improving it based on literature.

An adequate research subject could be implementing this research on domestic products and suppliers. However it focuses on container-shipped products, the developed (R, s, Q)-policy can also be used for domestic transported products.

However, the practical execution will differ, caused by the higher lead times and elevated lot sizes for container products. In the model, these inflexibilities are covered with relatively high safety stocks. As stated in chapter 3.1.2, domestic products are often more flexible with their lower lead times and lower or no MOQs, requiring less safety stock.

These differences need to be researched. Still, many findings of this research can be used as a base for this further research.

4.4.2. Behaviour Towards Non-Normal Products

Not all product demands are normally distributed. In this research, up to a certain level, not-normal products are still assumed normal to implement these in the model. This unsubstantiated, yet often done, normality assumption influences the model's accuracy and should be researched when optimizing inventory control. Testing applicable distributions for non-normal products and possible formulas and testing the optimal behaviour towards these products are possible subjects for further research. Literature about this topic can be found in the book 'Inventory Control' from Axsäter (2006).

Moreover, the influence of the erroneous assumption on normality can be tested. When no disadvantageous effects is be found, the normality assumption can be maintained.

4.4.3. Lead Time Volatilities and Lead Time Distributions

To correctly implement lead time uncertainties within an inventory control model, more must be known about lead time distributions and achievements on lead times of suppliers. As stated in chapter 3.4, standard deviations of lead time often do not represent actual lead time uncertainties.

In the higher range of CSLs, decreasing the lead time volatilities increases the required safety stock. In this range of CSLs, a manager who wants to decrease inventories should focus on decreasing lead times rather than lead time volatility. This contradicts the sequences from the normal approximation. (Chopra et al., 2004)

Furthermore, lead times can follow different distributions themselves. The gamma distribution is an often-assumed distribution for this parameter. When the lead time follows a gamma distribution, the prescriptions of the normal approximation are flawed over a wide range of cycle service levels. This range is narrower when lead times are uniformly distributed (Ramaekers & Gerrit, 2008).

All in all, the achieved lead time deviations and uncertainties, and their distribution can be a subject of further research.

4.4.4. Holt-Winters' (Seasonal) Method

Within this research, not only the SES method is considered as a forecasting method, also, Holt-Winters' method is studied as a possible addition to the solution design (chapter 2.2.6).

However, the method is studied, it is not further considered in the research results due to lack of applicable data and time. Therefore, applying this method can be a subject for further research, using the studied literature on this topic, mainly from Chase (2013), Chopra & Meindl (2016) and Axsäter (2006) as a base.

4.4.5. Behaviour Towards Furnishing Packages

As mentioned in chapter 1.1, Haco does only sell loose furniture but also furnishing packages. These packages consist of multiple furniture items, which could come from different suppliers. Narrowing the gap between arrival times for products of the same furnishing package can lower holding times for these items and release pressure on the warehouse. An improvement approach on this topic is introduced in (A.Estep, 2012) but demands a high level of professionalism on inventory management, as described in chapter 1.3.

4.5. Discussion

Because applying theoretical insights in practice goes along with assumptions and limitations, the most influencing aspects are discussed.

- Because of internal smoothing, the mentioned CSL on the current situation (chapter 3.1.2, Table 1) is a lower bound. Reserved products can be interchanged between shops, covering demand up until a certain level.

- In some cases, even if lead times are too long to adapt to demand shifts predicted by demand sensing, early detection of potential issues can itself provide benefits. For example, predicting potential shortage might provide an opportunity to explore alternative scenarios, one of which could be switching to a supplier closer to home with a shorter lead time (Sankaran et al., 2019).

- Products are generalized, materials and colours are taken together as one product, smoothing some volatilities and increasing the handled demand amounts.

- Lead times are not taken very precisely; the handled values are averages used for long-term analysis. Furthermore, no forecasting is done on lead times, nor seasonality is considered. Note that the developed model takes no account of state-dependent or autocorrelated lead times. Seasonal congestion in ports is a well-observed phenomenon, and this would lead one to suspect that lead times are positively auto-correlated (Disney et al., 2016).

- The effects of COVID-19 on consumer and supplier behaviour and demand are limitary taken into consideration. In its article (Nikolopoulos et al., 2021) provides predictive analytics tools for forecasting and planning during a pandemic and forecast COVID-19 growth rates with statistical, epidemiological, machine deep-learning models and a new hybrid forecasting method based on nearest neighbours and clustering. They further model and forecast the excess demand for products and services during the pandemic using Google trends and simulating governmental decisions. These empirical results can immediately help Haco to make better decisions during the ongoing and future pandemics.

- When thinking long-term, a business can choose not to handle CSL^*, as calculated with the Newsboy problem, as their CSL. Building up a reputation for being responsive to distinguish the business from competitors can be a tactical move to conquer market share. It may cause profitability in the long-term but can cause financial losses in the short-term. Therefore, the determination of a long-term profitable CSL in practice needs more consideration than only financials.

- Optimal CSL can differ from what they would be after the inclusion of interest costs for the new warehouse. These currently unknown costs are not included when calculating holding costs and therefore not considered when calculating the optimal CSL.

- Opportunity costs not considered for holding costs because of interest rates reaching zero/being negative. However, when investing the costs of inventory (solar panels, new shops, stocks), still a profit can be made

- No elaboration on risks of sourcing from low-cost countries, how to tackle them. Political influences, pandemic influences, higher chances of supply chain disrupting events.

- It is assumed that customers do not want to wait on their product; stocking out means that sales are lost. In practice, having a lead time is not always a dealbreaker.

- It is not tested for all products if the recommended reorder level and safety stock, coming from the developed model, can fit in the current warehouse. As stated in chapter 1.7, the implementation of the model was not doable in the given timeframe

Note that some discussion points are already mentioned earlier in the report but are stated in this chapter to improve the research's validity and applicability.

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Appendices

Appendix A: Current Numbers on Overseas Sales

When looking at these overseas-transported products' sales, the weekly number of sales within a year is more volatile, caused by COVID-19; no consistent trend can be derived from it.

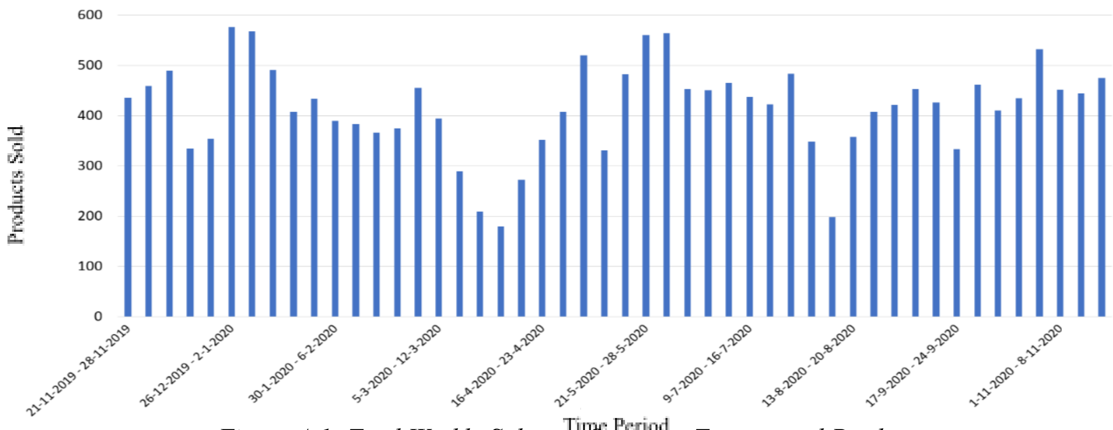

Figure A.1: Total Weekly Sales on Overseas-Transported Products

When looking at the annual sales for container shipped products (Figure A.1), consistent and robust growth of 68.3%, 60.9% and 29.4% year-on-year is seen, for which the effects of COVID-19 can explain the latest and lower percentual growth in 2020. Nevertheless, the dotted trend line implicates a constant rise of approximately 10.000 more products, container shipped per year. Where total revenue of Haco had grown by 1.0%, 12.9%, and 12.5%, respectively, for the same years. Therefore, it can be stated that each year, overseas-transported products play a more critical role within Haco.

Furthermore, overseas-transported products have the lowest purchasing flexibility and the most extended lead times. They contain many products per shipment and have the most significant influence on inventory volatility because they are reactively ordered with multiples simultaneously. To make inventory processes more structured and keep responsiveness on the same level (or higher, more attention must be paid to (analyses on) this part of the inventory.

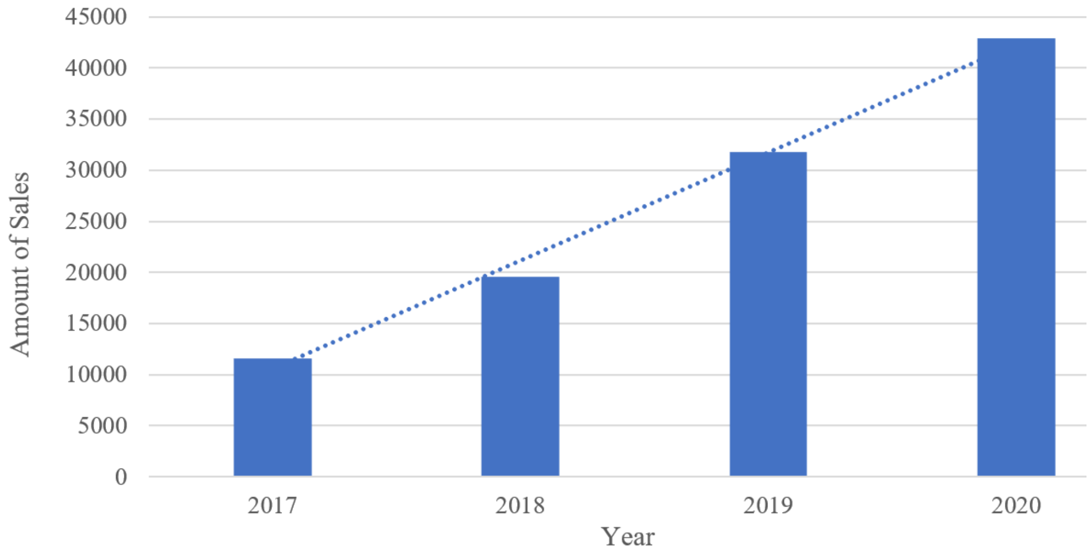

Figure A.2: Annual Container-Shipped Product Sales From 2017 to 2020

Because Haco is rapidly growing their yearly sales, they are preparing a second central warehouse construction. The lot's purchase has been completed, but the construction is expected to be finished in 2022. When the current growth rates would be maintained, and the inventory management policy would not be improved, the logistics centre needs to function already close to its maximum capacity to overtake the services of the rented decentral warehouses. This research is of even greater importance when the policy can also be applied in the new warehouse.

Appendix B: Identification of the Core Problem

The existing and relevant problems are identified and acquired to properly start the research, following the Managerial Problem-Solving Method (Heerkens & Van Winden, 2012). The problems are visualised in a problem cluster, which indicates the causes and consequences of each topic-related problem. This problem cluster helps to find the core problem, which is seen as the cause for all other problems and, therefore, the most influential. The core problem is furthermore found by doing semi-structured interviews with the purchasing manager and looking at data on inventory levels and lead times for different product types. During the semi-structured interviews, questions are prepared but can be added or adjusted during the interview. It is a flexible way of interviewing and appropriate for gathering information from well-informed or influential people in the organisation (Cooper & Schindler, 2014). The questions during the interview were based on remarkable data developments and poorly performing subjects within Haco.

The process starts with an action problem; an action problem is a discrepancy between the norm and reality, as perceived by the problem owner (Heerkens & Van Winden, 2017). The action problem Haco is dealing with is not having a regulated and predominantly data-driven purchasing policy, resulting in highly volatile inventory.

After the problem is identified, the causes and consequences are stated, which is essential during the Managerial Problem-Solving Method (MPSM) (Heerkens & Van Winden, 2012). These causes and consequences are visualised in Figure A.3, where boxes in red identify primarily observed consequences, blue boxes identify indirectly influenced consequences, yellow boxes identify directly influenced consequences and green boxes identify the most impactful causes.

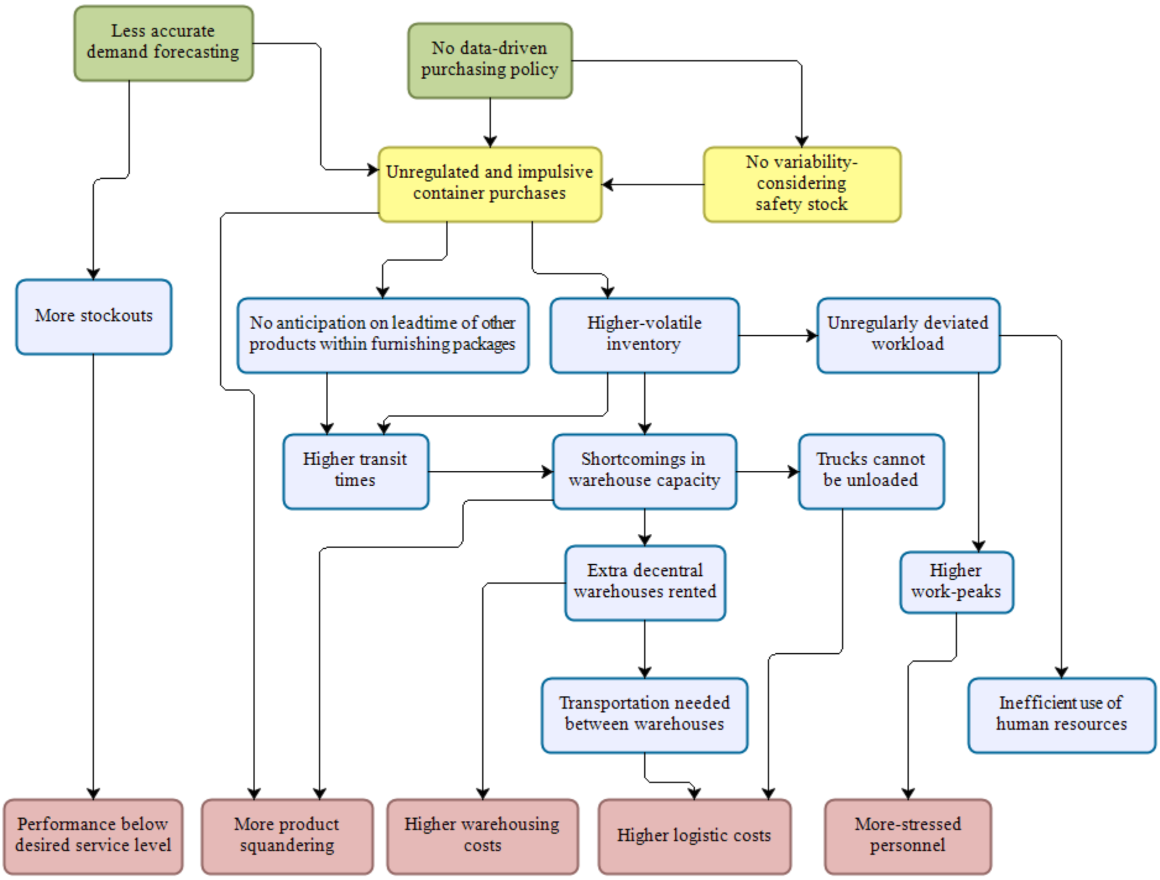

Figure A.3: The Problem Cluster

The highly volatile inventory, which is the direct cause of the explained consequences, is indirectly caused by not having a regulated and data-driven purchasing policy. Following Heerkens (2012), the core problem can be found at the top of the problem cluster. This rule is applied along with the four rules of thumb (Heerkens & Van Winden, 2017), resulting in the following core problem:

Not having a stable and predominantly data-driven purchasing policy for overseas-transported products.

This core problem is identified by combining the green boxes in Figure A.3: The problem cluster and primarily observed by the red boxes. The following observed effects show the impact of the core problem:

Higher Workload:
Because products come in voluminous amounts at the same time, the workload is not evenly distributed. The employees working at the warehouse lose their overview of the situation and act impulsively. Planning deliveries becomes undoable because warehouse personnel cannot process more than one container of products per day for several container-shipping suppliers. For these reasons, containers are waiting or delayed, or planners and warehouse personnel work above their capacity, resulting in stressed employees.

Higher transit times for furnishing packages:
Because the company delivers loose furniture but also furnishing packages, it can happen that items coming from different suppliers, but being sold in the same package, wait for months before being delivered. When this happens, the products occupy warehouse capacity for this period, waiting for the other container-shipped product. This topic will not be considered in the research because it requires a different problem-solving approach than the core problem, as stated in chapter 1.7 and is thus out of the research scope.

Extra warehouse capacity needed:
Because of the voluminous deliveries, there are times where the warehouse is full, and no capacity is left for new products. The total warehouse capabilities need to cover the peaks in deliveries, requiring more capacity than a stable inventory. Because the warehouse is currently unable to handle all peaks, situations occur where the products cannot be delivered before another truck is loaded. When the truck for loading has a delay or the unloading truck arrives early, the products cannot be unloaded, and the cargo truck must wait. This waiting time brings costs for disturbing the supply chain and thus creates unnecessary costs, which must be avoided to create a profitable logistics department.

Performance below desired service level
To distinguish itself from other furniture companies, Haco tries to maintain high service levels, being determined by general customer satisfaction. However, this satisfaction is not only determined by behaviour towards shopping customers but especially by product availability and delivery times. When a container-shipped product is not available, lead times and delivery times are extensively high, decreasing service levels.

More product squandering
Products which have been in the warehouse for too long are put through to the shops without being ordered. The shop will try to sell the product by stalling it on an eye-catching spot or create a discount. When hereafter the product is still not sold, it is destroyed with the hydraulic press. Destroying the product is an undesired last option, which destroys value due to improper demand anticipation.

Appendix C: Current Warehousing Situation

Determining how much stock a firm needs to hold to be the most efficient is an enormous challenge. This includes deciding how much inventory is held in total as well as addressing the capacity per product. In the last years, having too little inventory was a standard, causing lower CSLs and missing out on possible profits. When the number of backorders for a product became excessive, an enormous bulk was ordered, supplying the demand but unnecessarily filling the warehouse (see Figure 1.1).

Because container-shipped goods offer higher profit margins, the shortage costs of these products are exalted, compared to the holding costs. Resulting in a higher desired CSL and, therefore in, currently unperformable high, safety stock and reorder level levels.

Although Haco is renting several decentral locations already, capacity restrictions seem to be an everlasting challenge, which can be explained by their shifting business strategy, including more container shipments.

In Table 17, the efficiency performance of the warehouses is measured by the average inventory per m2. However, the total volume (m3) of the warehouse products is not measured, which would give more insight. When calculating inventory per m2, deviations in volume between products can give altered results.

No.	Adress	Monthly Costs	Type of Costs	Area (m^2)	Inventory on 01/12/2020	Inventory per m^2
1	Leehove 70, De Lier	X	Interest	6000	22711	3785
2	Kijckerweg 113B, De Lier	X	Rent	2000	8400	4.2
3	Honderdland 302, Maasdijk	X	Rent	1500	432	0.288
4	Hondert Margen 24, De Lier	X	Interest	2500	3722	1.488

Table 17: Warehouses of Haco and Their Characteristics

As shown in Table 17, the amount of inventory per m2 differs significantly; this uneven distribution of products is partially explainable by storing different product types. In warehouse 3, volume-demanding box springs are stored, while smaller seats are stored in warehouse 2. Overseas-transported products are mainly stored in warehouse 1.

However, the cost-efficiency per warehouse cannot be calculated - because revenue on products per warehouse is not measured - the total holding costs per product can be calculated. This calculation is done by dividing the rental costs and costs on insurances per month by the monthly number of sales for the same period.

The total warehouse costs per month are €20,156.80 per month, for which the most influencing ones are shown in Table 17. With an average of 39.458 total sales per month, this results in a rounded off holding cost per product of €0.51. For the researched products, the relevant holding costs are calculated by:

$$Holding\ costs\ per\ product\ type\ per\ month = €0.51 * \left(\frac{CS}{2} + SS\right) \qquad (15)$$

These holding costs are necessary for calculating the optimal CSL, which is done with the Newsboy Problem (chapter 2.5).

Investments in inventory bring so-called opportunity costs. These costs on missing out on potential interest on the present liquidity are not taken into with the calculation of holding costs because of the interest rates reaching zero or even being negative.

Filling in formula (15) on the calculation of holding costs for the selected products results in the holding costs per month, shown in Table 18.

Products	Current SS	Current CS	Current Holding Costs/Month
Stoel Army (2 stuks)	138	211	€124.21
Stoel Barossa (2 stuks)	118	412	€165.24
Stoel Bentley (Per stuk)	111	226	€114.24
Stoel Chip (2 stuks)	46	193	€72.68
Stoel Dahlia (2 stuks)	8	135	€38.51
Stoel Diamond (2 stuks)	127	478	€186.66
Stoel Exotic (2 stuks)	75	180	€84.15
Stoel Flame (2 stuks)	44	129	€55.34
Stoel Index (2 stuks)	62	206	€84.02
Stoel Issue (2 stuks)	15	75	€26.78
Stoel Jackson (2 stuks)	203	462	€221.34
Stoel Riga (2 stuks)	139	385	€169.07
Stoel Roady (2 stuks)	410	1173	€508.22
Stoel Rock (2 stuks)	149	386	€174.42
Stoel Scott (2 stuks)	43	167	€64.52
Stoel Station (2 stuks)	61	134	€65.28
Stoel Transfer/Grace (2 stuks)	306	866	€376.89
Stoel Utopia (2 stuks)	79	127	€72.65
Stoel Watson (2 stuks)	181	422	€199.92
Bonn Boxspring	1	3	€1.28
Boxspringset Bonn.	20	51	€23.21
Total	2336	6420	€2,828.58

Table 18: Holding Costs per Month for Each Product Type

Appendix D: Shapiro-Wilk Test on Normality

As explained in chapter 3.3.2, the Shapiro-Wilk test on normality is used to statistically determine if normality could be assumed for the selected products. The test results are shown in Table 4 and are dependent on the resulting P-Value, and the significance level determined beforehand. In this research, this significance level is 0.05, meaning demand is normally distributed if the P-Value is greater than 0.05.

Products	N	Median	Mean	SF	Excess Kurtosis	Tails Shape	P-Value	Normally distr? (P < 0.05)
Stoel Army (2 stuks)	12	13	16.0	0.718	-0.456	Mesokurtic	0.246	Normal
Stoel Barossa (2 stuks)	48	29.5	30.4	0.575	-0.305	Mesokurtic	0.028	Not-Normal
Stoel Bentley (Per stuk)	48	17	17.4	0.432	-0.636	Mesokurtic	0.044	Not-Normal
Stoel Chip (2 stuks)	45	16	17.9	0.617	0.013	Mesokurtic	0.070	Normal
Stoel Dahlia (2 stuks)	48	10	11.4	0.984	0.775	Mesokurtic	0.002	Not-Normal
Stoel Diamond (2 stuks)	48	25.5	27.4	0.691	0.199	Mesokurtic	0.029	Not-Normal
Stoel Exotic (2 stuks)	48	13	14.0	0.277	-0.169	Mesokurtic	0.365	Normal
Stoel Flame (2 stuks)	46	10	9.7	0.429	-0.245	Mesokurtic	0.290	Normal
Stoel Index (2 stuks)	9	9	11.9	0.485	-1.102	Mesokurtic	0.405	Normal
Stoel Issue (2 stuks)	43	2	3.0	1.164	0.680	Mesokurtic	0.000	Not-Normal
Stoel Jackson (2 stuks)	48	34	32.9	-0.561	-0.024	Mesokurtic	0.152	Normal
Stoel Riga (2 stuks)	42	18	20.4	0.464	-0.708	Mesokurtic	0.028	Not-Normal
Stoel Roady (2 stuks)	43	83	85.5	0.327	0.236	Mesokurtic	0.653	Normal
Stoel Rock (2 stuks)	47	24	24.1	-0.002	-0.429	Mesokurtic	0.169	Normal
Stoel Scott (2 stuks)	48	11.5	12.0	0.112	-0.408	Mesokurtic	0.291	Normal
Stoel Station (2 stuks)	48	11	10.7	0.464	0.000	Mesokurtic	0.205	Normal
Stoel Transfer/Grace (2 stuks)	48	54.5	56.2	0.210	-0.672	Mesokurtic	0.124	Normal
Stoel Utopia (2 stuks)	18	11	9.7	-0.083	-1.558	Mesokurtic	0.092	Normal
Stoel Watson (2 stuks)	48	31.5	31.6	0.312	-0.540	Mesokurtic	0.022	Not-Normal
Bonn Boxspring	41	0	0.0	0.000	0.000	Mesokurtic	0.000	Not-Normal
Boxspringset Bonn.	48	4	3.8	0.355	0.425	Mesokurtic	0.076	Normal

Table 19: Elaboration on the Shapiro-Wilk Test on Normality

Within Table 19, many factors of the demand distribution are tested. A small explanation will be given on important factors and most influencing relations:

- The number of data inclusions (N) indicates how many data points are included in the test. The maximum N is 48, while every smaller number indicates outliers or a shorter time in inventory. No direct relationship is found between shorter inventory and results on the test.

- The behaviour of the median towards the mean is an influencing indicator of the normal distribution. For the perfect normal distribution, the median and the mean are equal, while large deviations indicate abruption from the normality standard. Nevertheless, median and mean being equal or close does not directly prove normality.

- The skewness factor (SF) indicates the symmetry (symm.) of a distribution and is zero for a perfectly normal and thus symmetric distribution. High (SF > 1.00) or low (SF < -1.00) skewness factors indicate asymmetricity, which is a deviation from perfect normality. Generally, if the distribution is skewed to the right, the median is less than the mean. For skewness to the left, the opposite is true.

- The excess kurtosis and resulting tails shape describe the degree to which data cluster in the tails or the peak of a distribution. A perfect normal distribution follows a mesokurtic tail shape, being moderate in width and curves with a medium peaked height (McLeod, 2019).

- The P-Value indicates the final result of the test in the form of a probability of being normally distributed. The formula for this calculation will not be elaborated on because it is usually calculated automatically by software. If the resulting P-Value is greater than the stated significance, the distribution can be assumed normal.